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Research article

Industry clusters and firm performance: Evidence from the leather product industry in Addis Ababa

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ABSTRACT

Industrial clustering is the co-location of firms in a geographic area, which can lead to numerous economic benefits such as joint resources and knowledge pooling, R&D collaboration, technology sharing, and joint marketing. This study aims to examine the influence of industrial clustering on the performance of firms in the leather and leather products industry in Addis Ababa. Moreover, this study aims to investigates whether innovation capacity and collaboration networks indirectly contribute to the relationship between clustering factors and firms' performance. In this study, both primary and secondary data were collected for analysis. Partial Least Squares Structural Equation Modeling was employed to explore the impact of clustering on performance in terms of innovation, job creation, attracting investment, export intensity, and productivity growth. This study found that a one-unit increase in cluster factors is associated with a 0.43-unit increase in firm performance. The mediation analysis revealed that collaboration networks mediate the relationship between cluster factors and firm performance by 0.21 and innovation capacity mediates the relationship between cluster factors and firm performance by 0.15 units. The findings indicate that industrial clusters strongly influence firm performance within the leather industry in Addis Ababa. Therefore, the results suggest that innovation capacity and collaboration networks are mechanisms through which industrial clusters affect firm performance. Future researchers should explore the cluster effect in other industrial sectors and regions to validate the research findings.

1. Introduction

The Ethiopian leather industry is a vital sector with immense potential for industrial and economic development. It contributes significantly to employment, export earnings, and GDP growth, credited to the country's abundant livestock population that produces approximately 36 million square meters of leather annually [1,2]. Despite its growth potential and global demand, the industry faces significant challenges that impede its ability to achieve competitiveness and meet the nation's industrial development policy [3].

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One key challenge is the lack of adequate training and motivation among the workforce which is crucial element in leather goods production. This issue is further compounded by the scarcity of high-quality raw materials and limited access to industrial inputs such as chemicals, posing substantial constraints. Moreover, the industry's struggle to achieve global competitiveness represents a significant obstacle to realizing its full potential and meeting the objectives of Ethiopia's industrial development policy [4].

To address these challenges, Ethiopia has adopted a cluster-based strategy to integrate the leather sector into global value chains, aligning with the national development agenda. This aims to enhance productivity, competitiveness, and stakeholder capacity. The strategy is supported by initiatives like tannery upgrades, industrial park establishment, and ethical standards implementation. These efforts complement broader reforms aimed at promoting trade and strengthening the role of the private sector, which is central to Ethiopia's industrial development strategy [5].

Ethiopia's industrial development policy and strategies emphasize the creation of a favorable environment for sustainable growth. They focus on sectors like leather with a comparative advantage and potential for value addition. The policy aims to transform the industry from a raw material exporter to a finished goods manufacturer, thereby increasing its contribution to GDP and export earnings. The development of the leather product industry is also instrumental in promoting urbanization by creating employment opportunities and stimulating the growth of urban centers [6–8].

Despite these commendable efforts, the specific mechanisms through which industrial cluster development initiatives affect firm performance not sufficiently explored. Existing studies have mostly focused on the potential benefits of cluster factors without adequately examining how these resources translate into enhanced productivity, innovation, and competitiveness within the Ethiopian context [9]. This gap in understanding limits the ability of policymakers and industry stakeholders to effectively leverage them for sustainable development.

Underperforming industry clusters may be due to internal complexities, social and cultural factors, and inefficiencies in locational and institutional support. Policy and regulatory institutions may not sufficiently promote local products or firms to innovate and compete. Policymakers must address these challenges to promote enterprise growth in the leather sector. A recent study revealed a "missing middle" of firms in Ethiopia, where government support primarily targets new ones, leaving growing ones with insufficient attention [10]. Another study by Fleming [1] also found that government policies insufficiently supported micro/small enterprises, fostering mistrust rather than cooperation and innovation. The findings underscore the need to examine the institutional factors and complex power relations underlying domestic value chains and improve the situation to promote enterprise growth and sustain performance.

As a leather resource-rich country in Africa, Ethiopian leather clusters' performance is important for industrialization [11].While the impact of industrial clusters on firm performance has been explored in developed countries [12,13], there was limited research on the impact and the role of the mediating factors in transmitting the effect in developing countries, particularly within the context of the leather product industry. However, the findings of available studies have provided evidence which is inconsistent and sometimes contradictory. For instance, a study by Getahun [14] found that the performance of firms in government-created clusters has experienced significant declines in various metrics and another study by Lika [15] observed that government policies insufficiently supported micro/small enterprises, fostering mistrust rather than cooperation and innovation.

This study draws on agglomeration economies, network theory, and the resource-based view of the firm to investigate the influence of industrial clustering on firm performance in the context of Addis Ababa's leather and leather products industry to address the research gaps. It sought to answer the following research questions: How do industrial clusters impact firms' performance in the leather products industry in Addis Ababa? To what extent do innovation capacity and collaboration networks mediate the relationship between cluster factors and firm performance?

This study contributes to the literature on industrial clusters and firm performance. First, it fills gaps in understanding the nature of the leather products industry in Addis Ababa, a sector and region that have received limited empirical attention despite their significant economic potential. Second, the study employs partial least square structural equation modeling (PLS-SEM), which has not been sufficiently utilized in exploring the complex relationship of industry clustering, innovation capacity, collaboration networks, and firm performance. This methodological approach allows a comprehensive understanding of how these factors interact within the context of the Ethiopian leather industry. Furthermore, the study offers actionable implications and suggestions to policymakers and actors within the leather product based on how clustering affects firm growth and competitiveness to inform industrial development policies in developing countries.

The remainder of this article is structured as follows: Section 2 provides a literature review focusing on industrial clusters and firm performance analysis based on conceptual framework and prior research studies pertinent to this research. Section 3 focuses on the methods: data collection and analysis. The findings of the empirical analysis are presented in section 4. Discussion and analysis of the findings are presented in Section 5. The final section presents implications of the research, its limitations and the directions for future research.

2. Empirical literature and hypothesis development

This literature review and hypothesis development section examines the interplay between industry clusters, collaborative networks, innovation capacity, and firm performance. The review is structured into four main sections: the first section deals with the relationship between industry clusters and firm performance. The second section investigates how collaborative networks within clusters influence firm outcomes. The third section examines the role of innovation capacity in driving firm performance. The fourth section deals with the mediating effects of both collaborative networks and innovation capacity in the relationship between cluster factors and firm performance. By synthesizing current research in these areas, this review establishes a theoretical foundation for the study's hypotheses and the research question to be addressed.

2.1. Relationship between industry cluster and Firm performance

Firm performance refers to the extent to which a company achieves its operational and strategic goals, reflecting its efficiency and effectiveness in utilizing resources to generate value for stakeholders [16]. It is influenced by a complex interplay between cluster-level factors and firm-specific attributes [17,18].

Literature provides evidence supporting the positive influence of cluster factors on firm performance across various industries. A study by Stichhauerova et al. [19] found that clusters generally enhance competitiveness and performance, although the effects vary across sectors. This variability suggests the need for industry-specific examination, particularly in the leather goods sector.

Another study by Grashof [20] further elucidated that while clusters generally spur innovation and performance, the benefits depend on specific firm-level and regional dynamics. In the context of the leather goods industry, these dynamics may include access to specialized tanneries, shared distribution networks, and region-specific craftsmanship. Similarly, a meta-analysis by Gupta [21] in India provides compelling evidence that supports industrial clustering leading to significant increases in Gross Value Added (GVA) for firms, demonstrating tangible performance benefits of cluster membership.

The leather goods industry stands to benefit significantly from cluster factors. Physical resources within a cluster, such as shared testing facilities or specialized machinery, can enhance product quality and production efficiency [22]. A study by Tewari [23] on the Palar Valley leather cluster in India found that firms within the cluster experienced a 30 % increase in productivity due to shared infrastructure and specialized support services.

Institutional support, including industry-specific training programs or export promotion initiatives, can facilitate market access and compliance with international standards [24]. Research by Giuliani et al. [25] on the Biella textile cluster in Italy demonstrated that firms benefiting from strong institutional support were 40 % more likely to successfully enter international markets. Human capital, concentrated in a cluster, can foster knowledge spillovers and skill development crucial for innovation in leather product design and manufacturing techniques [26,27]. A study by Nadvi [28] on the Sialkot surgical instrument cluster in Pakistan revealed that firms within the cluster experienced a 25 % increase in product innovation rates due to the concentration of skilled labor and knowledge sharing.

Furthermore, a comprehensive analysis by Porter [29] across multiple industries found that companies operating within strong clusters achieved 2–4% higher annual growth rates compared to those outside clusters, underlining the competitive advantage of clustering in the leather goods industry.

Hypothesis (H1). Cluster factors (CF) which encompasses physical resources (PR), institutional support (IS), and human capital (HC) have a positive and significant impact on firm performance (FP) in the leather goods industry. Firms in well-developed clusters are expected to experience enhanced productivity, innovation capacity, and competitiveness.

2.2. Relationship between collaborative network and Firm performance

The literature provides strong support for the positive impact of collaborative networks on firm performance in the context of industrial clusters. A study by Stichhauerova et al. [19] demonstrated that clusters generally enhance competitiveness and performance across multiple industries in the Czech Republic, highlighting the role of inter-firm collaboration. This finding is further corroborated by Gupta [21], who revealed that collaboration within clusters can provide productivity gains.

In the specific context of the leather goods industry, collaborative networks can be particularly beneficial. The industry's complex supply chain, from raw material sourcing to final product distribution, necessitates strong inter-firm relationships. A study by Battaglia et al. [30] on the Italian leather industry found that firms engaged in collaborative networks experienced a 23 % increase in export performance and a 15 % improvement in product quality.

Collaborative networks can facilitate knowledge sharing about sustainable practices, a growing concern in the leather industry. Research by Kilduff and Tsai [31] demonstrated that firms in collaborative networks were 40 % more likely to successfully implement eco-friendly production processes, leading to improved market positioning and compliance with international standards.

Moreover, as Takahashi and Kongmanila [19] suggests, firms embedded in strong collaborative networks achieve superior performance due to enhanced learning and resource acquisition, which are crucial in the rapidly evolving fashion and accessories market that leather goods often serve. This is supported by a study from Ref. [32] on Spanish footwear clusters, which found that firms with strong collaborative ties were 30 % more innovative and 25 % more resilient to market fluctuations.

Furthermore, collaborative networks in the leather goods industry can lead to economies of scale and scope. A study by Schmitz [33] on the Sinos Valley shoe cluster in Brazil revealed that small and medium-sized enterprises (SMEs) engaged in joint actions increased their productivity by up to 40 % and significantly improved their global market access.

The literature supports the notion that collaborative networks have a positive and significant impact on firm performance in the leather goods industry. Specifically.

Hypothesis (H2). Collaborative networks (CN) have a positive and significant effect on firms' performance (FP) in the leather goods industry, with firms engaged in stronger collaborative networks experiencing enhanced productivity, innovation, and market performance.

2.3. Relationship between innovation capacity and Firm performance

The literature suggests a complex relationship between cluster factors, innovation capacity, and firm performance, particularly relevant to the leather goods industry. This relationship extends beyond direct effects, with Innovation capacity potentially serving as a mediating factor. Innovation capacity affects firm performance through enhancing organizational learning, absorptive capacity, and employee involvement in key areas of innovation outcome [34]. Extant research revealed that innovations serve as engines for firms to adapt to and shape the environment in which they operate [26], leading to firms continuous advancing, which helps to survive allowing firms to grow more quickly, be more efficient, and ultimately be more profitable than non-innovators [27]. Another empirical research by Calantone et al. [35] supports the notion that firms with strong innovation capabilities demonstrate better performance outcomes, including higher profitability and market share. Innovation capacity in this sector is particularly crucial given the rapidly changing consumer preferences and increasing demand for sustainable products. Research by Prajogo and Ahmed [36] demonstrated that firms with higher innovation capacity were 30 % more likely to successfully introduce new products and processes, leading to improved market performance. Drawing from previous studies, this research argues that innovation capacity positively affects firm performance in the leather goods industry.

Hypothesis (H3). Innovation capacity (IC) has a positive and significant effect on firm performance (FP).

2.4. Mediating role of collaborative network and innovation capacity on industry cluster and Firm performance nexus

While the direct relationships between industry clusters, collaborative networks, and innovation capacity with firm performance in the leather goods sector have been established, the unique characteristics of this industry merit further investigation on the interplay between these factors. The leather goods industry, with its blend of traditional craftsmanship and modern manufacturing processes, presents a distinctive environment for examining these relationships.

The leather goods value chain, from raw material sourcing to final product distribution, offers multiple opportunities for collaboration and innovation that can be enhanced by cluster dynamics. For instance, a study by Mukim [37] on the Indian leather industry found that firms in clusters were 20 % more productive than isolated firms, largely due to knowledge spillovers and shared resources. A report by the United Nations Industrial Development Organization (UNIDO) also highlighted that leather goods clusters in developing countries that fostered collaborative networks for eco-friendly practices saw a 15 % increase in export performance [38].

2.4.1. Innovation capacity as a mediator

The relationship between industrial clusters and firm performance extends beyond direct effects. Innovation capacity serves as a mediating factor, amplifying the benefits of cluster membership and translating them into tangible performance improvements. This mediation occurs through different mechanisms. This is particularly relevant in the leather goods industry, where innovation in sustainable practices and product design is crucial. For instance, a study of the Italian leather goods cluster in Tuscany by Randelli and Lombardi [39] revealed that firms with higher innovation capacity were 40 % more likely to successfully implement eco-friendly production processes, leading to improved market.

Empirical studies indicated that cluster benefits are often realized through improved innovation processes within firms [21,24]. This is exemplified in the leather goods industry, where cluster-based knowledge spillovers can lead to innovations in tanning processes, design techniques, and supply chain management. Research by Fundeanu and Badele [40] on the Romanian leather and footwear industry demonstrated that firms in clusters with strong innovation capacities were able to increase their export performance by up to 35 % compared to firms with lower innovation capacities.

Furthermore, the mediating role of innovation capacity is particularly pronounced in traditional industries like leather goods manufacturing, where the balance between craftsmanship and technological advancement is crucial. A study by Giuliani [41] on the wine industry, which shares similarities with leather goods in terms of traditional production methods, found that firms with higher absorptive capacity (a key component of innovation capacity) were 50 % more likely to benefit from cluster knowledge flows and improve their overall performance. These literature supports the notion on the mediating role of innovation capacity in the relationship between cluster factors and firm performance.

Hypothesis (H4). Innovation capacity (IC) mediates the relationship between cluster factors (physical resources, institutional support, and human capital) and firms' performance (FP).

2.4.2. Collaborative networks as a mediator

Research indicates that both collaborative networks and innovation capacity mediate the relationship between cluster factors and firm performance, highlighting the importance of these elements in achieving positive outcomes particularly relevant to the leather goods industry. A study by Inkpen and Tsang [42] demonstrated that clusters appear to boost performance primarily by stimulating cooperative networks between participating enterprises. For leather goods manufacturers, this could mean that the physical proximity and shared resources within a cluster (cluster factors) lead to enhanced performance largely through the formation of strong collaborative networks. These networks facilitate knowledge sharing about new tanning techniques, joint marketing initiatives, or collective bargaining with suppliers. A specific example from the Italian leather goods district of Santa Croce sull'Arno showed that firms engaged in collaborative networks experienced a 22 % increase in productivity compared to isolated firms [43].

A recent research by Giuliani [41] provides further evidence supporting the notion that the benefits of clusters are often mediated through the collaborative networks they foster. In the leather goods industry, this could imply that firms better able to form and leverage collaborative relationships within the cluster are more likely to translate cluster resources into improved performance outcomes. A study of the Pakistani leather industry by Nadvi [28] found that small firms in clusters that actively participated in joint actions and inter-firm cooperation were 35 % more likely to meet international quality standards and access global markets. This underscores the critical role of collaborative networks in translating cluster advantages into firm-level performance.

Moreover, research on the Brazilian footwear cluster by Schmitz [44] revealed that firms engaged in strong collaborative networks were 40 % more resilient to market shocks and able to adapt more quickly to changing consumer demands. This resilience and adaptability directly contribute to improved firm performance in volatile market conditions.

Therefore, it is reasonable to hypothesize that collaborative networks mediate the relationship between cluster factors and firm performance.

Hypothesis (H5). Collaboration network (CN) mediates the relationship between cluster factors (physical resources, institutional support, and human capital) and firms' performance (FP).

2.5. Conceptual framework

Having examined the direct and mediating relationships between cluster factors, collaborative networks, innovation capacity, and firm performance in the context of leather goods manufacturing, this study presents a conceptual framework that integrates these key constructs, providing a holistic view of their interconnections within the leather goods industry. This framework incorporates cluster factors built from physical resources, human capital, and institutional support, along with firm performance, as depicted in Fig. 1. Each component of the framework is designed to address main research questions, particularly how these cluster factors interact with innovation capacity and collaboration networks to enhance firm performance.

The framework begins with the cluster factors which comprise shared and unique resources that provide specialized inputs, knowledge exchange platforms, and collaborative networks that individual firms operating in isolation cannot readily access [18,48]. Furthermore, the conceptual framework considers collaboration networks and innovation capabilities as mediators that strengthen the performance of firms in the leather product industry. Collaborative networks, expressed by the strength and quality of interactions among firms, suppliers, customers, and other stakeholders, are crucial for achieving product distinctiveness and leveraging cluster-level performances [49,50]. In addition to collaboration networks, a firm's innovation capacity explains its internal innovation capabilities, i.e., the firm's position to capitalize on knowledge spillovers and complementarities facilitated by clusters, thereby enhancing its performance outcomes [51,52].

3. Methodology

The research adopted a quantitative research approach to examine the impact of industrial clusters on the performance of firms in the leather product industry in Addis Ababa. This quantitative research design is well suited to testing the hypothesized relationships between the key constructs, as it allows for the statistical analysis of numerical data and the estimation of the magnitude and significance of the effects. The research employed a cross-sectional survey design, where data was collected from the target population at a single point in time. This design is appropriate for the current study, as it aims to capture the perceptions and experiences of leather product firms operating within the industrial clusters at the time of the research. The primary data analysis technique for this study was Partial Least Squares Structural Equation Modeling (PLS-SEM) using Smart PLS 3.2.9. PLS-SEM is a well-established multivariate analysis method that is particularly suitable for complex models with multiple latent variables and mediating effects, discussed in the conceptual framework of the study. Application of the PLS-SEM allows for the estimation of the measurement model (reliability and validity of the constructs) and the structural model (the relationships between the constructs), providing a comprehensive assessment

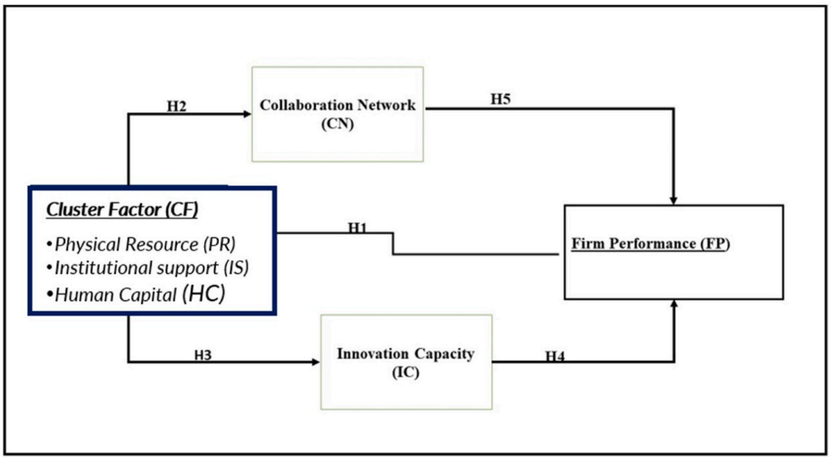

Fig. 1. Conceptual framework of the study from [45–47].

of the hypothesized model. PLS-SEM is preferred over covariance-based SEM (CB-SEM) due to its efficiency in handling small sample sizes and its usefulness in exploratory and predictive research Hair et al. [53], which complies with the research objective of the current study. In addition, PLS-SEM is suitable for models with higher-order constructs, the construct Cluster factors, in the proposed conceptual framework since it can effectively evaluate these complex relationships.

3.1. Measures to constructs

To ensure the reliability and validity of the findings, the study employed established scales to measure key constructs. All items were measured using a 5-point Likert scale for performance ranging from 1 (significantly declined) to 5 (significantly improved); for availability of factors/resources ranging from 1 (none/very poor) to 5 (excellent), and for strength of collaboration network and innovation capacity ranging from 1 (Very low) to 5 (Very high). The number of items for each construct was specified to ensure clarity and consistency in measurement.

Cluster factors, built from three important dimensions, are considered as exogenous factors in this study. The physical resources (PR), one of the subdimensions, was measured using six reflective items on a 5-point Likert scale, ranging from 1 (none/very poor) to 5 (excellent), adapted from established sources [54–56]. Institutional Support (IS), the second subdimension, was measured using four reflective items on a 5-point Likert scale ranging from 1 (none/very poor) to 5 (excellent), adapted from Refs. [14,57]. The sub-dimension Human Capital (HC) was assessed using five reflective items on a 5-point Likert scale, from 1 (none/very poor) to 5 (excellent), adapted from Ref. [58].

The mediating variable collaborative networks (CN) was designed to measure the extent of collaborative networks within the clusters and firms outside the cluster. To measure the construct a 6-item measurement questions with a 5-point Likert scale items was employed, ranging from 1 (Very low) to 5 (Very high), adapted from Ref. [59]. Similarly, the mediating variable innovation capacity (IC) was designed to assess a firm's ability to introduce new products or processes, upgrade the existing product, and identify and penetrate new markets for their products. The construct was measured using a 6-item scale adapted from Refs. [60–62].

The dependent variable firm performance was measured using a multidimensional 6-item scale ranging from 1 (significantly declined) to 5 (significantly improved), adapted from Refs. [63,64]. This scale captures various aspects of performance including financial performance, market performance, and operational efficiency. Details of the measurement items and scales for the items in each construct are presented in Table 10.

3.2. Data collection and sampling strategy

3.2.1. Data collection Tools and process

The primary method for data collection in this study was a structured questionnaire, designed to capture detailed information on key constructs, such as cluster factors, innovation capacity, collaborative networks, and firm performance. The questionnaire was adapted from validated scales that were proven effective in previous research, with modifications to better fit the local context of the leather product sector in Addis Ababa. To ensure content validity, the questionnaire underwent a rigorous review process involving both industry practitioners and academic researchers.

3.2.2. Population and sampling framework

The research focused on the leather product firms within the industrial clusters of Addis Ababa, Ethiopia. As of mid-2023, there were 538 operational leather product firms in the city, according to data from the Addis Ababa Industry, Labor, and Skill Development Bureau. The study excluded firms that were either not yet operational or had been active for less than a year, as these did not reflect established production practices accurately. The target population for this study included firms that were active and had established practices, to provide a more accurate reflection of the industry's dynamics.

3.2.3. Sampling size determination and selection

Guided by the recommendations of Hair et al. [65] and Bentler and Chou [66], the study proposed a sample size of 150 leather product firms. This size is considered sufficient to conduct a robust Partial Least Squares Structural Equation Modeling (PLS-SEM (Partial Least Squares Structural Equation Modeling) analysis, accommodating the complexity of the model, which involves multiple constructs and indicators. To account for potential non-responses or missing data, the survey was distributed to a larger initial sample, ensuring that at least 150 complete responses were collected. The firms were systematically selected, and the questionnaires were distributed and collected by three trained enumerators, ensuring a high response rate.

3.2.4. Ethical consideration

To ensure a professional and ethical research process, ethical issues were a top priority throughout the study, including data collection and analysis. Kivunja and Kuyin [67] emphasizes the importance of ethical principles such as privacy, accuracy, property, and accessibility when working with research respondents. Similarly, obtaining approval from relevant authorities to access study sites and participants is crucial [68].

In this study, the research was conducted ethically, treating respondents with courtesy and respect. The investigator obtained a formal letter from the College of Urban Development and Engineering (CUDE) before commencing data collection. Respondents were briefed on the study's purpose and informed that their participation was voluntary, allowing them to withdraw at any stage. They were also assured that the research results would be used solely for academic purposes and would not be used to harm them. Confidentiality and anonymity were guaranteed for all information provided. Informed consent was obtained from each respondent before they were politely requested to answer the study questions. All materials used in this research were properly acknowledged, and the researcher ensured accurate presentation of data without plagiarism [68].

3.3. Data analysis

The Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis was conducted using Smart PLS 3.2.9 software. The data reliability and validity of the measurement model were evaluated using the recommended techniques. After the structural model of the measurement was developed, a structural model assessment was conducted. Finally, the structural model was assessed to find out whether the proposed hypotheses within the framework was empirically validated or not (hypothesis testing). For the structural model assessment, bootstrapping was performed with 5000 resamples to determine whether the path coefficients were significant or not. The presentations are provided in the subsequent result section.

4. Results

4.1. Measurement model (outer model) evaluation

Measurement model evaluation is mainly composed of checking discriminant validity and internal consistency reliability, which are important steps for establishing the reliability of the constructs. We have used commonly accepted criteria for our measurement model assessment, placing a threshold of 0.7 for indicator reliability, 0.8 for internal consistency reliability, 0.5 for convergent validity, and the Fornell-Larcker criterion for discriminant validity. Each threshold is justified by alpha reliability standards in our field, facilitating confidence in our model's robustness. The assessment of the measurement model process begins with a detailed examination of the measurement indicators and their relationship to the constructs they are intended to represent.

Through the measurement model evaluation, the researcher determines discriminant validity, internal consistency reliability, and convergent validity. These evaluations have been conducted using the threshold values recommended by the assessment. The results have also been evaluated for different types of validity including discriminant validity, internal consistency reliability, convergent validity, and construct validity [69,70].

Through this approach, we aim to ensure that the measurement model for the SEM analysis is rigorous and that each construct correctly expresses the concept of cluster factors and their influence on the firm's success. This step allows us to validate the relationships in the research model and make reliable conclusions about the cluster effect on the performance of firms within the given industry.

4.2. Indicator reliability- factor loadings

Indicator reliability is one of the essential steps of an assessment that deals with the validity and direction of each observed phenomenon and its underlying construct. This relationship is measured with outer loadings, which in turn estimate how well a selected variable reflects the construct it is supposed to represent [71]. The range of the threshold for factor loadings is from −1 to 1, thus, the factors and variables with correlations are revealed. Positive loadings imply a positive relationship while negative loadings suggest a negative relationship [72]. From the analysis, all the items had a factor loading of above 0.7 as depicted in Table 10. This implies that the variables had a strong relationship with their given constructs and assured the reliability of the indicators in measuring the impact of the cluster on the firm's performance. The factor loads confirm the indicator's reliability as recommended by Hair et al. [73] provide confidence in the measurement model's ability to capture the constructs of interest in the study.

4.3. Internal consistency reliability

Internal consistency reliability, which measures the agreement among the indicators that form one latent construct, is considered to be among the fundamental measures for assessing the level of intertwining between the indicators in a latent construct [74]. It is necessary to take into account the reliability of the theoretical model creation, which is particularly significant in this case, as we are aiming to identify cluster factors and a company's performance.

In the present work, two kinds of measurement indices: Cronbach's Alpha (CA) and Composite Reliability (CR) were utilized to measure Internal Consistency Reliability. Cronbach's Alpha, which is a classical measure of internal reliability, presumes that indicators within the construct contribute equally to the construct's reliability [75]. The internal consistency assessment in the study shows complete internal consistency, where Cronbach's Alpha values ranged from 0.85 to 0.91. These values indicated that the items within each construct are reliable measures of the same underlying concept, which is vital for the accurate assessment of cluster effects.

Composite Reliability (CR) is the next measure of assessment that offers a more comprehensive understanding as it recognizes the varying contributions of each indicator [54,55]. This point is especially important in research where the strength of the link between indicators and constructs may be different. The composite reliability values for each construct of the survey exceeded the advised level of 0.7, with values from 0.90 to 0.93, according to Table 10. This high value also indicates the SEM model has good internal consistency reliability, which could support further SEM analysis and thereby improve the model's reliability.

By ensuring that the constructs demonstrate high internal consistency, further research could proceed with confidence in the SEM analysis. Considering that the proposed measurement model for the research is capable of accurately capturing the complex interplay between cluster factors and firm's performance.

4.4. Assessment of convergent and discriminant validity

4.4.1. Convergent validity

Convergent validity is an essential part of construct validity, especially in the PLS-SEM framework, regarding the level of agreement of multiple measures of a single construct. This form of convergent validity is critical for making sure that the indicators used in the study truly measure the same underlying construct, which is crucial for investigating the cluster effect on firm performance [56].

To establish convergent validity, Average Variance Extracted (AVE) was calculated for each construct, based on the amount of common variance that each indicator shares. In our measurement model, the AVE values range between 0.63 and 0.68 as demonstrated in Table 10. The values are above the recommended threshold of 0.5, indicating the contribution from the underlying concept that is supposed to be measured is quite high. This confirms the notion of convergent validity based on the consistency of the indicators, which make up the measurement model.

The satisfaction of convergent validity in the present study indicates the constructs of Cluster factors, Collaborative Networking, Innovation Capacity, and Firm Performance are well-supported and measured with precision. It is important to note that this step is essential in validating the structural measures employed, and the ensuing step of SEM analysis, which aims to decipher the influence of the clustering of firms within the industry on their performance.

4.4.2. Discriminant validity

The discriminant validity demonstrates the variables in one construct are different from those in other constructs. Discriminant validity can be assessed by analyzing the components of AVE for each variable and comparing them with others. The current body of literature proposes two prominent approaches to assess discriminant validity: the Fornell and Larcker criterion, the cross-loadings approach among the latent variables, and the HTMT criterion are suggested to check for discriminant validity.

4.4.3. Fornell and Larcker criterion

The Fornell and Larcker criterion is an important indicator for evaluating discriminant validity. According to this criterion, discriminant validity is established when two conditions are met: (1) The square root of the average variance extracted (AVE) for each construct should be greater than the correlations between that construct and all others, and (2) each latent variable should explain more variance in its indicators than it shares with other constructs [57].

In this study, the square root values of AVE for each construct indeed exceeded the inter-correlations with other constructs, as evidenced in Table 1. The diagonal elements, presented in bold, represent the square root of AVE, while the non-bolded figures below the diagonal show the inter-correlation values between constructs. The fact that all off-diagonal elements are lower than the corresponding diagonal elements confirms that the constructs in our model are distinct and that the Fornell and Larcker criterion for discriminant validity is met [58]. The results show the constructs of Cluster factors, Collaborative Networking, Innovation Capacity, and Firms' Performance are uniquely captured and not correlated with each other in this SEM analysis.

4.4.4. Cross-loadings

The cross-loading value is another important consideration when checking discriminant validity. According to this approach, discriminant validity is established if the indicators of a specific construct have higher loadings on their corresponding construct than on other constructs [76].

The results presented in Table 2 illustrate the findings from the Smart PLS algorithm with all indicators in the measurement model having higher loadings on their designated latent variables than on any other variables. This pattern is consistent across each block of indicators, with loadings being higher within their construct than across the other constructs, both within the same rows and columns. Such findings validate the assumptions of the conceptual model regarding the distinctiveness of each latent variable.

The cross-loading results demonstrated that the constructs Collaborative Networking, Innovation Capacity, and Firm Performance were uniquely defined and measured and confidently it can interpret the relationships within the model.

4.4.5. Discriminant validity HTMT

HTMT is another metric for checking discriminant validity. Results reveal that all HTMT values are below the conservative

Table 1
Discriminant validity -Fornell-Larcker Criterion.

Construct	CN	FP	HC	IC	IS	PR
Collaboration network	**0.80**					
Firm performance	0.75	**0.82**				
Human resource	0.31	0.21	**0.80**			
Innovation capacity	0.62	0.71	0.11	**0.84**		
Institutional support	0.19	0.21	0.10	0.15	**0.83**	
Physical resource	0.62	0.76	0.04	0.64	0.14	**0.82**

Notes: Highlighted values on the diagonal are the square root of average variance extracted (AVE) and correlations are off-diagonal

Table 2
Cross-loadings for discriminant validity assessment.

Item	CN	FP	HC	IC	IS	PR
CN1	**0.74**	0.51	0.27	0.35	0.09	0.34
CN2	**0.83**	0.63	0.25	0.52	0.11	0.50
CN3	**0.83**	0.62	0.24	0.51	0.17	0.49
CN4	**0.82**	0.65	0.34	0.50	0.15	0.51
CN5	**0.78**	0.55	0.23	0.52	0.16	0.53
CN6	**0.77**	0.60	0.16	0.54	0.21	0.56
FP1	0.57	**0.74**	0.17	0.44	0.10	0.50
FP2	0.67	**0.86**	0.16	0.64	0.14	0.68
FP3	0.63	**0.85**	0.15	0.62	0.20	0.66
FP4	0.65	**0.87**	0.25	0.61	0.22	0.64
FP5	0.63	**0.85**	0.19	0.62	0.19	0.69
FP6	0.51	**0.76**	0.14	0.51	0.20	0.57
HC1	0.24	0.17	**0.75**	0.00	0.12	0.05
HC2	0.20	0.15	**0.80**	0.12	0.09	0.03
HC3	0.27	0.14	**0.82**	0.09	0.09	0.02
HC4	0.24	0.08	**0.83**	0.08	0.11	−0.01
HC5	0.28	0.26	**0.81**	0.13	0.02	0.05
IC1	0.44	0.48	0.12	**0.71**	0.04	0.39
IC2	0.56	0.60	0.07	**0.87**	0.10	0.56
IC3	0.54	0.62	0.07	**0.87**	0.15	0.55
IC4	0.54	0.61	0.15	**0.85**	0.16	0.52
IC5	0.53	0.61	0.09	**0.86**	0.14	0.60
IC6	0.51	0.61	0.06	**0.85**	0.15	0.58
IS1	0.18	0.25	0.04	0.16	**0.84**	0.22
IS2	0.12	0.15	0.05	0.11	**0.83**	0.12
IS3	0.16	0.15	0.09	0.12	**0.85**	0.08
IS4	0.15	0.12	0.17	0.09	**0.79**	−0.02
PR1	0.49	0.60	0.05	0.45	0.04	**0.76**
PR2	0.54	0.67	0.04	0.57	0.10	**0.84**
PR3	0.53	0.66	0.01	0.55	0.15	**0.84**
PR4	0.50	0.66	0.10	0.52	0.13	**0.84**
PR5	0.49	0.58	0.02	0.54	0.11	**0.82**
PR6	0.50	0.60	−0.03	0.55	0.16	**0.83**

Source: Field Survey, 2023

threshold of 0.85 as evidenced in Table 3, which is an important indicator to check for the distinctiveness of the items in their latent construct. The findings provide strong support for the presence of discriminant validity, supporting that the indicators in the measurement model are indeed capturing their intended constructs with a high degree of specificity. The confirmation of discriminant validity through the HTMT criterion adds another layer of assurance to our SEM analysis, ensuring that the constructs of Cluster factors, Collaborative Networking, Innovation Capacity, and Firm Performance are distinctly and accurately measured.

Overall, the measurement model assessment indicated the presence of high reliability, convergent validity, and discriminant validity for variables. The large values of CR, AVE, and CR indicate the stability of the measurement model and the validity of their ability to explain underlying factors. Additionally, a discriminant validity analysis has confirmed the uniqueness of all the constructs. Reliability and validity results create a foundation for the next step of SEM analysis (structural model assessment) analysis.

4.5. Higher order construct (HOC) establishment

Following the establishment of a measurement model characterized by strong reliability, convergent validity, and discriminant validity, the next stage is a validating the higher-order constructs. Within the PLS-SEM framework, the extended repeated indicators approach and the two-stage approach are widely used approaches utilized to validate higher-order constructs [56].

In the two-stage approach, to validate a formative higher-order construct (HOC), it is necessary first to compute the scores of the

Table 3
Discriminant validity HTMT.

Construct	CN	FP	HC	IC	IS	PR
Collaboration Network (CN)						
Firm Performance (PR)	0.84					
Human Capital (HC)	0.35	0.23				
Innovation Capacity (IC)	0.69	0.77	0.13			
Institutional Support (IS)	0.21	0.23	0.14	0.16		
Physical Resource (PR)	0.69	0.84	0.07	0.70	0.16	

Source: Field Survey, 2023

lower-order constructs (LOCs), which are measured by multiple reflective items. The latent scores generated in the LOCs measurement analysis are used as indicators for the higher-order constructs. In this study, the higher-order construct is the Cluster factors comprise the Physical Resources (PR), Institutional Support (IS), and Human Capital (HC). Collaborative Networking (CN), Innovation capacity (IC), and firm performance (FP) have been previously validated as LOCs.

To establish the validity of the higher-order construct, we examined values for outer weights, outer loadings, and variance inflation factor (VIF). The outer weights indicated the relative contribution of each lower-order and higher-order construct, and in our analysis, outer weights were found to be statistically significant. The outer loadings were also significant indicating their relevance to the HOC. Furthermore, the VIF values were all below the recommended threshold of 5 [77], indicating the absence of multicollinearity concerns (see Table 4). Meeting all these criteria suggested that the validity of the HOC, Cluster factors, in our model.

The establishment of the HOC supports the structural model analysis, where the effect of Cluster factors on Firms' Performance, mediated by Collaborative Networking and Innovation Capacity, can be explored.

4.6. Structural model assessment

Once the higher-order construct (HOC) is established and validated, attention shifts to the assessment of the structural model. The statistical significance of the path coefficients was assessed using the bootstrapping procedure (5000 bootstrap samples). The results of the PLS-SEM including the path coefficients and their significance, along with their respective R^2 values, are presented in Fig. 2. Before discussing the evaluation of the model, collinearity diagnostics were performed. Assessment of the structural model is a critical step as it examines the functional relationships between constructs, which are essential to understanding the factors that influence firm performance within a specific geographic context. The analysis of the structural model quantifies the strength and direction of relationships among latent constructs, specifically the cluster factors (CF) and firm performance (FP).

4.6.1. Assessment of collinearity issues

One of the requirements in the PLS-SEM evaluation is determining collinearity issues between the predictor constructs. This is achieved by looking at the VIF values, especially the inner VIF values. As seen from Table 5, for all combinations between endogenous constructs and their exogenous predictors, the VIF values are below the threshold value of 5. Such results indicate that multicollinearity is not an issue for the model. The absence of collinearity problems means that path coefficients are reliable and, thus, the influence of each predictor on the endogenous variables can accurately be interpreted. This analysis further describes the parts of cluster factors, innovation capacity, and collaborative networking to understand how they drive firm performance.

4.6.2. Assessment of coefficient of determination (R^2)

The coefficient of determination, or R-Square (R^2), the proportion of variance in the dependent variable explained by the independent variables. The goodness of fit of a model reflects the model's predictive accuracy and the combined effect of exogenous constructs on endogenous variables. The greater the R^2 value, the closer it is to 1, the greater the predictive power of the model. Using the Smart PLS algorithm and bootstrapping with 5000 samples, R^2 values were obtained and corresponding t-statistics values were calculated, as displayed in Table 6. These R^2 values for collaboration networking (CN) is 0.46, indicating that approximately 46 % of its variance in the collaboration network is accounted for by the model. Similarly, the innovation capacity (IC) has an average value of 0.42, denoting that the model captures 42 % of its variance. The analysis revealed the highest R^2 for firm performance (FP) at 0.74, suggesting that the model explains 74 % of its variation.

According to Chin [54], R^2 values of approximately 0.670, 0.333, and 0.190 indicate of substantial, moderate, and weak predictive abilities, respectively. With an R^2 of 0.74 for the firm's performance, this model has significant explanatory power, surpassing Chin's threshold for substantial explaining power.

4.6.3. The effect size (f^2)

The f^2 values quantify the magnitude of an exogenous construct's effect on an endogenous construct, which helps to identify the relative importance of each predictor, being one of the model components. The f^2 value of 0.02 means a small effect, the f^2 value of 0.15 shows a medium effect, and the f^2 value of 0.35 or higher demonstrates a large effect [78]. The results of this research show that path coefficients from collaboration networking (CN) and innovation capacity (IC) to firm performance (FP) have the values $f^2 = 0.18$ and $f^2 = 0.11$ respectively. These values of the medium effect size denote that the CN and IC contribute a significant impact to the FP in case of this study.

Table 4
Higher order construct measurement mode assessment.

HOC	LOC	Outer weights	T Statistics	P Values	Outer loading	P Values	VIF
CF	HC	0.26	2.47	0.01	0.30	0.01	1.01
	IS	0.10	1.64	0.05	0.27	0.00	1.03
	PR	0.93	21.61	0.00	0.96	0.00	1.02

Source: Field Survey, 2023

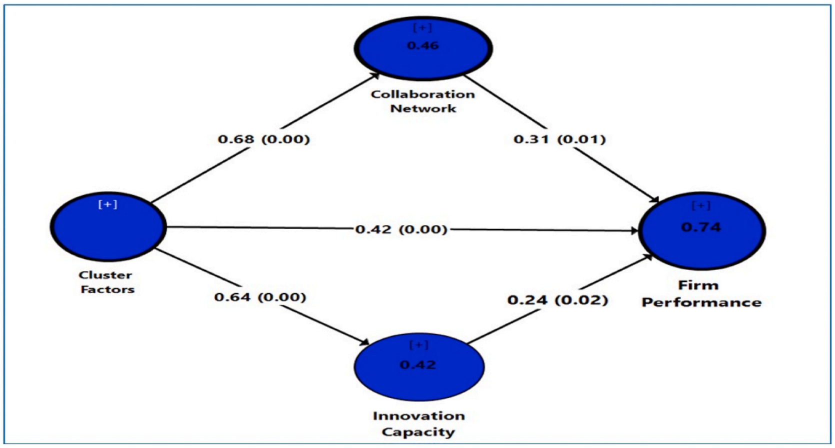

Fig. 2. Structural model assessment for higher order construct (HOC)

Table 5
Collinearity Statistics (VIF values in the structural model).

	CF	CN	FP	IC
CF		1.00	2.17	1.00
CN			2.08	
FP				
IC			1.92	

Source: Field Survey, 2023

Table 6
R-Square (R^2).

Construct	R-Squared	SE	T Statistics (|O/STDEV|)	P Values
Collaboration Network	0.46	0.09	5.37	0.00
Firm performance	0.74	0.05	16.06	0.00
Innovation capacity	0.42	0.09	4.71	0.00

Source: Field Survey (2023)

4.6.4. Predictive relevance of the model

In conducting PLS-SEM analysis using Smart PLS, researchers recommend checking the model's predictive relevance to evaluate the model's quality [65]. A model construct cross-validated redundancy (Q^2) is a metric that helps to assess the predictive relevance [79]. Using squared cross-validated redundancy (Q^2), it is possible to assess how much the construct differs from the other constructs. The positive Q^2 indicates that the model is a good predictor of the construct relationship, which in turn implies that the construct successfully captures a significant part of the variance of the other constructs [80].

According to the literature, a Q^2 value greater than zero is considered to have predictive relevance, while values below zero indicate a lack of predictive relevance. The threshold of 0.25 is often cited as a benchmark for assessing low versus high predictive relevance, with values above this threshold suggesting that the constructs have substantial predictive relevance [80].

In this study, the Q^2 values for all constructs exceed the 0.25 threshold values, as can be observed in Table 7. This result indicates that each endogenous construct in the model demonstrates high predictive relevance. The high redundancy values for the constructs in this model provide confidence in the practical utility of the findings. The model suggests that the constructs collaboration networking (CN), innovation capacity (IC), and firm performance (FP) are not only theoretically sound but also empirically robust in predicting

Table 7
Construct cross-validated redundancy (Q^2).

Constructs	SSO	SSE	Q^2 (=1-SSE/SSO)
Cluster Factors	450	450	
Collaboration Network	900	644	0.29
Firm performance	900	468	0.48
Innovation capacity	900	643	0.29

Source: Field Survey, 2023

firm success in clustered environments.

4.6.5. *Hypothesis testing on the effect of cluster factors on firm performance*

Having verified the validity and reliability of the measurement model and ensuring that the quality criteria are met; now this is the time to proceed to hypothesis testing. Table 5. 8 presents the regression results obtained by bootstrapping with 5000 resamples for the inner model. The significance of the regression paths was assessed by the bias-corrected at 95 % confidence intervals, using an alpha value of 0.05 as a basis [55,81,82]. This strategy gives a good estimate of confidence intervals that is unbiased considering the possible biases in the bootstrap distribution. The estimated regression coefficients are based on these bias-corrected confidence intervals to assess the significance of the hypothesized causal relationships in the structural model.

4.6.5.1. Cluster factors and Firm performance (H1). hypothesis one (H1) posited that the cluster factors (Physical resources (PR), institutional support (IS), and human capital (HC)) have a positive and significant effect on the performance of firms in the leather product industry within the specified city context. The analysis supported this hypothesis, revealing a significant and positive relationship between cluster factors and firm performance. The path coefficient demonstrates (see Table 8) a positive and significant relationship between cluster factors and firm performance within the leather product clusters. The analysis revealed that cluster factors significantly and positively predicted firm performance with ($\beta = 0.43$, 95 % CI [0.27, 0.62], $p < .001$). The result implies that a one-unit increase in cluster factors (access to Physical resources, institutional support, and human capital) is associated with a 0.43-unit increase in the expected value of firm performance. Therefore, hypothesis H1 is supported by the findings.

4.6.5.2. Collaboration network and Firm performance (H2). H2: Collaborative networks (CN) were believed to play a positive and significant role in the performance of firms (FP) in the leather product industry. The findings show the positive and significant domain from collaborative networks to company performance ($\beta = 0.31$, 95 % CI (0.11, 0.56), $p < .05$). In this context, the path coefficient of 0.31 indicates that for every 1-unit increase in collaborative networks, there is a 0.31-unit rise in firm's performance. Thus, the above empirical results support H2 and underline that collaborative networks highly influence the firm's performance positively. It implies that the company may do that by creating and improving the collaboration between it and these networks like partners or suppliers, industries and customers.

4.6.5.3. Innovation capacity and Firm's performance (H3). The study uses empirical data as a basis to investigate the influence of IC on FP. Hypothesis H3 states that innovation capacity has a positive and significant effect on firm performance. The results of the analysis indicated a positive and statistically significant coefficient ($\beta = 0.24$, 95 % CI [0.06, 0.44], $p < .05$) as we can observe from Table 8.

Since the path coefficient for innovation capacity (IC) = 0.24, it suggests that there will be a 0.24-point increase in firm performance for a unit increase in innovation capacity. With this in mind, the empirical results suggest that innovation capacity is key to the firm's performance.

4.7. *Mediation analysis*

The study explored the mediating role of collaboration networks and innovation capacity in the link between cluster factors and firm performance. A mediation analysis was performed using the bootstrapping approach in Smart PLS 3 with a 95 % CI (with a threshold of 1.96, p-value <0.05 to explore the significance of direct and indirect effects [83]. The results are presented in Table 9.

4.7.1. *Direct effect*

The direct effect means the impact that is brought about by an independent variable on a dependent variable in the presence of the mediating variable. To conduct the direct effect estimation, a bootstrap analysis of 5000 samples was carried out. The bootstrap regression showed that the cluster factors have a highly and positively significant effect on firm performance ($\beta = 0.43$, $t = 3.93$). This finding implies that a one-unit increase in the presence of cluster factors is associated with a 0.43 growth in firm's performance. The result implies that the cluster factors including availability of physical resources, institutional support, and human capital together have a positive and significant effect on the performance of firms in the leather sector.

4.7.2. *Indirect effects*

Cluster factors (CF) not only affect firm's performance directly, but also indirectly affect firm performance (FP) through the

Table 8
Hypothesis testing and path coefficients results for the inner model.

Hypotheses	Path Coefficient	SD	T Statistics	P Values
Cluster _Factors - > Collaboration Network	0.68	0.06	10.83	0.00
Cluster _Factors - > Firm _Performance	0.43	0.11	3.93	0.00
Cluster _Factors - > Innovation Capacity	0.64	0.07	9.34	0.00
Collaboration Network - > Firm _Performance	0.31	0.14	2.31	0.01
Innovation Capacity - > Firm _Performance	0.24	0.11	2.07	0.02

Source: Field survey (2023)

Table 9
Mediating Effect of Innovation capacity and collaboration networking.

Path	Direct effect				Path	Indirect effect				Total effect				
	Coeff.	SD	T-Statistics	P-Values		Coeff.	SD	T Statistics	P Values	Path	Coeff.	SD	T Statistics	P Values
CF - > FP	0.43	0.11	3.93	0.00	CF- > CN - > FP	0.21	0.10	2.12	0.02	CF- > FP	0.79	0.05	17.74	0.00
CN - > FP	0.31	0.14	2.31	0.01	CLF - > IC - > FP	0.15	0.08	1.93	0.03					
IC - > FP	0.24	0.11	2.07	0.02										

Note: CF=Cluster Factor, CN=Collaboration Network, Coeff. = Coefficients, IC=Innovation Capacity, FP=Firm Performance, SD=Standard Deviation

Table 10
Reliability and validity Analysis (Cronbach's Alpha, Composite Reliability, and Convergent Validity.

Construct	Indicators	Construct validity (outer loading)	Cronbach Alpha	CR	AVE
Firm Performance (FP)					
Productivity growth (FP1)	FP1	0.74	0.90	0.92	0.67
Cost efficiency (FP2)	FP 2	0.86			
Export performance (FP3)	FP 3	0.85			
Employment growth (FP4)	FP 4	0.87			
Sale volume (FP5)	FP 5	0.85			
Market share growth (FP6)	FP 6	0.76			
Innovation capacity (IC)					
Product line upgrade (IC1)	IC1	0.71	0.91	0.93	0.70
Introducing new technology or process (IC2)	IC2	0.87			
Frequency of new product development (IC3)	IC3	0.87			
New market discovery (IC4)	IC4	0.85			
Innovative marketing and promotion (IC5)	IC5	0.86			
Overall innovation activities (IC6)	IC6	0.85			
Institution Support (IS)					
Research and development (R&D) supporting activities (IS1)	IS 1	0.84	0.85	0.90	0.68
Tailored training programs for firms employees (IS2)	IS 2	0.83			
Collective promotion and marketing initiatives for the leather products (IS3)	IS 3	0.85			
Access to information from local institutions (IS4)	IS 4	0.79			
Physical Resource (PR)					
Reliability and accessibility of critical infrastructure (PR1)	PR1	0.76	0.90	0.93	0.68
Availability of quality raw materials (PR2)	PR 2	0.84			
Availability of raw material with a fair price (PR3)	PR 3	0.84			
Sustainability of industrial input supply (PR4)	PR 4	0.84			
Accessibility and efficiency of transport network (PR5)	PR 5	0.82			
Consistency of local supply chain (PR6)	PR 6	0.83			
Collaboration network (CN)					
Horizontal cooperation (CN1)	CN1	0.74	0.88	0.91	0.63
Supplier-distributor partnerships (CN2)	CN 2	0.83			
cooperation with Customer (CN3)	CN 3	0.83			
Competitor cooperation (CN4)	CN 4	0.82			
Joint projects and knowledge sharing (CN5)	CN 5	0.78			
Exchange of Information and experience share (CN6)	CN 6	0.77			
Human Capital (HC)					
Availability of unskilled labor (HC1)	HC 1	0.75	0.86	0.90	0.64
Availability of semi-skilled labor (HC2)	HC 2	0.80			
Availability of skilled labor (HC3)	HC 3	0.82			
Workforce readiness in the leather product industry (HC4)	HC 4	0.83			
Availability of Labor with technical expertise (HC5)	HC 5	0.81			

Abbreviations: AVE-average variance extracted; CR-composite reliability.

innovation capacity (IC) of firms. Results displayed in Table 9 reveal that about 0.15 units of the firm's performance in the relationship between cluster factor and firm's performance are transmitted through innovation capacity (IC). The path through which cluster factor to firm performance is positively associated and significant at 95 % CI ($\beta = 0.15$, 95 % CI [0.04, 0.30]). The standardized indirect effect (β) of 0.15 suggests a moderate indirect effect, indicating that a one-unit increase in cluster factor (CF) is associated with a 0.15-unit increase in the firm's performance (FP) through the mediating effect of innovation capacity (IC).

Similarly, the analysis revealed a significant indirect effect of cluster factors (CF) on the firm's performance (FP) through the mediator collaboration network (CN) ($\beta = 0.21$, 95 % CI [0.08, 0.40]). The standardized indirect effect (β) of 0.21 suggests a moderate indirect effect, implying that a one-unit increase in cluster factors is associated with a 0.21-unit increase in the Firm's Performance through the mediating effect of the collaboration network.

4.7.3. Total effect

The results indicated the overall effect of cluster factors on firm performance, disregarding the impact of mediating variables equal to 0.79. This total effect can be disaggregated into two components: the direct effect (0.43) and the sum of the indirect effects through the mediators ($0.21 + 0.15 = 0.36$).

Specifically, the indirect effects can be calculated as follows:

Indirect Effect 1 (collaboration network as a Mediator): The path from cluster factors (CF) through the collaboration network (CN) to the firm's performance (FP) yields an effect of 0.21, calculated as 0.68×0.31.

Indirect Effect 2 (innovation capacity as a Mediator): Similarly, the path from cluster factors (CF) through innovation capacity (IC) to firm performance (FP) manifests an effect of 0.15, calculated as 0.64×0.24.

Combining these effects with the direct effect provides a holistic view of the total impact:

Total Effect = Direct Effect + Indirect Effect 1 + Indirect Effect 2 = $0.43 + 0.21 + 0.15 = 0.79$.

The result revealed (see Table 9) that both the direct effect of cluster factor and the mediating effect through the collaboration network and innovation capacity was significant. Thus, it could be concluded that there is a partial mediation between cluster factors and firm performance in the leather product industry cluster [84].

5. Discussion

5.1. The effects of clusters resources on Firm performance

The objective of the study was to examine the impact of cluster factors on the performance of firms producing leather goods in Addis Ababa. In particular, this study attempts to determine the direct and indirect effects of innovation capacity and collaborative networks on the relationship between cluster factors and firm performance.

5.1.1. Cluster factors and firm performance

The presence and efficient utilization of various cluster factors, such as physical resources, institutional support, and human capital, promote the activity of firms within the cluster. This result demonstrates that the presence of cluster factors increases the capacity of the leather goods industry. With access to key resources such as skilled labor, raw materials, knowledge, technology, and supportive policies, firms can utilize them more productively and cost-effectively, leading to increased exports, higher employment, and greater market share. The results of this study have shown that there is a positive and significant path coefficient on firm performance (path coefficient = 0.43, t-statistic = 3.93, $p < .05$), which supports the theoretical foundations of the literature on industry clusters. As mentioned by Refs. [53,83], a path coefficient above 0.5 can be considered a strong effect size.

The productivity improvement of clusters on the performance of companies is proven by several empirical studies. A study by Petry et al. [85] found that access to resources within clusters and agglomeration advantages positively influence the performance of foreign subsidiaries. Another study by Kukalis [86] reported that innovative activities, inter-firm collaboration, knowledge spillovers and resource sharing lead to higher firm performance in industry clusters, which are required to enhance agglomeration effects. A study by Diez-Vial and Fernández-Olmos [87] emphasizes the role of clusters in improving firms' access to internal resources and capabilities in addition to innovation, which enhances their performance. These studies jointly emphasize that cluster factors contribute to maintaining business efficiency and the success of industrial clusters.

Both the presence and efficiency of cluster factors, which include physical resources, institutional support, and human capital in general, contribute to improving the performance of firms in their clusters [18,88]. The priority of policy makers, industry associations, and company managers must be to develop strategies that promote the emergence and optimal utilization of cluster factors that ultimately improve a company's competitiveness and performance in the industry.

Nevertheless, the relationship between the cluster factors and firms' performance is not clearly positive in some studies. For example a study by Petry et al. [85] on foreign subsidiaries in Brazil points out that cluster factors sometimes have no significant influence on company performance. A study by Suyanto et al. [89], on "clustering and firm productivity spillovers in Indonesian manufacturing" also shows that the productivity spillover effects of clusters vary greatly depending on whether firms are labor-intensive or not. Their results show that labor-intensive clusters tend to have negative productivity effects, while capital-intensive clusters have positive productivity effects. This divergence in results is an indicator of the complexity of the impact of clusters on firms and indicates other factors that influence the potential of clusters.

In a chemical industry context Tufa et al. [90], investigated targeted industrial support policies, or interventions targeting only sectors showing high growth prospects. From their analysis, it was established that these mechanisms have a favorable impact on the productive capacity of the firms that benefit from the program but there is no evidence to prove the effectiveness of the program when it comes to employment generation in the industrial sector.

5.1.2. Mediating effect of innovation capacity and collaborative networks

This section deals with the discussion of the mediating roles of innovation capacity and collaborative networks between cluster factors and firm performance. Collectively, the two factors provide valuable mechanisms as to how clusters work to generate benefits for their competitiveness and broader economies.

5.1.2.1. Innovation capacity as a mediator. The results indicate that innovation capacity partially mediates the relationship between cluster factors and firm performance. Specifically, a one-unit increase in cluster factors is associated with a 0.15-unit increase in firm performance through the mediating effect of innovation capacity. Earlier studies offer the theoretical and empirical grounds for the definition of innovation capacity as a central process that enables assets to create advantages. Research by Cohen and Levinthal [91] introduced the notion of absorptive capacity to explain the external knowledge that an organization could assimilate via internal R&D activities. This opens the way for perceiving the innovation capacity in an absorptive and transformational manner. For example, a study by Zahra and George [92] demonstrates that it integrates knowledge and builds organizational competencies by the KBV theory that emphasizes integration and application of knowledge for competitive advantage [93].

The above fact not only indicates that innovation capacity is a vital element of factors within clusters that positively influences the business' performance but also serves as the basis for reinforcing the hypothesis. The study fits into the research framework and bumps up to the knowledge gauze. In a former study, the researchers emphasized that the capacity of innovation is specifically significant. It is obvious that the effect it has on the transformation of factors within the clusters when they are used properly [94,95]. Moreover, the conclusion of the study by Singh and Hanafi [96] was congruent, as they emphasized the joint impact of the innovation capacity and firm success on each other. Their findings provide evidence confirming that, for firms' successful performance differentiation ability is an important factor and a competitive advantage in the global environment. It is consistent with the resource-based view (RBV) theory approach, which is aimed at considering resources that are valuable, rare, and inimitable providing a sustained competitive advantage [97].

Moreover, the mediating effect of innovation capacity unveiled in this study provides a multidimensional perspective of how factors within clusters contribute to performance gains. It demonstrates that the path from resource availability to performance enhancement is not direct but rather influenced by the firm's ability to transform these resources into innovative outputs through knowledge acquisition, assimilation, transformation, and exploitation processes [92]. This transformation process entails assimilating new knowledge, employing creative thinking, and implementing innovative practices. In its turn, transformation process reflects the dynamic capabilities perspective's emphasis on the reconfiguration and integration of resources [98].

Considering all those, innovation capacity becomes not an optional strategy, but a must for those companies operating in a cluster. Governments and cluster managers should therefore, ensure that the strategies implemented do not just create institutions and policies that meet resource demands but actively support the firms to innovate at the same time. This could entail setting up innovation hubs, supporting knowledge transfer consortia, and offering grants aimed at promoting research and development.

5.1.2.2. Collaboration networks as a mediator. The findings of the analysis illustrate that collaboration networks serve as a mediating factor between factors (factors such as physical resources, institutional support, and human resources) and firm performance in the leather industry in Addis Ababa city. There is a positive association between a unit increase in factors within clusters and 0.21 units of firm performance, which is mediated by collaboration networks. This is in consistency with the existing literature on the role of the competitive advantage and business performance especially in the developing countries.

The findings are consistent with the findings by Dewally and Shao's [99], who discovered positive consequences of co-location in clusters, like sharing of resources. This leads to progressive improvements in asset turnover. In the study of Fitjar et al. [100], the important role played by collaborative networks is also highlighted. Particularly, the firms that belong to triple-helix networks are shown to have a higher income share from new products. This stresses how the networks of collaborations can help in the process of innovation and the achievement of economic growth by using the knowledge spillover theory which argues the benefits of sharing and cooperation in innovation [101,102].

Furthermore, in very newly created clusters proximate to the urban core, the interaction between Cluster Factors will play a key role in increasing a company's performance. They enable to adapt changing business needs through leveraging synergy, opening up new markets, and giving businesses a competitive advantage. Thus, they become a bridge in the Cluster of Factors linked to further performance and development. It is possible to conclude that the viewpoints about strong relationships and complementary resources; contribute to an edge over the competitors by taking the perspective of the relational view [103]

Concisely, the mediating impact of networking capacities and innovation becomes the extension of the mainstream literature on clusters of industry and the firm's performance, and the mechanism is explained by that impact. The study points to the role of strong collaborative networks in the framework of cluster factors and the basis for subsequent research on the relationship between cluster factors, collaborative networks, and firms′ performance. Future research could explore the specific mechanisms that influence the effectiveness of collaborative networks in different cluster contexts focusing on other theoretical frameworks.

6. Conclusion

This study aimed to examine the impact of industrial clusters on firm performance within the leather product industry in the case of Addis Ababa City, Ethiopia. To meet the research objectives, data were collected from 150 leather product firms in the city. For the analysis, a partial least square structural equation modeling (PLS-SEM) was employed as an analytical model using Smart PLS 3.2.9. The analysis was based on RBV and network theory as supporting theories, and agglomeration theory as the foundational theory. The findings of the study indicated that firms within these clusters benefit significantly from improved innovation capacity and established collaborative networks, leading to improved performance metrics (firm productivity, market share growth, sales, cost efficiency, employment …). Further, these findings also highlight that to achieve industrial clusters as instruments for industrial development, the government needs to work on creating 'innovation hubs' within the leather clusters that are specifically designed for the needs of the leather industry.

Theoretical implication: This study enhances our understanding of the relationship between cluster resources and firm performance by examining the leather industry as a case study. The findings highlight the significant role that cluster resources play in improving firm performance, especially in developing countries such as Ethiopia. Moreover, the study offers empirical evidence that supports the theoretical framework of cluster development and its positive impact on firm competitiveness.

Managerial implication: This study provides insights for managers how collaboration networks and innovation capacity can enhance overall performance within cluster environments. By utilizing the dynamics of effective resource allocation, skill development, and collaboration strategies, managers can better leverage network strength and innovation for improved knowledge transfer and competitiveness. Additionally, the findings inform policymakers on strategies to support industrial clusters in developing countries, potentially fostering economic growth in the sector.

Implications for Policy and Practice: Policymakers and industry leaders might benefit from the evidence in developing strong collaborative networks and strengthening innovation capabilities within clusters to enhance firm performance in the leather product industries. For instance, policies, programs, and services aimed at motivating research and development and promoting knowledge sharing and technology transfer among clusters might be successful.

Limitation of the study: While these findings provide important insights into the Ethiopian leather industry, there are limitations in the generalizability of results to other countries with a different setup of clusters. The unique socio-economic conditions and industrial structure may influence firm performance differently than in other regions or industries. Therefore, it is hoped that future research will test the model used in this exercise in diverse contexts to establish the broader applicability of the research results derived from this study.

Directions for Future Research: This study provides empirical evidence that supports the impact of cluster factors on firm performance and the mediating effect of innovation capacity and collaborative networks in the relationship between cluster factors and firm performance within a single industry and a specific urban context (Addis Ababa). Hence, researchers could conduct other comparative studies that involve other sectors and regions in developing country contexts.

CRediT authorship contribution statement

Abaynew Wudu: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Kanchan Singh:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Samson Kassahun:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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