

SWOT Framework Based on Fuzzy Logic, AHP, and Fuzzy TOPSIS for Sustainable Retail Second-hand Clothing in Liberia

Peter Davis Sumo^{1,2*}, Xiaofen Ji¹, Liling Cai¹

¹ Zhejiang Sci-Tech University School of Textile Science and Engineering, Hangzhou, Zhejiang, China, 310018

² Organization of African Academic Doctors (OAAD)

* Corresponding author. E-mail: petersumo3@gmail.com

Abstract

The fast-fashion business model is marred by high resource consumption and enormous emission of greenhouse gases. It is based on inaccurate forecasts, resulting in excess supply than demand. Globally, 85% of two-week-old garments end up as unfashionable or worn-out items that must be discarded as waste, disposed of for recycling, or donated to charities. With this colossal increase in textile waste, resource efficiency is one of the biggest challenges facing the fashion industry, which now calls for a swift implementation of a new sustainable business and consumption model to extend product life cycles. This demand for sustainable consumption encourages consumers to reuse, recycle and resell. The resell campaign known as second-hand clothing is a growing market worldwide. Current global forecasts predict a 185% increase over the next ten years, compared to FF, which will expand by just 20%. Africa is a top destination, with more than 80% of its population wearing SHCs. We contribute to this literature by assessing the significance of SHC trade in Liberia. We extend this assessment by developing a hybrid MCDM tool incorporating AHP, fuzzy logic, Ensemble, and TOPSIS to build a SWOT framework to identify criteria and sub-criteria for prioritizing SHC retailing in Liberia and Africa. Data for this study were gathered from a survey involving 100 SHC retailers from the Red-Light, Waterside, Duala, and Omega markets in Monrovia, Liberia. We identified several important factors in implementing sustainable SHC and recommended strategic directions towards their successful implementation.

Keywords

SWOT, second-hand clothing, sustainability, fuzzy AHP, TOPSIS, Liberia.

1. Introduction

There has been a significant increase in output volume following technological breakthroughs and the Industrial Revolution, particularly for the textile industry. The rise of fast fashion (FF) since the early 2000s as a fast-paced manufacturing and consumption pattern for profit maximization is hastening the growth of the volume and value of discarded clothing. According to [1], in the previous two decades, worldwide textile consumption has climbed from 7 to 13 kg per person, totaling 100 million tonnes, of which two-thirds end up in landfills. The FF supply chain is characterized by erroneous projections, leading to excess production against demand and a shorter life cycle. Globally, 85% of two-week-old garments end up as unfashionable or worn-out items that must be discarded as waste, disposed of for recycling, or donated to charities [2, 3].

A recent survey by THREDUP [4] estimates that, in the US alone, 36 billion clothing items are annually trashed, of

which 95% are reusable. According to the same survey, over 94,000 tons of waste of single-used garments were produced in 2019 alone. A similar study from the UK highlights that consumers across the country currently have an estimated \$64.7 billion worth of unworn clothes in their closets [5].

With this colossal increase in textile waste, resource efficiency is one of the biggest challenges facing the fashion industry, which now calls for a swift implementation of new sustainable business and consumption models to extend garments life cycles [6]. This demand for sustainable consumption encourages consumers to reuse, recycle and resell while addressing textile waste as a renewable resource [7]. The resell campaign known as second-hand clothing (SHC) has immensely flourished with nearly 11% of annual growth, extensively reshaping the fashion industry [8].

SHC retailing is a growing market worldwide, with over 70% of the world's population using SHC. The

figure is poised to increase yearly, with current global forecasts predicting a 185% increase over the next ten years, compared to FF, which will expand by just 20%. This growth proliferation is primarily due to price affordability in underdeveloped nations and consumers' consciousness of sustainability in the developed world [9–10].

Most SHCs are processed and resold to developing markets [11], essential in getting clothing and associated commodities to consumers in poor African countries [12]. Over 80% of Africa's population is estimated to wear SHCs imported mainly from the US., Europe, India, Pakistan, and China [13]. These clothing items have ready markets across the continent since they are less expensive, easier to wear, more durable, and more trendy than those locally manufactured [14]. The African SHC trade has far-reaching consumers benefits due to the limited purchasing power of consumers and the shift in taste to western-style clothing from traditional African style clothing [15]. The trade now

holds significant market shares in Ghana, Nigeria, Ivory Coast, Tanzania, Benin, Uganda, and Kenya [11]. Its demand is creating employment avenues such as trading, distribution, repairs, laundry services, and upcycling, which sustain hundreds of thousands of livelihoods on the continent [15–16].

Studies on Africa's SHC trade lack significant official datasets [17]. As such, the majority of the few pieces of works of literature [12, 14, 15], [18–24] draw analysis and conclusions using qualitative and secondary data sources.

To close some of these gaps, we empirically contribute to the literature by assessing the significance of SHC trade in Liberia. In part one of our study on the SHC trade in Africa, we extend this assessment by developing a SWOT framework to identify criteria and sub-criteria prioritizing SHC retailing in Liberia and Africa. We achieve this by conducting multi-criteria decision-making (MCDM) research among 100 retailers from the four largest markets in Liberia (Red-Light, Waterside, Duala, and Omega markets). SWOT has wide usage in the textile industry for evaluating and improving strategies. Since SWOT and its subsequent strategies do not determine the importance of factors nor provide implementation details, we, therefore, transform the framework into a hierarchical structure for further assessment of each factor. We use the Analytical Hierarchical Process (AHP) developed by Saaty [25] to compare multiple factors and sub-factors for their SWOT priorities. We apply fuzzy logic to resolve the resulting impression in human judgments arising from discrete decision-making during our survey. To consolidate the results derived from the two-hybrid approaches (AHP and Fuzzy AHP), we employ the Ensemble method, which finds the average of the two weights. Finally, we introduce the TOPSIS method for ranking attributes most important to SHC retailing, livelihoods, sustainability, and poverty alleviation from a developing country's perspective.

This paper is organized as follows: in section two, we provide a literature

review of SHC in Africa, next section three details our methodology, study points, and methods data collection and analysis. Section four analyzes our findings and generates results, while section five presents the conclusion and implications.

2. Literature Review

The fast-paced manufacturing and consumption patterns are hastening the growth of the volume of discarded clothing [26, 27]. A significant number of fast-fashion products are often discarded just after two weeks of use, with an estimated 95% of these clothing items recyclable [4, 28]. Many studies have been conducted to devise sustainable clothing consumption models for minimizing environmental impacts. For example, [29–31], among many others, have identified the important consumer drivers of sustainable consumption patterns, which now calls for a swift implementation of new sustainable business models to extend garments life cycles [6]. This sustainable consumption encourages consumers to reuse, recycle and resell while addressing textile waste as a renewable resource [7]. Thus, the resell campaign known as second-hand clothing (SHC) has immensely flourished with nearly 11% of annual growth, extensively reshaping the fashion industry [8].

Africa is the biggest consumer of SHCs. Used clothes were shipped to Africa as donations during colonial times and were transformed to trade during the economic liberalization in the 1980s. The SHC trade is reshaping African textile consumption. For instance, SHC is a striving business and a crucial role player for Ethiopia's textile consumption and retail segment and key sustenance of livelihoods [32]. Findings from [33] share similar concerns—the research conducted across Angola, Malawi, and Mozambique on 3485 respondents highlight that participants instead used second-hand items to replace worn-out garments due to their low purchasing power. In particular, affordability and availability place Malawians as one of the principal consumers of SHC with the need for an organizational structure

and interconnection between sales and distribution channels that will lead to the growth of small businesses in the country's SHC formal sector [12].

With the growing sense of sustainability, the circular economy model applied to clothing items provides new knowledge about how old clothes, widely available in markets around Africa, can be creatively rebranded into new clothes and accessories [22]. More people are turning to fashion re-consumption [34]. This sense of consciousness is advocated as replacing the more resource-intensive production systems. In addition, SHC rebranding has been seen as a new way of adding African styles and values. As Thompson & Peter [34] find among retailers in Port Harcourt, Nigeria, formal education on value addition and innovation techniques is an excellent step in improving used clothing with a sense of Africanness. Findings from James & Kent's [22] workshop position SHC as reviving the African textile industry since applying the circular economy model provides new knowledge for creatively extracting and rebranding used clothes into new ones allowing for African designs and innovation.

However, Frazer [35] and several East African leaders argue that there is a negative relationship between domestic textile production and SHC import. [35] draws his argument on a regression analysis of panel data of selected Sub-Saharan African (SSA) countries obtained from UNComtrade between 1981 and 2000. He highlights a 40% decline in output and a 50% decline in employment on the continent due to SHC import.

However, Brooks & Simons [17] disagree, claiming that studies on Africa's SHC trade lack official and frequently updated datasets. In addition, Africa's textile manufacturing capability is dwarfed by infrastructural limitations intensified by obsolete technology, low productivity, the high unemployment rate for textile graduates and the intense competition in its value chain, mainly from cheap imports from China and other Asian nations [36].

Many of the papers surveyed so far derived conclusions based on secondary data sources (see for instance [12, 15, 17, 23, 24, 35]). As such, linking Africa's textile industrial decline to the continent's importation of used clothes in the absence of official data sets on SHC's import (either legal or illegal) is entirely difficult [17].

The extant literature has identified issues relating to the growth of used clothing commercialization in Africa [15, 32, 33], [37–40]. Some efforts have been made to use MCDM tools such as AHP to prioritize livelihood measures to support effective and sustainable interventions for alleviating poverty in developing countries [41]. However, no work in the extant literature has combined SWOT, AHP, fuzzy logic, and TOPSIS to classify attributes most important to SHC retailing, livelihoods, sustainability, and poverty alleviation from a developing country's perspective. In addition, there is no research on Liberia's SHC retail sector. Examining the SHC retail sector in Liberia is essential to this study and the entire SHC literature.

In the following sub-sections, we provide brief literary overviews of each method used.

2.1. SWOT

SWOT (Strengths, Weaknesses, Opportunities, and Threats) is a simple analytical tool vital for strategic planning. It follows a structured approach for assessing an organization's strategic position in planning, identifying an institution's strengths and weaknesses, and comparing them to opportunities and threats in their inner and outer environments [42–43]. SWOT has received immense attention in the extant literature, especially in the textile industry. For instance, [44] used SWOT to evaluate the educational system of a textile university to devise ways for improving the syllabus for students pursuing careers in the textile industry in Turkey. A similar approach by [45] uses SWOT to analyze the challenges facing Pakistan's textile industry.

Strength relates to attributes distinguishing an institution and its competitors; weaknesses are inherent features that need improvement. Opportunities are openings or chances for growth, while threats refer to environmental characteristics that cause derailment for an organization. Employing SWOT analysis allows for decision-making about where and how an improvement can be made [46].

2.2. AHP

The Analytical Hierarchy Process (AHP), developed by Professor Thomas L. Saaty in the 1970s, is an MCDM tool [47]. Hierarchical decision-making criteria or objectives characterize MCDM problems to find an ultimate goal. They are usually based on some criteria or sub-criteria that influence the decision-making process with some degree of importance. Many MCDM problems are psychological, and selecting multiple criteria without carefully vetting the alternatives is detrimental to the project management. Applying an AHP approach in an MCDM problem transforms psychological attributes to mathematical reasoning with relative importance using hierarchical structures [46]. It uses pairwise comparisons to design a quantitative framework that guides the criteria and alternatives for the required objective. In this way, each criterion's relative importance or weightage is evaluated and scored for comparison at each level.

The mathematical nature, methodological convenience, and the flexibility of obtaining input data in a hierarchical structure make AHP a versatile MCDM tool with widespread adoption and use in various research fields [48], including the textile and apparel (TA) industry. [49] applied AHP and TOPSIS methods in a complex decision-making process that required optimal distribution of work to subcontractors in a garment factory in Turkey. Their model enabled decision-makers to select subcontractors, providing companies with the benefits of quality products and on-time delivery. The strength of AHP has been tested well beyond just a pairwise comparison

of criteria. [50] combined AHP, DEA, and TOPSIS to develop an integrated framework incorporating suppliers' selection and comprehensive evaluation of their overall performance. A UK-based retailer has implemented their framework with over 7000 supermarkets and 460,000 employees. [51] used the technique combined with TOPSIS to develop a decision support system (DSS) software for classifying and selecting cotton fibers under all aspects of yarn quality. AHP was employed to infer the relative weights of the cotton fiber properties. Using a similar approach, [52] compared fabrics from three different fibers (regenerated bamboo, polyester, and cotton) for mechanical, thermal comfort, and moisture properties. Computation of AHP pairwise comparison revealed 100% cotton fabric as mostly preferred for summer consumption. Extending this idea, [53] combined fuzzy logic and AHP to develop a conceptual framework for functional, expressive, and aesthetic considerations in designing raincoats for children aged 7 and 8. Their model accounts for three significant levels—development, requirement, and design solutions for creating children raincoats. In addition to selection and allocation problems, AHP has assisted in gaining an understanding of fashion consumers. [54] used AHP and VIKOR techniques to identify factors influencing consumers' preferences for online fashion retailers. Forty factors divided into seven categories were most preferred among online fashion retailers in India. A similar consumer study by [55] used AHP to examine the effect of the perceived value of Omni-channel service attributes on users' decision-making processes about omnichannel use in Japan and Korea.

2.3. Fuzzy TOPSIS

Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) is an MCDM methodology used to evaluate alternative options involving subjective assessments [56]. The method uses a similar pairwise comparison technique found in traditional AHP to aid decision-makers in making comparative judgments while

using a linguistic evaluation approach to deliver final assessments [57]. TOPSIS has received widespread attention in the MCDM literature mainly due to its simple calculation and simultaneous evaluation of the shortest distance from the positive ideal solution (PIS) and the farthest from the negative ideal solution (NIS) [58]. However, TOPSIS cannot cope with the ambiguities and uncertainties that decision-makers face. Decision-makers, therefore, utilize fuzzy set theory to include unquantifiable, incomplete, and non-available information into the decision model [59]. The inclusion of fuzzy set theory enables fuzzy values in the decision-making since it takes a more realistic approach by relying on linguistic judgments rather than numerical values [60].

Due to these flexibilities, fuzzy TOPSIS is now widely used for handling difficulties associated with ranking in MCDM, especially in the textile industry. For example [61] use fuzzy TOPSIS combined with AHP to diagnose critical areas for implementing Lean tools in a textile sector. [62] extend the power of TOPSIS by combining TOPSIS and Pythagorean fuzzy sets (PFSs) to select the best cotton fabric comfortability. Their results highlight a significantly high correlation coefficient with other distance measures and aggregation operators. [63] used the FTOPSIS model to prioritize 19 major sustainable supply chain management (SSCM) practices, particularly for India's automobile, textile, and food industries. Their result ranks ISO 14000 and 14001 certification, value stream mapping, and corporate social responsibility as the topmost priorities when making decisions to ensure perfect sustainability in supply chains.

The combination of several MCDM methods to form a hybrid technique has proven very robust in solving complex decision problems. [64] study proposes a new hybrid methodology based on FAHP and FTOPSIS for helping textile industry workers select the optimal waste-water treatment process. Similarly, a recent study by [65] proposes a hybrid MCDM model that combines fuzzy AHP and fuzzy TOPSIS to aid the garment

industry's supplier selection process in a fuzzy decision-making environment in Vietnam. The authors used FAHP to analyze the performance and weightage of each criterion, while TOPSIS was used for ranking the possible suppliers.

3. Methodology

3.1. Study Area

Interviews and data collected for this study were taken from four (4) large markets—Red Light market district, Waterside market, Duala market, and Omega market—in Monrovia, Liberia. These markets are the most prominent shopping points in Liberia. They host diverse marketeers, including SHC retailers. The Red Light market is the largest and busiest market in Liberia, with a massive population of various vendors exceeding 15,000. Duala market has a population of more than 7,000 marketeers. In contrast, the Waterside market is the most significant commercial area in central Monrovia, offering almost everything for sale, including colorful textiles, shoes, leather goods, and ceramics, with a population of over 10,000 marketeers [66]. On the other hand, the Omega market is a new development for relocating marketeers of the old Gobachop and Red Light markets, hosting over 3000 marketeers [67].

3.2. Defining the SHC SWOT Factors

The Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis is an effective and efficient tool for strategic planning. It, therefore, has been used in this study to assess the direction of development strategies for SHC trade. We use [43, 68] to explain the framework of Strengths relating to the company's characteristics or projects seen as weaknesses compared to others. Weaknesses as characteristics that classify one company or project as a loss compared to another; Opportunities as elements in the outer environment that a company or project can use to its advantage and Threats as elements in the

external environment that tend to derail the company or project.

This paper aims to identify factors for a sustainable enrichment of the SHC trade in Africa, particularly Liberia. We conduct the SWOT analysis in three stages. First, we obtain the SWOT factors from a survey of SHC retailers in the four markets. Second, we group the factors to develop the SWOT framework. Third, we conduct pairwise comparisons of 21 factors in total (five from the strengths group, six factors of weaknesses, four factors of opportunities, and five from the threats group) see table 1.

The first stage of this process was a survey to assess SHC import, economic performance, contribution to society and trade, and the challenges its retailers face in Red Light, Waterside, Duala, and Omega markets. Questionnaires for the survey were gathered from a thorough study of existing literature. The total sample size from the four study points includes 100 respondents of SHC retailers, see table 2. The 100 respondents gave us access to basic primary data on retail activities and challenges from various stages of the SHC supply chain between June 25, 2021, and August 25, 2021. Using this time frame enabled us to capture the July 26 (Independence Day) sales since there were more buyers and sellers during this period. Inclusion criteria for our respondents were straight but brief: respondents must be the owner of the business, must have not less than two years of SHC retail experience, and that the business should constitute more than 70% of SHC.

The second stage of data processing included refining and categorizing the data collected from the survey into each SWOT group. All outside of this paper, six experts were asked to categorize factors into each SWOT group (see table 1).

SWOT and its subsequent strategies do not determine the importance of factors nor provide implementation details. Therefore, we transform the framework into a hierarchical structure by integrating the analysis with AHP, whose calculations are based on eigenvalues [42]. Using

Strengths		Weaknesses	
S1	There is a strong presence of SHC country-wide with a great variety of products and increased choosability options	W1	Lack of storage/warehouse facilities and pressure to provide lower prices in the competitive environment
S2	SHC are quality products, durable and affordable for the local majority	W2	Prices from wholesalers are high because of the high importation and other related costs
S3	Retailers and suppliers can independently operate businesses and grow financially faster	W3	Obtaining financial assistance to startups is difficult for young entrepreneurs
S4	The serviceability range is more comprehensive for consumers such that it extends garment's life-cycle and reduces fast fashion demand	W4	Poor supply chain delivery systems. There is no good logistics infrastructure to transport goods around
S5	It's easier shopping second-hand; this gives space to boost sales and market growth improvements	W5	Clothes are less hygienic and sometimes require alteration for which there are existing skillset-gaps
		W6	Low level of corporation between members of the supply chain
Opportunities		Treats	
O1	Selling SHC creates employment avenues that lead to poverty alleviation	T1	Increased competition from new entrants
O2	Favorable conditions for investment that support women empowerment	T2	Fast-changing consumers' choices in the clothing segment
O3	Loan opportunities may lead to growth in demand and promote new market expansion	T3	Unstable tax schemes and import duties
O4	Quantity discount from wholesalers to retailers has the potential to allow the low capital requirement for beginners	T4	Competition from the Fast Fashion market that changes the taste of consumers
		T5	High likelihood of banning SHC to promote the local textile industry
		T6	Unstable prices and exchange rates due to dual currency and frequent government demolition of market structures

Table 1. SWOT factors for SHC retailing

Measure	Items	Red Light		Waterside		Duala		Omega	
		Freq	%	Freq	%	Freq	%	Freq	%
Gender	Male	4	10	9	30	3	15	1	10
	Female	36	90	21	70	17	85	11	90
Age	10-19	2	5	3	10	1	5	1	10
	20-29	18	45	9	30	5	25	2	20
	30-39	5	12.5	9	30	6	30	3	30
	40-49	6	15	5	16.7	5	25	2	20
	50-59	4	10	2	6.7	2	10	1	10
	60 & above	5	12.5	2	6.7	1	5	1	10
Total		40	100	30	100	20	100	10	100

Table 2. Respondents

AHP prioritizes attributes by comparing them in pairwise matrices to devise strategic actions for SWOT. Following experts' identification of the 21 factors, a panel of 100 SHC retailers, all with over five years of selling experience, were asked to prioritize them based on AHP, completing the third phase. Compared to

previous literature, a consistency check is performed after analyzing the strategy, generating proposals [68].

To reduce errors or overcome the ambiguity of human thoughts, [69] introduced the fuzzy set theory. It is based on the rationality of uncertainty

that arises from the imprecision of human judgment. Weights obtained from the AHP analysis were fuzzified for a more refined grading of factors. This MCDM method analyzes the importance of each factor, thus allowing the incorporation of strategies that are vital indicators for the sustainable development of SHC trade.

Internal Environment	Strengths	Weaknesses
External Environment		
Opportunities	SO	WO
Threats	ST	WT

Fig. 1. SWOT group matrix analysis

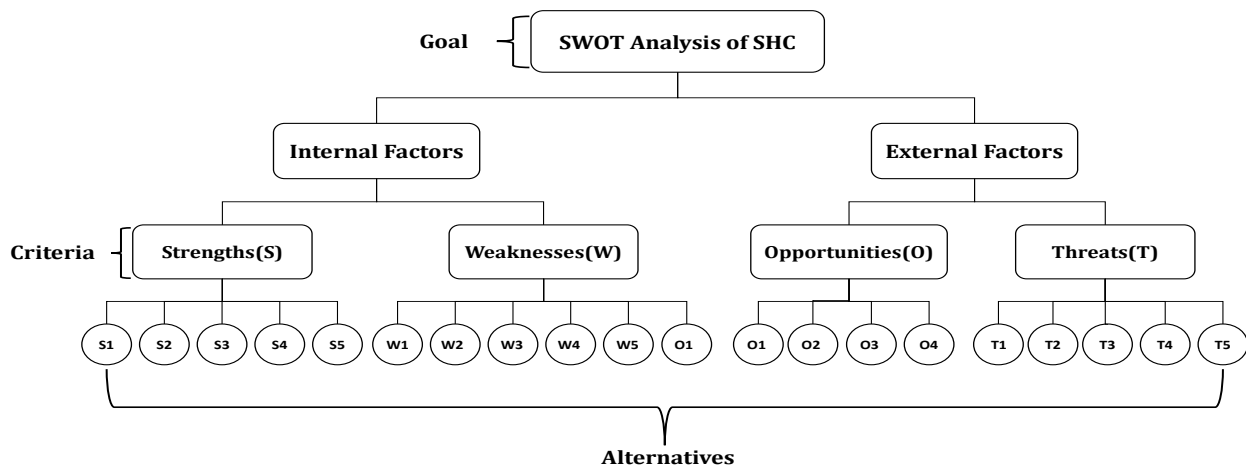


Fig. 2. The SWOT AHP hierarchical model

For fuzzy and AHP methods, we use Saaty’s comparison scale in table A2 to evaluate the alternative strategies from the most preferred to the least preferred.

Finally, we introduce the TOPSIS method to rank the most suitable strategies for the sustainable enhancement of SHC trade in Liberia. The factors for the sustainable development of SHC are considered and compared to determine the essential improvement factors.

3.3. The Decision-Making Analysis

3.3.1. AHP

We begin the decision-making analysis by a goal, a set of criteria, and sub-criteria, which we fed to the AHP model to extract important alternatives relevant to the SHC supply chain. We generated pairwise comparisons based on

judgments of 100 retailers by following the steps below:

Step 1: We obtained criteria weights through pairwise comparison of factors gathered from each respondent and found the average of each response for each criterion from all respondents. Assuming the weight of importance for each n^{th} factor denoted as a_n , we used Saaty’s scale in table A2 to compare criteria on the same level. If grading attached to the decision criterion is in column 1 of table A2, the graded value is considered; otherwise, reciprocal values in the column of table A2 are considered. On this principle, we obtained a pairwise comparison of matrix A.

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & a_{ij} & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \quad (1)$$

where $i, j = 1, \dots, n$

Step 2: We divide each element in the pairwise comparison matrix by its column total to obtain a normalized pairwise comparison matrix using equations 2 & 3.

$$X_{ij}^* = \frac{a_{ij}}{\sum_{i=1}^n a_{ij}} \quad (2)$$

for all $j=1,2,\dots,n$

$$X = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1n} \\ X_{21} & X_{22} & \dots & X_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ X_{n1} & X_{n2} & \dots & X_{nn} \end{bmatrix} \quad (3)$$

Step 3: We compute the average of row elements in the normalized matrix to obtain the weighted matrix (4).

$$W_i = \frac{\sum_{j=1}^n X_{ij}}{n} = \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix} \quad (4)$$

for all $j=1,2,\dots,n$

The elements of the weighted matrix show the relative weights between the criteria being compared. A higher value indicates a higher preference for each criterion.

$$W = \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix} \quad (5)$$

Step 4: Since respondents' opinions may be subjected to several inconsistencies, we conducted a consistency analysis of all preferences provided by the respondents. We achieved this by summing the column element of the pairwise comparison of the matrix (C), multiplied by the corresponding weight (W_i) to derive the consistency vector.

$$Cv_1 = [C_{1i} + C_{2i} \dots C_{ni}] \times W_i \quad (6)$$

where $i=1,2,\dots,n$

$$\text{Consistency Vector } Cv = \begin{bmatrix} Cv_1 \\ Cv_2 \\ \cdot \\ Cv_i \\ \cdot \\ Cv_n \end{bmatrix} \quad (7)$$

Step 5: Summing all elements of consistency vector (C_v), we obtained a principal eigen value (λ_{max}) using equation 8.

$$\lambda_{max} = \sum_{i=1}^n Cv_i \quad (8)$$

Step 6: Consistency Index (CI) is used to measure the level of consistency of respondents' opinions. CI expressed as the difference between the minimal eigenvalues and dimension of comparison matrix (n), measures the deviation from the consistency of respondents' opinions

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (9)$$

A comparison between the computed CI and values of random index formulated

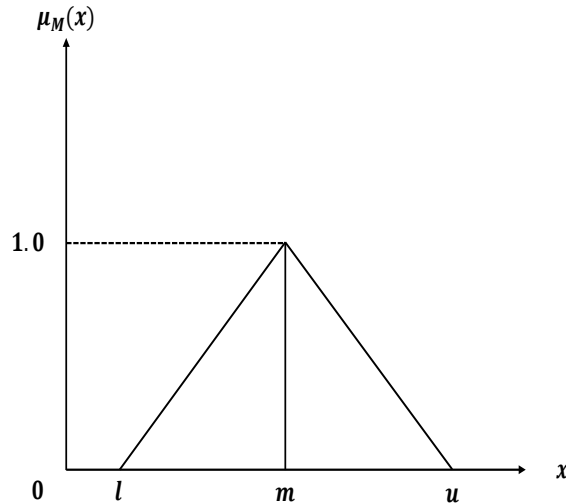


Fig. 3. A Triangular fuzzy number (TFN)

Matrix	1	2	3	4	5	6	7	8	9	10	11	12
Random index (RI)	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.58

Table 3. Radom index values

by Saaty (see table 3) is carried out to derive the Random Consistency Index (RI), which depends on the number of criteria.

Step 7: We computed the consistency ratio between CI and (RI) by using equation 10.

$$CR = \frac{CI}{RI} \quad (10)$$

Their pairwise comparisons were revised for responses with higher consistency values exceeding the 0.10 (10%) threshold.

3.3.2. Fuzzy AHP

The fuzzy set theory differs from classical set theory in that it uses triangular or trapezoidal fuzzy arguments to reflect the uncertainty of parameters association. However, this paper uses triangular fuzzy numbers (see figure 3) to express the fuzzy relative importance of factors and sub-factors of SHC SWOT analysis.

Step 8: TFN is defined by $\tilde{M} = (l, m, u)$ with l and u as lower and upper bounds, respectively. u defines the point at

which $\mu_{\tilde{M}}(x): U \subseteq R \rightarrow [0,1]$, with membership function as in equation 11, where $\mu_{\tilde{M}}(x) = 1$:

$$\mu_{\tilde{M}}(x) = \begin{cases} \frac{x}{m-l} - \frac{l}{m-l} & x \in [l, m] \\ \frac{x}{m-u} - \frac{u}{m-u} & x \in [m, u] \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

Step 9: If $\tilde{M}_1 = l_1, m_1, u_1$ and $\tilde{M}_2 = l_2, m_2, u_2$ then the operational laws of addition, multiplication, reciprocal, and division for these two TFN can be presented as follows:

$$\tilde{M}_1 \oplus \tilde{M}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (12)$$

$$\tilde{M}_1 \otimes \tilde{M}_2 = (l_1 + u_2, m_1 - m_2, u_1, u_1 + l_2) \quad (13)$$

$$\tilde{M}_1 \oplus \tilde{M}_2 = (l_1 l_2, m_1 m_2, u_1 u_2) \quad (14)$$

$$\tilde{M}_1 \otimes \tilde{M}_2 = \left(\frac{l_1}{u_2}, \frac{m_1}{m_2}, \frac{u_1}{l_2} \right) \quad (15)$$

$$\tilde{M}_1 \tilde{M}_1^{-1} \approx \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1} \right) \quad (16)$$

for $l, m, u > 0$

The scale level for each indicator and the weighting of the criteria are obtained

from the matrix \tilde{A} of fuzzy estimates with fuzzy comparison values \tilde{a}_{ij} that expresses the decision maker's judgment about the relative importance of factor i relative to factor j at the same hierarchical level.

$$\tilde{A} = \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & \tilde{a}_{22} & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \tilde{a}_{ij} & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & \tilde{a}_{nn} \end{bmatrix} \quad (17)$$

Step 10: Next, we estimate the fuzzy priority using the geometric mean method proposed by [70]

$$\tilde{r}_i = \left(\prod_{j=1}^n \tilde{P}_{ij} \right)^{\frac{1}{n}} \quad (18)$$

and

$$\tilde{w}_i = \tilde{r}_i \otimes \left(\sum_{i=1}^n \tilde{r}_i \right)^{-1}, \quad i=1,2,\dots,n \quad (19)$$

Where \tilde{r}_i is the geometric mean of fuzzy priority, n denotes the number of criteria or alternatives, while \tilde{w}_i denotes the fuzzy number. We employ the center of area (COA) method to defuzzify \tilde{w}_i as expressed in equation (20):

$$\tilde{w}_i = \left(\frac{l + m + u}{3} \right) \quad (20)$$

3.3.3. Ensemble of AHP and Fuzzy Weights

Step 11: To remove the inaccuracy associated with AHP and fuzzy methods, we employ the ensemble method [71–72]. The ensemble method delivers more reliable and integrated results. It requires finding the average of the two-hybrid approaches (AHP and Fuzzy AHP), and the resulting weights (Ensemble weights) are considered for onwards analysis.

Thus,

$$\text{Ensemble weight} = \frac{AHP_{gw(n)} + FAHP_{gw(n)}}{2} \quad (21)$$

Where $gw(n)$ is the global weight value of the same alternative or criterion derived by AHP and Fuzzy AHP at the same hierarchical level.

3.3.4. Fuzzy TOPSIS

We define an aggregated alternative and criteria weightage of fuzzy decision matrix for SO1, SO2, SO3, WO1, WO2, WO3, ST1, ST2, ST3, WT1, WT2, and WT3 using the fuzzy-TOPSIS method to rank the strategies.

Step 12: We first determine weights of criteria and aggregated fuzzy ratings to identify the aggregated fuzzy rating of i^{th} alternative in relation to j^{th} criterion and the aggregated fuzzy ratings \tilde{w}_i of alternatives with respect to each criterion.

Step 13: Next, we compute the normalized fuzzy decision matrix \tilde{R} as:

$$\tilde{R} = [\tilde{r}_{ij}]_{m \times n} \quad (22)$$

where B is the beneficial criteria while C denotes cost or non-beneficial criteria

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+} \right), \quad j \in B$$

$$c_j^+ = \max_i \{c_{ij}\} \quad (23)$$

if $j \in B$ beneficial criteria

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{b_j^-}{b_{ij}}, \frac{c_j^-}{a_{ij}} \right), \quad j \in C$$

$$a_j^- = \min_i \{a_{ij}\} \quad (24)$$

if $j \in C$ non – beneficial criteria

Step 14: We calculate the weighted normalized fuzzy decision matrix. All $\tilde{v}_{ij} \forall i, j$ are normalized positive triangular fuzzy numbers that range between $[0,1]$ following a weighted normalized matrix of the fuzzy solution. The fuzzy positive ideal solution (FPIS, A^+) consists of the best performance values of the weighted normalized decision matrix while the fuzzy negative ideal solution (FNIS, A^-) consists of the worst values as expressed below:

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_n^+) \quad (25)$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-) \quad (26)$$

where $\tilde{v}_j^+ = (1,1,1)$ and $\tilde{v}_j^- = (0,0,0)$, $j = 1,2, \dots, n$

Step 15: The distance of each alternative from A^+ and A^- can thus be computed as follows:

$$d_i^+ = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^+), \quad i = 1,2, \dots, m \quad (27)$$

$$d_i^- = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^-), \quad i = 1,2, \dots, m \quad (28)$$

where $d(\cdot, \cdot)$ is the Euclidean distance measurement between two TFNs. The distance between two TFNs ρ and τ is computed by using the following formula:

$$d(\tilde{\rho}, \tilde{\tau}) = \sqrt{\frac{1}{3}[(\rho_1 - \tau_1)^2 + (\rho_2 - \tau_2)^2 + (\rho_3 - \tau_3)^2]} \quad (29)$$

where $\tilde{\rho} = \rho_1, \rho_2, \rho_3$ and $\tilde{\tau} = \tau_1, \tau_2, \tau_3$ are two TFNs.

Step 16: Lastly, we calculate the ranking of all alternatives by determining the closeness coefficient following the calculation of \tilde{d}_j^+ and \tilde{d}_j^- of each alternative as:

$$CC_i = \frac{\tilde{d}_j^-}{\tilde{d}_j^+ + \tilde{d}_j^-}, \quad i = 1,2, \dots, m \quad (30)$$

The alternative with the highest closeness coefficient is the ideal solution. Thus, the alternative that defines the ideal solution is the alternative with the shortest distance from the positive ideal solution (FPIS) and the shortest distance from the negative ideal solution (FNIS).

Factors	Group Weights		Ensemble Weights
	AHP	FAHP	
S	0.255	0.321	0.288
W	0.111	0.197	0.154
O	0.193	0.185	0.189
T	0.442	0.298	0.370

Table 4. Group and ensemble weights of SWOT group from AHP & FAHP computations

Factors	Local Weights		Group Weights		Global Weights		Ensemble Weights
	AHP	FAHP	AHP	FAHP	AHP	FAHP	
S1	0.086	0.056			0.022	0.018	0.020
S2	0.280	0.316			0.071	0.102	0.086
S3	0.255	0.279	0.255	0.321	0.065	0.089	0.077
S4	0.136	0.112			0.035	0.036	0.035
S5	0.243	0.237			0.062	0.076	0.069
W1	0.082	0.065			0.009	0.013	0.011
W2	0.321	0.353			0.036	0.070	0.053
W3	0.324	0.360	0.111	0.197	0.036	0.071	0.053
W4	0.150	0.141			0.017	0.028	0.022
W5	0.059	0.037			0.007	0.007	0.007
W6	0.064	0.043			0.007	0.008	0.008
O1	0.474	0.581			0.091	0.107	0.099
O2	0.247	0.230	0.193	0.185	0.048	0.043	0.045
O3	0.097	0.053			0.019	0.010	0.014
O4	0.182	0.136			0.035	0.025	0.030
T1	0.060	0.040			0.027	0.012	0.019
T2	0.043	0.028			0.019	0.008	0.014
T3	0.230	0.252	0.442	0.298	0.102	0.075	0.088
T4	0.060	0.047			0.027	0.014	0.020
T5	0.420	0.469			0.186	0.140	0.163
T6	0.186	0.164			0.082	0.049	0.065

Table 5. Local, global, and ensemble weights of all sub-factors from AHP & FAHP computations

4. Results and Discussion

4.1. Results of AHP and Fuzzy Logic

The primary aim of this paper was to assess the significance of SHC trade in Liberia. We extend this assessment by developing a SWOT framework to identify criteria and sub-criteria prioritizing SHC retailing in Liberia and Africa. We applied fuzzy logic and AHP to develop matrices from pairwise comparisons of the SWOT group and sub-factors groups using a comparison scale of 1-9 [25]. We first

determined the weights of both factors and sub-factors and then obtained the global weight by multiplying the factor and sub-factor weights. The results are presented in tables 4 & 5. Ensemble values in table 4 show that SHC, with a Strength of 28.8%, is a potential contributor to revenue generation, employment avenues, and improvement of livelihoods. However, it faces enormous Threats (37%) mainly due to poor import and market regulations [15].

We further conducted pairwise comparisons of each alternative of the

SWOT matrix within each SWOT group. To obtain global weights, we multiplied the local weights of each sub-factors by the weights obtained in the parent/category pairwise comparison matrix. We achieve the ensemble values by averaging global weights from fuzzy logic and AHP.

From Ensemble weights in table 5, sub-factor S2 (8.6%) for the Strengths strategy has the highest weightage—*used clothes are of high-quality products, durable, and most importantly, affordable by the local majority*. Therefore, the second factor in rank (S3, 7.7%) affords retailers and suppliers the space to operate businesses and grow financially faster independently.

Results from our survey indicate a high level of entrepreneurial intentions among SHC retailers. But, as shown in the Weaknesses sub-factor of table 5, W3 (5.3%)—*obtaining financial resources for startups is the most significant barrier identified, particularly for young entrepreneurs*. These young entrepreneurs face substantial obstacles to raising the necessary financial resources because they do not have a market history or adequate collateral to secure loans. W2 (5.3%)—*prices from wholesalers are high because of the high importation and other related costs*—was identified as the next significant Weakness strategy. This largely can be attributed to poor regulations on import duties and local market prices. Summary of all local weights from both AHP and FAHP methods are in figure 4.

Over 1 billion people in Africa wear SHC. Its demand is creating employment avenues (O1, 9.9% from table 5 of the Opportunities sub-factors strategy) such as trading, distribution, repairs, laundry services, and upcycling, which sustain hundreds of thousands of livelihoods on the continent [15]. These employment opportunities are vital enablers of women’s empowerment in Africa (O2, 4.5%). The two Opportunities sub-factors, in particular, are significant prioritizations that seek investments to attain economic growth and transfer of technology.

[35] argues that the trade of SHC in Africa is the major contributing factor to the

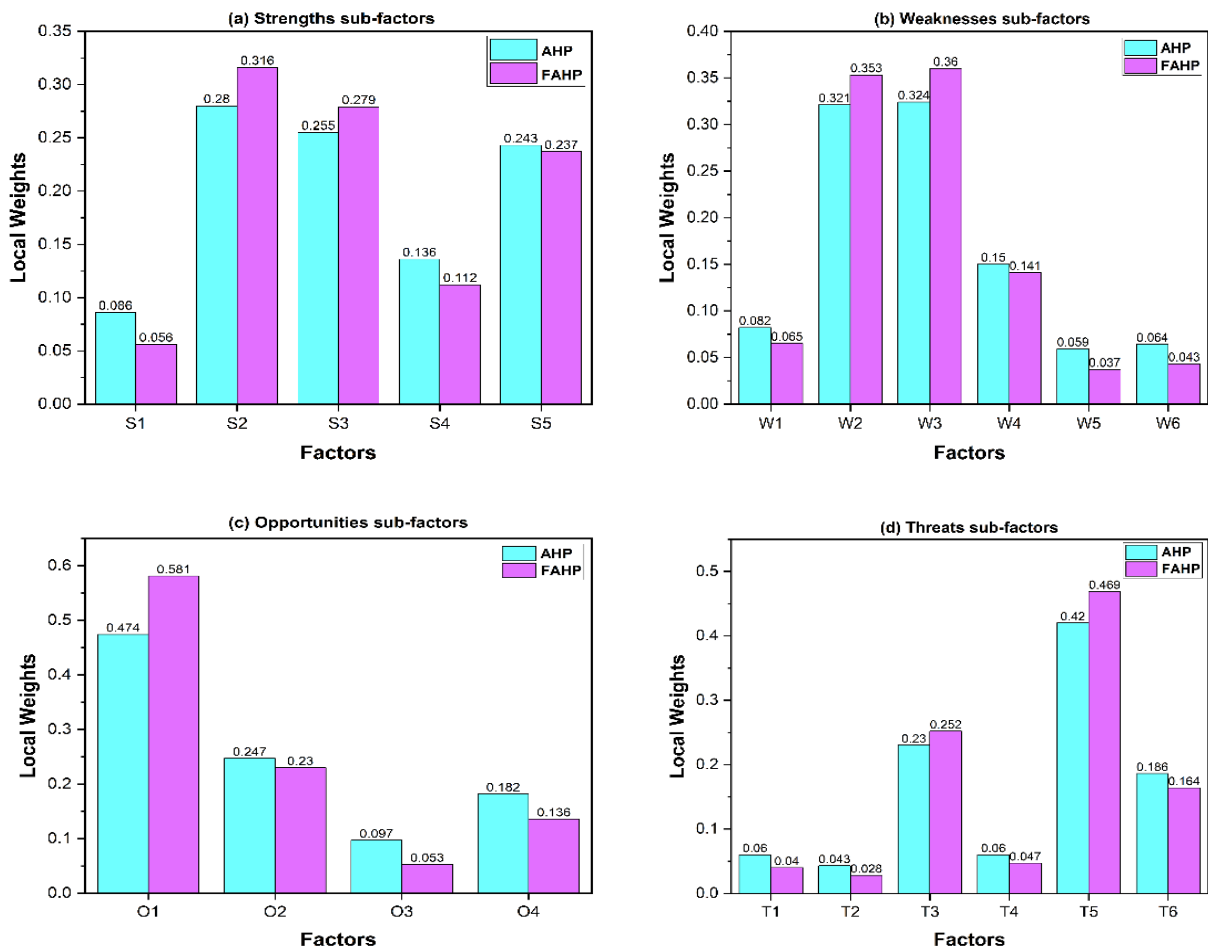


Fig. 4. Local Weights of both AHP & FAHP

Strategy	d^+_i	d^-_i	CC_i	Rank
SO1	3.660	3.536	0.491	4
SO2	5.705	1.481	0.206	6
SO3	4.808	2.387	0.332	5
WO1	5.865	1.307	0.182	7
WO2	6.669	0.488	0.068	11
WO3	6.661	0.498	0.070	10
ST1	6.352	0.795	0.111	8
ST2	2.306	4.886	0.679	2
ST3	2.027	5.138	0.717	1
WT1	2.535	4.651	0.647	3
WT2	6.585	0.595	0.083	9
WT3	7.041	0.107	0.015	12

Table 6. TOPSIS

demise of textile industries. Predicated upon this, some governments, particularly East Africa, have instituted bans on SHC to “promote the local textile industry”

(T5, 16.3% table 5 of the Threats sub-factors strategy). However, it is unclear whether local textile production and employment would recover even without

SHC. Local African markets are now flooded with low-cost textiles imports from Asia [15, 17]. Even though the trade has enormous Opportunities such as O1 9.9%, it is impeded by *Unstable tax schemes and import duties* (T3, 8.8%) was graded as the second most crucial sub-factor of concern in the Threats sub-factors strategy. Easing import duties and stabilizing tax schemes will allow retailers to offer lower prices for high-quality SHC products. A summary of all global weights from both AHP and FAHP methods is in figure 5.

4.2. Results of Fuzzy Logic and TOPSIS

We introduce the TOPSIS method to rank strategies that need immediate improvement. The most critical aspects

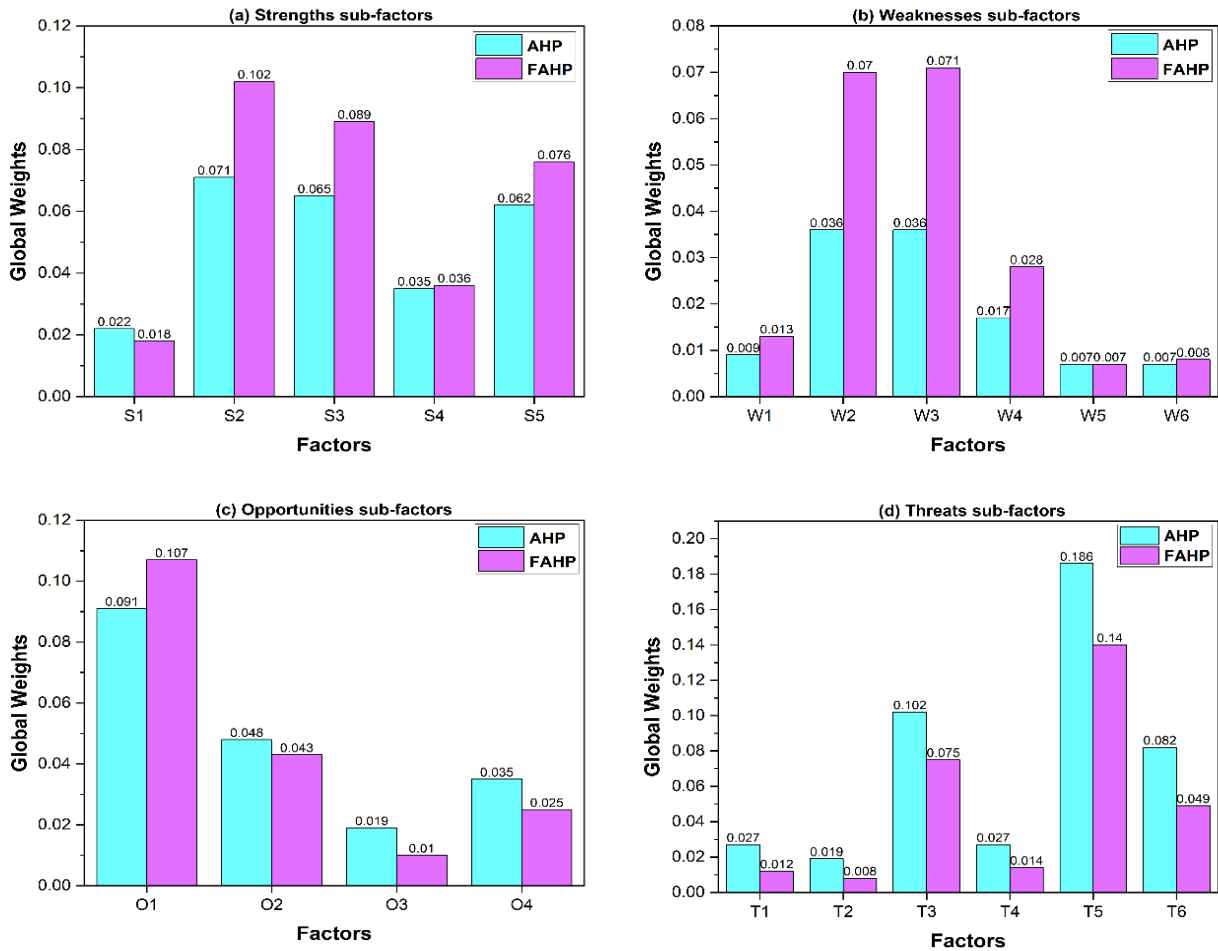


Fig. 5. Global weights of both AHP & FAHP

of SHC’s sustainable development are considered and contrasted to find the essential criteria for advancement. Both FAHP and TOPSIS methods thus extend the SWOT strategy by identifying key issues to improve. The weighting results calculated in Fuzzy AHP were used to derive the TOPSIS aggregated fuzzy weights. Table 6 shows the weighted performance score of the alternatives and their closeness coefficient (CC_i) using the fuzzy TOPSIS method.

ST3 with a CC_i of 0.717 is ranked as the strategy needing the most improvement. Regulatory efforts in addressing unstable market prices, fluctuating exchange rates, and the frequent demolition of market structures will promote the local textile industry through upcycling, remanufacturing, or rebranding. Dual currency was an issue of concern highlighted by our respondents. Using a dual-exchange system will generate

inflation in the long term as different exchange rates lead a government to lose money on foreign currency transactions. This forces the central bank to print additional money to make up for the loss, which is precisely the case of Liberia today. In addition, policies on banning the importation of SHC tend to derail progress in poverty alleviation and women empowerment. ST3 strategy calls for investors, regulators, and policymakers to consider a careful move on banning the importation of SHC. ST2 with CC_i of 0.679 and WT1 with CC_i of 0.647 are ranked second and third. The rest of the strategies are summarized in table A6 of the Appendix section.

5. Conclusion and Implications

In this research, we used a mixture of SWOT, AHP, fuzzy TOPSIS, and

the Ensemble methods in an MCDM preference analysis to evaluate essential factors in implementing a sustainable SHC supply chain to recommend strategic directions towards their successful implementation. Our results highlight that SHC has received more preferences over local and imported clothing due to its low cost and availability. In our survey, we also learned from wholesalers, retailers, and consumers that there is a strong positive relationship between SHC and revenue generation, creation of employment avenues, women empowerment, and the improvement of livelihoods (more on these matrices in our forthcoming paper). This is indicated by the SWOT group analysis score of 28.8% for Strengths. However, results show that SHC faces enormous Threats (37%) mainly due to poor import and market regulations. The trade is constrained from threats of governments’ plans to ban its importation completely.

However, as respondents of our survey highlighted, many smaller countries such as Liberia, Sierra Leone, Gambia, Guinea Bissau, etc., lack the financial resources to establish textile industries that will withstand the competition from China and other Asian countries while offering low costs with broad coverage for the local majority.

Both W3 and W2 provide important implications of this study for potential policy interventions. They emphasize the need for governments and regulatory bodies to stimulate employment opportunities by promoting strategies that will provide better financial access to young entrepreneurs.

Additionally, many of our respondents expressed satisfaction with the fashion remanufacturing, rebranding, and upcycling initiatives already begun in many parts of Africa. Remanufacturing, rebranding, and upcycling are adding African styles and values more cost-effectively. Governments investing in more such initiatives would open more employment opportunities that will lead to women's empowerment.

Lastly, our hybrid model can handle ambiguity, inaccuracy, and complexity of choices from several varied and competing criteria. Future researchers could continue developing the model by adding new criteria that might be utilized

to undertake a more complete study of the possibilities provided and integrate more information about the study point. Our method could also be applied to other countries to assist policymakers in mapping the critical factors in their SHC supply chains.

Acknowledgement

This research was supported by Zhejiang Philosophy and Social Science Foundation (Project No.: 21NDJC062YB), Zhejiang Soft Science Research Project (Project No.: 2020C35038), the Fundamental Research Funds for Zhejiang Sci-Tech University (Project No.: 2021Q063).

References

1. E. Hur, "Rebirth fashion: Secondhand clothing consumption values and perceived risks," *Journal of Cleaner Production*, vol. 273, p. 122951, Nov. 2020, doi: 10.1016/j.jclepro.2020.122951.
2. R. Maiti, "Fast Fashion: Its Detrimental Effect on the Environment," *Earth. Org - Past | Present | Future*, Jan. 29, 2020. <https://earth.org/fast-fashion-detrimental-effect-on-the-environment/> (accessed Oct. 19, 2021).
3. C. Sunhilde and T. Simona, "FAST FASHION AND SECOND HAND CLOTHES BETWEEN ECOLOGICAL CONCERNS AND GLOBAL BUSINESS," p. 5, Jan. 2014.
4. THREDUP, "2021 Fashion Resale Market and Trend Report," 2021. <https://www.thredup.com/resale/> (accessed Oct. 24, 2021).
5. M. Mush, "Sustainable Shopping: Keeping it Circular - Sustainable Fashion - Luxiders Magazine," *Sustainable Fashion - Eco Design - Healthy Lifestyle - Luxiders Magazine*, Aug. 08, 2018. <https://luxiders.com/sustainable-shopping/> (accessed Oct. 25, 2021).
6. S. Gopalakrishnan and D. Matthews, "Collaborative consumption: a business model analysis of second-hand fashion," *JFMM*, vol. 22, no. 3, pp. 354–368, Jun. 2018, doi: 10.1108/JFMM-05-2017-0049.
7. K. T. Hansen and J. Le Zotte, "Changing Secondhand Economies," *Business History*, vol. 61, no. 1, pp. 1–16, Jan. 2019, doi: 10.1080/00076791.2018.1543041.
8. M. Zaman, H. Park, Y.-K. Kim, and S.-H. Park, "Consumer orientations of second-hand clothing shoppers," *Journal of Global Fashion Marketing*, vol. 10, no. 2, pp. 163–176, Apr. 2019, doi: 10.1080/20932685.2019.1576060.
9. L. Norris, "Urban prototypes: Growing local circular cloth economies," *Business History*, vol. 61, no. 1, pp. 205–224, Jan. 2019, doi: 10.1080/00076791.2017.1389902.
10. H. Park and C. M. J. Martinez, "Secondhand clothing sales are booming – and may help solve the sustainability crisis in the fashion industry," Nov. 17, 2020. <https://theconversation.com/secondhand-clothing-sales-are-booming-and-may-help-solve-the-sustainability-crisis-in-the-fashion-industry-148403> (accessed Oct. 25, 2021).
11. E. Katende-Magezi, "The Impact of Second Hand Clothes and Shoes in East Africa," pp. 5–39, 2017.
12. M. W. Mhango and L. S. Niehm, "The second-hand clothing distribution channel: Opportunities for retail entrepreneurs in Malawi," *Journal of Fashion Marketing and Management*, vol. 9, no. 3, pp. 342–356, 2005, doi: 10.1108/13612020510610462.
13. U. L. Mwasomola and E. Ojwang, "THE INFLUX OF SECOND-HAND CLOTHING TRADE AND ITS IMPACTS ON THE GROWTH OF THE LOCAL TEXTILE SECTOR IN TANZANIA," p. 10, Jul. 2021.
14. F. A. Emefa, G. R. Selase, A. Joana, and G. Selorm, "The Impact of the Use of Second-Hand Clothing on the Garment and Textile Industries in Ghana: A Case Study of the Ho Municipality," *Online*, vol. 5, no. 21, pp. 2225–0484, 2015.
15. S. Baden and C. Barber, "The impact of the second-hand clothing trade on developing countries," *Interdisciplinary Science Reviews*, vol. 2, no. February 2005, pp. 10–12, 2005.
16. USAID, "Overview of the Used Clothing Market in East Africa: Analysis of Determinants and Implications," no. July, pp. 1–32, 2017.
17. A. Brooks and D. Simon, "Unravelling the Relationships between Used-Clothing Imports and the Decline of African Clothing Industries," *Development and Change*, vol. 43, no. 6, pp. 1265–1290, 2012, doi: 10.1111/j.1467-7660.2012.01797.x.
18. O. Abimbola, "The international trade in secondhand clothing: Managing information asymmetry between west African and British traders," *Textile: The Journal of Cloth and Culture*, vol. 10, no. 2, pp. 184–199, 2012, doi: 10.2752/175183512X13315695424310.
19. J. Amankwah-Amoah, "Explaining declining industries in developing

- countries: The case of textiles and apparel in Ghana,” *Competition and Change*, vol. 19, no. 1, pp. 19–35, 2015, doi: 10.1177/1024529414563004.
20. A. Brooks, “Riches from rags or persistent poverty? The working lives of secondhand clothing vendors in Maputo, Mozambique,” *Textile: The Journal of Cloth and Culture*, vol. 10, no. 2, pp. 222–237, 2012, doi: 10.2752/175183512X13315695424239.
 21. W. Chipambwa, L. Sithole, and D. F. Chisosa, “Consumer perceptions towards second-hand undergarments in Zimbabwe: a case of Harare urban dwellers,” *International Journal of Fashion Design, Technology and Education*, vol. 9, no. 3, pp. 176–182, Sep. 2016, doi: 10.1080/17543266.2016.1151555.
 22. A. St. J. James and A. Kent, “Clothing Sustainability and Upcycling in Ghana Alberta,” *Paper Knowledge . Toward a Media History of Documents*, pp. 12–26, 2020.
 23. T. Mangieri, “African cloth, export production and second-hand clothing in Kenya,” *The Moving Frontier: The Changing Geography of Production in Labour-Intensive Industries*, vol. 2006, no. January, pp. 301–318, 2019, doi: 10.4324/9780429052682-15.
 24. K. K. Wetengere, “Is the Banning of Importation of Second-Hand Clothes and Shoes a Panacea to Industrialization in East Africa?,” *African Journal of Economic Review*, vol. 6, no. 1, pp. 119–141, 2018, doi: 10.22004/ag.econ.274747.
 25. T. L. Saaty, “What is the Analytic Hierarchy Process?,” in *Mathematical Models for Decision Support*, Berlin, Heidelberg: Springer Berlin Heidelberg, 1988, pp. 109–121. doi: 10.1007/978-3-642-83555-1_5.
 26. P. H. N. Rao, N. S. Vihari, and S. S. Jabeen, “Reimagining the Fashion Retail Industry Through the Implications of COVID-19 in the Gulf Cooperation Council (GCC) Countries,” *FIIIB Business Review*, vol. 10, no. 4, pp. 327–338, Dec. 2021, doi: 10.1177/23197145211039580.
 27. S. Tarai and K. Shailaja, “Consumer perception towards sale of second-hand clothes in the localities of Odisha, States of India,” *JTEFT*, vol. 6, no. 4, Aug. 2020, doi: 10.15406/jteft.2020.06.00245.
 28. J. King and A. Wheeler, “Setting the record straight,” Oct. 27, 2016. <https://www.recyclingwasteworld.co.uk/opinion/setting-the-record-straight/147367/> (accessed Dec. 22, 2021).
 29. C. M. Armstrong, K. Niimimäki, S. Kujala, E. Karell, and C. Lang, “Sustainable product-service systems for clothing: exploring consumer perceptions of consumption alternatives in Finland,” *Journal of Cleaner Production*, vol. 97, pp. 30–39, Jun. 2015, doi: 10.1016/j.jclepro.2014.01.046.
 30. S. Bly, W. Gwozdz, and L. A. Reisch, “Exit from the high street: an exploratory study of sustainable fashion consumption pioneers: Sustainable fashion consumption pioneers study,” *International Journal of Consumer Studies*, vol. 39, no. 2, pp. 125–135, Mar. 2015, doi: 10.1111/ijcs.12159.
 31. T. Jägel, K. Keeling, A. Reppel, and T. Gruber, “Individual values and motivational complexities in ethical clothing consumption: A means-end approach,” *Journal of Marketing Management*, vol. 28, no. 3–4, pp. 373–396, Mar. 2012, doi: 10.1080/0267257X.2012.659280.
 32. K. Khurana and R. Tadesse, “A study on relevance of second hand clothing retailing in Ethiopia,” *Research Journal of Textile and Apparel*, vol. 23, no. 4, pp. 323–339, 2019, doi: 10.1108/RJTA-12-2018-0063.
 33. N. Nørup, K. Pihl, A. Damgaard, and C. Scheutz, “Replacement rates for second-hand clothing and household textiles – A survey study from Malawi, Mozambique and Angola,” *Journal of Cleaner Production*, vol. 235, pp. 1026–1036, 2019, doi: 10.1016/j.jclepro.2019.06.177.
 34. D. Thompson and G. S. Peter, “A Survey of Fashion Reconsumption Techniques Employed by Second Hand Clothing Retailers in Port,” *American Journal of Environmental Policy and Management*, vol. 1, no. 4, pp. 72–77, 2015.
 35. G. Frazer, “Used-clothing donations and apparel production in Africa,” *Economic Journal*, vol. 118, no. 532, pp. 1764–1784, 2008, doi: 10.1111/j.1468-0297.2008.02190.x.
 36. E. K. Howard, I. Aboagye, and J. N. Quarcoo, “Causes and Effects of the Dwindled State of the Ghana Textile Industry,” *International Journal of Advanced Scientific Research & Development*, no. November, 2016, [Online]. Available: https://www.researchgate.net/publication/332859288_Causes_and_Effects_of_the_Dwindled_State_of_the_Ghana_Textile_Industry
 37. A. Brooks, “Riches from rags or persistent poverty? The working lives of secondhand clothing vendors in Maputo, Mozambique,” *Textile: The Journal of Cloth and Culture*, vol. 10, no. 2, pp. 222–237, 2012, doi: 10.2752/175183512X13315695424239.
 38. A. Brooks, “Clothing Poverty: The Hidden World of Fast Fashion and Second-hand Clothes Clothing Poverty,” no. September, 2015, doi: 10.13140/RG.2.1.3268.0161.
 39. K. T. Hansen, “Helping or hindering? Outline,” vol. 20, no. May, 2006.
 40. K. T. Hansen, “The Secondhand Clothing Market in Africa and its Influence on Local Fashions Secondhand Clothing Market in Africa and its Influence on Local Fashions,” *DRESSTUDY Autumn*, vol. 64, 2014, [Online]. Available: http://www.kci.or.jp/research/dressstudy/pdf/K_D64_HANSEN_The_Secondhand_Clothing_ENG.pdf
 41. G. Baffoe, “Exploring the utility of Analytic Hierarchy Process (AHP) in ranking livelihood activities for effective and sustainable rural development interventions in developing countries,” *Evaluation and Program Planning*, vol. 72, pp. 197–204, Feb. 2019, doi: 10.1016/j.evalprogplan.2018.10.017.
 42. A. Görener, K. Toker, and K. Uluçay, “Application of Combined SWOT and AHP: A Case Study for a Manufacturing Firm,” *Procedia - Social and Behavioral Sciences*, vol. 58, pp. 1525–1534, Oct. 2012, doi: 10.1016/j.sbspro.2012.09.1139.
 43. N. Piercy and W. Giles, “Making SWOT Analysis Work,” *Marketing Intelligence & Plan*, vol. 7, no. 5/6, pp. 5–7, May 1989, doi: 10.1108/EUM000000001042.
 44. N. Ç. İlgören and C. Ayla, “Evaluation on textile-apparel education by Swot analysis,” *Procedia - Social and Behavioral Sciences*, vol. 1, no. 1, pp. 1307–1312, 2009, doi: 10.1016/j.sbspro.2009.01.231.
 45. K. Seher, A. Sadaf Aftab, P. Mazhar Hussain, and A. Turan, “SWOT analysis of Pakistan’s textile and clothing industry,” *Industria Textila*, vol. 69, no. 06, pp. 502–510, Jan. 2019, doi: 10.35530/IT.069.06.1488.
 46. R. Lin, Y. Liu, Y. Man, and J. Ren, “Towards a sustainable distributed energy

- system in China: decision-making for strategies and policy implications,” *Energy Sustain Soc*, vol. 9, no. 1, p. 51, Dec. 2019, doi: 10.1186/s13705-019-0237-9.
47. A. A. Patil and M. B. Kumthekar, “Supplier Evaluation and selection methods in construction industry,” vol. 03, no. 06, p. 7, Jun. 2016.
 48. İ. Kaya, M. Çolak, and F. Terzi, “A comprehensive review of fuzzy multi criteria decision making methodologies for energy policy making,” *Energy Strategy Reviews*, vol. 24, pp. 207–228, Apr. 2019, doi: 10.1016/j.esr.2019.03.003.
 49. Ö. C. Bulur and M. Kayar, “Using topsis and ahp methods in job distribution to subcontractors in apparel companies and comparing the results,” *Fibres and Textiles in Eastern Europe*, vol. 29, no. 4, pp. 24–31, 2021, doi: 10.5604/01.3001.0014.8227.
 50. C. Sariçam and S. M. Yilmaz, “An integrated framework for supplier selection and performance evaluation for apparel retail industry,” *Textile Research Journal*, p. 004051752199235, Feb. 2021, doi: 10.1177/0040517521992353.
 51. A. Majumdar, R. Mangla, and A. Gupta, “Developing a decision support system software for cotton fibre grading and selection,” *INDIAN J. FIBRE TEXT. RES.*, p. 6, 2010.
 52. C. Saricam and N. Okur, “Evaluation of Regenerated Bamboo, Polyester and Cotton Knitted Fabrics for Summer Clothing,” *FIBRES & TEXTILES in Eastern Europe 2018; 26, 4(130): 82-89*, vol. 26, no. 4(130), pp. 82–89, 2018, doi: 10.5604/01.3001.0012.1317.
 53. L. Pu, Y. Hong, and H. Mu, “Conceptual fuzzy AHP model for perception analysis of a children’s raincoat,” *Fibres and Textiles in Eastern Europe*, vol. 28, no. 2, pp. 96–102, 2020, doi: 10.5604/01.3001.0013.7322.
 54. V. Kaushik, A. Khare, R. Boardman, and M. B. Cano, “Why do online retailers succeed? The identification and prioritization of success factors for Indian fashion retailers,” *Electronic Commerce Research and Applications*, vol. 39, p. 100906, Jan. 2020, doi: 10.1016/j.elerap.2019.100906.
 55. R. B. Kim, T. Matsui, Y. J. Park, and T. Okutani, “Perceived Consumer Value of Omni-Channel Service Attributes in Japan and Korea,” *EE*, vol. 30, no. 5, pp. 621–630, Dec. 2019, doi: 10.5755/j01.ee.30.5.22820.
 56. K. Khalili-Damghani, S. Sadi-Nezhad, and M. Tavana, “Solving multi-period project selection problems with fuzzy goal programming based on TOPSIS and a fuzzy preference relation,” *Information Sciences*, vol. 252, pp. 42–61, Dec. 2013, doi: 10.1016/j.ins.2013.05.005.
 57. C. Karakosta, “A Holistic Approach for Addressing the Issue of Effective Technology Transfer in the Frame of Climate Change,” *Energies*, vol. 9, no. 7, p. 503, Jun. 2016, doi: 10.3390/en9070503.
 58. S. Erpolat Taşabat, “A Novel Multicriteria Decision-Making Method Based on Distance, Similarity, and Correlation: DSC TOPSIS,” *Mathematical Problems in Engineering*, vol. 2019, pp. 1–20, Apr. 2019, doi: 10.1155/2019/9125754.
 59. K. Palczewski and W. Sałabun, “The fuzzy TOPSIS applications in the last decade,” *Procedia Computer Science*, vol. 159, pp. 2294–2303, 2019, doi: 10.1016/j.procs.2019.09.404.
 60. C. Kahraman, S. C. Onar, and B. Oztaysi, “Fuzzy Multicriteria Decision-Making: A Literature Review:,” *IJCIS*, vol. 8, no. 4, p. 637, 2015, doi: 10.1080/18756891.2015.1046325.
 61. J. C. Sá *et al.*, “Assessing the Impact of Lean Tools on Production and Safety by a Multicriteria Decision-Making Model and Statistical Analysis: A Case Study in Textile Sector,” in *HCI International 2021 - Late Breaking Papers: HCI Applications in Health, Transport, and Industry*, vol. 13097, C. Stephanidis, V. G. Duffy, H. Krömker, F. Fui-Hoon Nah, K. Siau, G. Salvendy, and J. Wei, Eds. Cham: Springer International Publishing, 2021, pp. 616–638. doi: 10.1007/978-3-030-90966-6_42.
 62. J. Ye and T.-Y. Chen, “Selection of Cotton Fabrics Using Pythagorean Fuzzy TOPSIS Approach,” *Journal of Natural Fibers*, pp. 1–16, Oct. 2021, doi: 10.1080/15440478.2021.1982439.
 63. K. Mathiyazhagan and S. Ahuja, “Modelling the sustainable supply chain management practices in Indian industries: a business model using the fuzzy TOPSIS approach,” *IJOR*, vol. 41, no. 3, p. 324, 2021, doi: 10.1504/IJOR.2021.116252.
 64. P. Pattnaik and G. S. Dangayach, “Sustainability of textile waste-water management by using an integrated fuzzy AHP-TOPSIS method: a case study,” *IJESD*, vol. 20, no. 2, p. 105, 2021, doi: 10.1504/IJESD.2021.114543.
 65. C.-N. Wang, C.-F. Pan, V. Tinh Nguyen, and S. Tam Husain, “Sustainable Supplier Selection Model in Supply Chains During the COVID-19 Pandemic,” *Computers, Materials & Continua*, vol. 70, no. 2, pp. 3005–3019, 2022, doi: 10.32604/cmc.2022.020206.
 66. LISGIS, “Report on the Liberia Labour Force Survey 2010.” 2010. [Online]. Available: https://lisgis.net/pg_img/2010%20Labour%20Force%20Report.pdf
 67. W. N. Tokpah, “Liberia: Redlight Market Finally Relocated to 14 Gobachop Market,” *FrontPageAfrica*, Jul. 13, 2021. <https://frontpageafricaonline.com/news/liberia-redlight-market-finally-relocated-to-14-gobachop-market/> (accessed Dec. 04, 2021).
 68. H.-H. Chang and W.-C. Huang, “Application of a quantification SWOT analytical method,” *Mathematical and Computer Modelling*, vol. 43, no. 1–2, pp. 158–169, Jan. 2006, doi: 10.1016/j.mcm.2005.08.016.
 69. L. A. Zadeh, “Fuzzy sets,” *Information and Control*, vol. 8, no. 3, pp. 338–353, Jun. 1965, doi: 10.1016/S0019-9958(65)90241-X.
 70. J. J. Buckley, “Fuzzy hierarchical analysis,” *Fuzzy Sets and Systems*, vol. 17, no. 3, pp. 233–247, Dec. 1985, doi: 10.1016/0165-0114(85)90090-9.
 71. B. Das and S. C. Pal, “Assessment of groundwater vulnerability to over-exploitation using MCDA, AHP, fuzzy logic and novel ensemble models: a case study of Goghat-I and II blocks of West Bengal, India,” *Environ Earth Sci*, vol. 79, no. 5, p. 104, Mar. 2020, doi: 10.1007/s12665-020-8843-6.
 72. N. Sahani, “Application of hybrid SWOT-AHP-FuzzyAHP model for formulation and prioritization of ecotourism strategies in Western Himalaya, India,” *International Journal of Geoheritage and Parks*, vol. 9, no. 3, pp. 349–362, Sep. 2021, doi: 10.1016/j.ijgeop.2021.08.001.

Appendix

Expert	Years of experience	Academic Qualification
1	>17	PhD
2	>14	PhD
3	>14	PhD
4	>12	PhD Candidate
5	>10	MBA
6	>8	MSc

Table A1. Experts involved in the identification, and categorization of SWOT factors

AHP Rating	Inverse	Fuzzy Number	Linguistic Scale	TFN	Inverse TFN
1	1	$\tilde{1}$	Equally important (EI)	(1,1,1)	(1,1,1)
2	1/2	$\tilde{2}$	Intermediate value (IV)	(1,2,3)	(1/3, 1/2, 1)
3	1/3	$\tilde{3}$	Moderately important	(2,3,4)	(1/4, 1/3, 1/2)
4	1/4	$\tilde{4}$	Intermediate value (IV)	(3,4,5)	(1/5, 1/4, 1/3)
5	1/5	$\tilde{5}$	Strongly more important (SMI)	(4,5,6)	(1/6, 1/5, 1/4)
6	1/6	$\tilde{6}$	Intermediate value (IV)	(5,6,7)	(1/7, 1/6, 1/5)
7	1/7	$\tilde{7}$	Very strongly important (VSI)	(6,7,8)	(1/8, 1/7, 1/6)
8	1/8	$\tilde{8}$	Intermediate value (IV)	(7,8,9)	(1/9, 1/8, 1/7)
9	1/9	$\tilde{9}$	Extremely more important (EMI)	(8,9,9)	(1/9, 1/9, 1/7)

Table A2. Saaty's AHP and fuzzy pairwise comparing scale

	X_1	X_2	X_3	X_4	X_5
X_1	a_1/a_1	a_1/a_2	a_1/a_3	a_1/a_j	a_1/a_n
X_2	a_2/a_1	a_2/a_2	a_2/a_3	a_2/a_j	a_2/a_n
X_3	a_3/a_1	a_3/a_2	a_3/a_3	a_3/a_j	a_3/a_n
X_4	a_j/a_1	a_j/a_2	a_j/a_3	a_j/a_j	a_j/a_n
X_5	a_n/a_1	a_n/a_2	a_n/a_3	a_n/a_j	a_n/a_n

Table A3. Pairwise comparison matrix

			AHP			
SWOT Grp	S	W	O	T		
S	1.000	2.000	2.000	0.500		
W	0.500	1.000	0.333	0.333		
O	0.500	3.000	1.000	0.333		
T	2.000	3.000	3.000	1.000		
CR=0.07	$\lambda_{max}=4.19$		CI=0.06			
Strengths	S1	S2	S3	S4	S5	
S1	1.000	0.500	0.333	0.500	0.250	
S2	2.000	1.000	1.000	2.000	2.000	
S3	3.000	1.000	1.000	2.000	1.000	
S4	2.000	0.500	0.500	1.000	0.500	
S5	4.000	0.500	1.000	2.000	1.000	
CR=0.03	$\lambda_{max}=5.16$		CI=0.04			
Weaknesses	W1	W2	W3	W4	W5	W6
W1	1.000	0.250	0.250	0.500	2.000	1.000
W2	4.000	1.000	1.000	4.000	4.000	4.000
W3	4.000	1.000	1.000	3.000	5.000	5.000
W4	2.000	0.250	0.333	1.000	3.000	4.000
W5	0.500	0.250	0.200	0.333	1.000	1.000
W6	1.000	0.250	0.200	0.250	1.000	1.000
CR=0.04	$\lambda_{max}=6.27$		CI=0.05			
Opportunities	O1	O2	O3	O4		
O1	1.000	3.000	3.000	3.000		
O2	0.333	1.000	3.000	2.000		
O3	0.333	0.333	1.000	0.333		
O4	0.333	0.500	3.000	1.000		
CR=0.09	$\lambda_{max}=4.26$		CI=0.08			
Threats	T1	T2	T3	T4	T5	T6
T1	1.000	3.000	0.250	0.500	0.142	0.166
T2	0.333	1.000	0.200	1.000	0.142	0.200
T3	4.000	5.000	1.000	4.000	0.500	2.000
T4	2.000	1.000	0.250	1.000	0.142	0.250
T5	7.000	7.000	2.000	7.000	1.000	4.000
T6	6.000	5.000	0.500	4.000	0.250	1.000
CR=0.08	$\lambda_{max}=6.51$		CI=0.10	CR=0.08		

Table A4. Results of AHP pairwise comparison of SWOT group and sub-factors

	Fuzzy AHP					
SWOT Grp	S	W	O	T		
S	(1, 1, 1)	(2, 3, 4)	(2, 3, 4)	(0.25, 0.333, 0.5)		
W	(0.25, 0.333, 0.5)	(1, 1, 1)	(4, 5, 6)	(0.2, 0.25, 0.333)		
O	(0.25, 0.333, 0.5)	(0.166, 0.2, 0.25)	(1, 1, 1)	(4, 5, 6)		
T	(2, 3, 4)	(3, 4, 5)	(0.166, 0.2, 0.25)	(1, 1, 1)		
Strengths	S1	S2	S3	S4	S5	
S1	(1, 1, 1)	(0.25, 0.333, 0.5)	(0.166, 0.2, 0.25)	(0.25, 0.333, 0.5)	(0.142, 0.166, 0.2)	
S2	(2, 3, 4)	(1, 1, 1)	(1, 1, 1)	(2, 3, 4)	(2, 3, 4)	
S3	(4, 5, 6)	(1, 1, 1)	(1, 1, 1)	(2, 3, 4)	(1, 1, 1)	
S4	(2, 3, 4)	(0.25, 0.333, 0.5)	(0.25, 0.333, 0.5)	(1, 1, 1)	(0.25, 0.333, 0.5)	
S5	(5, 6, 7)	(0.25, 0.333, 0.5)	(1, 1, 1)	(2, 3, 4)	(1, 1, 1)	
Weaknesses	W1	W2	W3	W4	W5	W6
W1	(1, 1, 1)	(0.142, 0.166, 0.2)	(0.142, 0.166, 0.2)	(0.25, 0.333, 0.5)	(4, 5, 6)	(1, 1, 1)
W2	(5, 6, 7)	(1, 1, 1)	(1, 1, 1)	(5, 6, 7)	(5, 6, 7)	(5, 6, 7)
W3	(5, 6, 7)	(1, 1, 1)	(1, 1, 1)	(4, 5, 6)	(6, 7, 8)	(6, 7, 8)
W4	(4, 5, 6)	(0.142, 0.166, 0.2)	(0.166, 0.2, 0.25)	(1, 1, 1)	(4, 5, 6)	(5, 6, 7)
W5	(0.25, 0.333, 0.5)	(0.142, 0.166, 0.2)	(0.125, 0.142, 0.166)	(0.166, 0.2, 0.25)	(1, 1, 1)	(1, 1, 1)
W6	(1, 1, 1)	(0.142, 0.166, 0.2)	(0.125, 0.142, 0.166)	(0.142, 0.166, 0.2)	(1, 1, 1)	(1, 1, 1)
Opportunities	O1	O2	O3	O4		
O1	(1, 1, 1)	(4, 5, 6)	(4, 5, 6)	(4, 5, 6)		
O2	(0.166, 0.2, 0.25)	(1, 1, 1)	(4, 5, 6)	(2, 3, 4)		
O3	(0.166, 0.2, 0.25)	(0.166, 0.2, 0.25)	(1, 1, 1)	(0.166, 0.2, 0.25)		
O4	(0.166, 0.2, 0.25)	(0.25, 0.333, 0.5)	(4, 5, 6)	(1, 1, 1)		
Threats	T1	T2	T3	T4	T5	T6
T1	(1, 1, 1)	(4, 5, 6)	(0.142, 0.166, 0.2)	(0.25, 0.333, 0.5)	(0.111, 0.111, 0.125)	(0.111, 0.125, 0.142)
T2	(0.166, 0.2, 0.25)	(1, 1, 1)	(0.125, 0.142, 0.166)	(1, 1, 1)	(0.111, 0.111, 0.125)	(0.125, 0.142, 0.166)
T3	(5, 6, 7)	(6, 7, 8)	(1, 1, 1)	(5, 6, 7)	(0.25, 0.333, 0.5)	(2, 3, 4)
T4	(2, 3, 4)	(1, 1, 1)	(0.166, 0.2, 0.25)	(1, 1, 1)	(0.111, 0.111, 0.125)	(0.142, 0.166, 0.2)
T5	(8, 9, 9)	(8, 9, 9)	(2, 3, 4)	(8, 9, 9)	(1, 1, 1)	(5, 6, 7)
T6	(7, 8, 9)	(6, 7, 8)	(0.25, 0.333, 0.5)	(5, 6, 7)	(0.142, 0.166, 0.2)	(1, 1, 1)

Table A5. Results of FAHP pairwise comparison of SWOT group and sub-factors

SO1	It's easier shopping second-hand clothes because it has a solid country-wide presence with a great variety of products and increased choosability options which creates employment avenues that lead to poverty alleviation and women empowerment in particular
SO2	SHC are quality products, durable and affordable for the local majority. Both retailers and suppliers can independently operate businesses with a much faster realization of improvements. If its serviceability range is more comprehensive for consumers, it will extend the garment's life-cycle and reduce fast fashion demand
SO3	Institutional loan opportunities coupled with quantity discounts from wholesalers to retailers may lead to low capital requirements for beginners as well as promote market expansion
WO1	Obtaining financial assistance to startups will promote new market expansion for young entrepreneurs
WO2	Providing skillsets that will improve those clothes that sometimes require alteration creates additional employment avenues.
WO3	The corporation between members of the supply chain could ease the lack of storage/warehouse facilities as well as regulate the increasing pressure to provide lower prices in the competitive environment
ST1	Fast-changing consumers' choices, particularly in the clothing segment, has created a strong demand for SHC nation-wide upsetting intense competition from new entrants
ST2	Unstable tax schemes and import duties will significantly affect the importation of quality and affordable SHC products for the local majority
ST3	Regulators improving on unstable prices and exchange rates due to dual currency and frequent demolition of market structures will promote the local textile industry in upcycling. Policies on banning the importation of SHC will derail progress in poverty alleviation and women empowerment.
WT1	Due to a volatile tax system, exchange rates, dual currencies, import duties, and the constant breakdown of market structures, retailers face more uncertainties as prices from wholesalers are high, and consumers are reluctant to buy
WT2	The supply chain lacks a sound delivery system due to poor logistics infrastructure to transport goods around
WT3	Consumers' choices keep changing at a faster pace due to competition from the Fast Fashion market and the growing number of new entrants

Table A6. Summarized table of SWOT categorized strategies