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Managing Product Returns at the Source: Associations between SCOR Processes and Return Performance - Multimethod Evidence from the Gaziantep Carpet Manufacturing Industry

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Abstract. Product returns are not merely a post-sale reverse-logistics activity; they can also represent the visible outcome of deficiencies in planning, sourcing, production, delivery, and supply chain governance. This study examines associations between the Plan, Source, Make, Deliver, and Enable processes in the SCOR Model 12.0 and a perception-based Return construct and identifies processes that merit managerial attention for return prevention. A multimethod design is employed. A total of 119 valid questionnaires collected from carpet manufacturing firms operating in Gaziantep, Türkiye, were analyzed via exploratory factor analysis, correlation analysis, and multiple linear regression. Evaluations of 28 SCOR metrics obtained from 10 supply chain managers were then weighted via the entropy method, and semistructured interviews with four stakeholders connected to one large carpet manufacturer were used for contextual interpretation. Because the survey is cross-sectional and all the constructs were measured from the same respondents at one measurement occasion, the regression coefficients are interpreted as associations rather than causal effects, and common-method variance cannot be ruled out. The main regression model accounts for 75.7% of the variance in the Return construct ($R^2 = .757$; adjusted $R^2 = .747$; $p < .001$). Plan is the strongest predictor ($\beta = -.559$; $p < .001$), followed by Enable ($\beta = -.253$; $p = .004$), Make ($\beta = -.200$; $p = .017$), and Deliver ($\beta = -.170$; $p = .021$); Source is not statistically significant ($\beta = -.091$; $p = .115$). Exploratory item-level regressions identify supply chain data and information management ($\beta = -.668$; $p < .001$) and engineer-to-order production ($\beta = -.546$; $p < .001$) as the strongest nominal associations, but these item-level p values are unadjusted for multiple testing and are treated as hypothesis-generating. Within the 10-manager panel, entropy-derived weights rank Plan first, and an indicator-count-normalized sensitivity check also leaves Plan first, although the ordering of intermediate processes changes. Overall, the findings are consistent with a preventive, upstream approach to returns centered on planning, information governance, customized production, and fulfillment control.

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Keywords: SCOR model, supply chain performance, reverse logistics, entropy weighting, carpet manufacturing.

1 Introduction

Increasing product variety, shorter lead times, rising customer expectations, and intensified cost pressure have made it necessary for firms to evaluate performance problems through end-to-end processes rather than isolated functions. Product returns are a particularly critical indicator in this context. When a product moves back from the customer to the firm, the consequences extend beyond reverse transportation, handling, inspection, repackaging, storage, resale, or disposal costs. Returns may also affect customer trust and the operational reputation of the firm. The depreciation of returned products, delays in remarketing, and the need to manage reverse flows across multiple channels show that the issue cannot be confined to after-sales service or a reverse logistics department.

Although a return is usually observed at the downstream end of the supply chain, its underlying cause may originate much earlier. Inaccurate demand forecasts or weak planning can result in excess production; inappropriate materials or incorrect technical specifications can create quality problems; deviations in manufacturing can cause nonconformity with customer requirements; and insufficient delivery controls can generate incorrect products, quantities, or timings. Similarly, poor data management, managerial turnover, and weak process standardization can be organizational causes behind physical product failure. Accordingly, the key question in return management should not be limited to how returned products can be processed more efficiently; it should also ask where the process failures that cause returns originate.

The supply chain operations reference (SCOR) model is one of the most widely used process-reference frameworks for describing supply chain activities in a common language, measuring performance, and identifying improvement opportunities. SCOR 12.0 structures supply chains around six major processes: plan, source, make, delivery, return, and enable (APICS, 2017). Its major strength lies in integrating process definitions, performance metrics, and best practices within a common architecture that supports benchmarking and process standardization. The model has been applied to performance measurement, process improvement, supplier evaluation, simulation, and multicriteria decision-making across a wide range of industries (Huan et al., 2004; Sellitto et al., 2015; Dissanayake & Cross, 2018; Nguyen, 2024).

Relationships among Plan, Source, Make, and Deliver have been widely discussed in the SCOR literature, but studies that compare their relative associations with product returns in a single empirical model remain limited. In manufacturing research, return is frequently treated as one component of a broader performance framework rather than as an outcome reflecting failures in upstream processes. However, evidence from Türkiye indicates that criteria such as the traceability of returned products and shipment in accordance with promised dates may be decisive for supplier performance (Yılmaz et al., 2020). Moreover, SCOR-based research has long emphasized the need to adapt the generic framework to sectoral and organizational contexts (Georgise et al., 2012; Dissanayake & Cross, 2018). Beyond firm-level operational outcomes, sector-specific

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economic activities can also contribute to regional development by generating employment, stimulating local businesses, and strengthening regional economic vitality (Kutluay Tutar & Abukalloub, 2025).

The Gaziantep carpet manufacturing industry offers an analytically useful context. The yarn type, pattern, color palette, quality grade, and customer specifications are central to production; make-to-order and engineer-to-order arrangements are common; shipment volumes to international markets are high; and carpets are bulky products for which reverse transportation can be expensive. The interviews conducted for this study indicate that firms may prefer discounts or rerouting products to another market rather than physically returning products from overseas destinations, illustrating the high economic significance of preventable returns.

This study contributes in three ways. First, Plan, Source, Make, Deliver, and Enable are compared within the same construct-level regression model to identify which SCOR processes are most strongly associated with the Return construct. Second, the survey-based regression results are compared with entropy-derived priorities from 10 supply chain managers, and an indicator-count-normalized sensitivity check is used to assess whether unequal numbers of metrics influence process-level rankings. Third, semistructured interviews with actors in one large carpet manufacturer's supply chain are used to contextualize and qualify the quantitative patterns rather than to provide independent qualitative validation.

The study retains SCOR 12.0 because it was a valid framework during data collection. Nevertheless, the current SCOR Digital Standard (SCOR DS) reorganizes the architecture around Orchestrate at Level 0 and six Level-1 processes: plan, order, source, transform, fulfill, and return. In the official SCOR DS crosswalk, the former Make process is expanded into Transform, Deliver is separated into Order and Fulfill, and many former Enable activities are elevated into Orchestrate, including business rules, performance management, data and technology, human resources, contracts, and network design (ASCM, 2025, 2026). The discussion therefore provides a systematic mapping from the study's SCOR 12.0 findings to the current SCOR DS so that the managerial implications remain applicable to contemporary supply-chain practice.

Against this background, the study asks the following questions: which SCOR 12.0 processes are most strongly associated with the perception-based return construct, and which processes do managers prioritize when evaluating return-related supply chain improvement? The following sections review the literature and hypotheses, explain the multimethod research design, present the empirical findings, and discuss their theoretical and managerial implications.

2 Literature Review

2.1 Supply Chain Performance and the SCOR Model

Supply chain performance measurement requires firms to evaluate not only internal activities but also connected processes extending from suppliers to customers. The limitations of exclusively financial indicators have led researchers and practitioners to incorporate operational measures such as delivery reliability, responsiveness, agility,

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cost, and asset utilization into performance systems (Akyuz & Erkan, 2010; Maestrini et al., 2017). SCOR responds to this need by defining supply chain processes and performance dimensions within a common reference model.

SCOR 12.0 divides complex supply chains into standardized process categories. The plan concerns balancing demand and resources and coordinating other supply chain activities; the source concerns the acquisition of materials and services; Make transforms inputs into products; Deliver encompasses order fulfillment and physical distribution; Return governs reverse flows; and Enable provides the managerial, informational, human-resource, and governance infrastructure that supports execution (APICS, 2017). This integrated architecture makes interdependencies among supply chain processes visible.

The role of SCOR in supply chain performance has been tested across sectors. Huan et al. (2004) emphasized its process-based approach. Lockamy and McCormack (2004) reported that planning practices, collaboration, process integration, and information technology are central to performance. Li et al. (2011), using data from 232 ISO 9000-certified firms, showed that SCOR decision areas contribute to supply chain quality performance, with planning and sourcing being particularly important from a customer-oriented perspective. Zhou et al. (2011), using data from 125 North American manufacturing firms, empirically validated the relationships among SCOR processes and showed that planning significantly influences Source, Make, and Deliver.

SCOR is also flexible enough to be integrated with decision-support and organization-specific performance systems. Sellitto et al. (2015) combined SCOR processes and performance standards with AHP in the footwear industry. Lima-Junior and Carpinetti (2016) integrated SCOR and fuzzy TOPSIS for supplier evaluation. Dissanayake and Cross (2018) combined SCOR with structural equation modeling and managerial AHP assessments to compare the relative importance of performance areas. These studies demonstrate the value of combining statistical evidence with managerial prioritization.

More recent studies confirm SCOR's continuing relevance. Nguyen (2024) documents its broad use across sectors and research designs, while newer applications increasingly integrate digital technologies, sustainability, and multicriteria decision approaches. For example, Çıkmak et al. (2024) assessed blockchain characteristics against SCOR performance attributes via an integrated fuzzy MCDM methodology, and Purnomo and Syafrianita (2024) applied a Green SCOR approach in textile supply chains. These developments suggest that SCOR functions less as a static scorecard than as an adaptable process architecture.

2.2 Product Returns, Reverse Logistics, and Interprocess Dependence

The return process covers reverse flows associated with defective, excess, obsolete, maintenance-related, or otherwise unacceptable products. In SCOR, return includes identifying the need for a return, authorizing and planning it, transporting the item backward, receiving and evaluating it, and routing it to an appropriate subsequent disposition. Return is therefore not merely reverse transportation; it also includes information, decision, and revaluation activities.

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Reverse logistics research links product returns with reuse, repair, remanufacturing, recycling, and disposal. The SCOR perspective adds value by connecting these reverse activities with forward processes rather than treating them as isolated operations. This connection has become even more important in circular-economy and sustainable logistics research. From a broader perspective, sustainability-oriented international logistics require economic and operational decisions to be considered together with their sustainability implications (Çat & Abukalloub, 2025). Similarly, van Engelenhoven et al. (2023) systematically analyzed SCOR from a circular-economy perspective and argued for stronger integration of reverse flows and postuse activities into process architecture. The contemporary SCOR Digital Standard likewise treats return in relation to reverse product and service flows and subsequent circular activities (ASCM, 2026).

However, the return event is often not where the problem begins. An incorrect customer requirement, a capacity or timing error in planning, the sourcing of unsuitable material, deviation from technical specifications in manufacturing, or loading the wrong product during delivery may eventually trigger a return. Measuring return performance without considering these upstream causes risks masking the source of failure. Process-integration research consistently emphasizes information sharing and coordination across supply chain boundaries, and SCOR provides a structured way to represent those dependencies.

This interdependence is particularly pronounced in carpet manufacturing. Technical yarn properties, color palettes, design details, and market-specific requirements can determine whether the final product will be accepted. In make-to-order and engineer-to-order production, incorrect material selection or specification errors may create more severe rework and return risks than in standardized make-to-stock settings. High reverse-transportation costs further increase the value of preventive process control.

2.3 Plan and Return Performance

The plan links demand, capacity, resources, and timing decisions across the supply chain. Poor alignment can generate excess inventory, delivery deviations, and an inappropriate product mix. Previous SCOR studies repeatedly identify planning as a central process. Lockamy and McCormack (2004) emphasized collaboration and process integration in planning, whereas Zhou et al. (2011) reported that planning significantly influences Source, Make, and Deliver.

From a return perspective, planning is important because it anticipates both forward and reverse requirements. The better coordination of production, delivery, and return-related resources may be associated with fewer quantity and timing problems. Delivery planning is especially consequential because even a correctly manufactured product may become return prone if it reaches the wrong customer, at the wrong time, or under inappropriate conditions.

H1: The SCOR plan process is significantly associated with return performance.

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2.4 Source and Return Performance

Source is linked to production quality through material characteristics, quantities, delivery timing, and supplier coordination. Li et al. (2011) demonstrate the importance of sourcing decisions for customer-oriented quality performance. SCOR-based supplier evaluation studies also emphasize reliability, flexibility, cost, and traceability (Lima-Junior & Carpinetti, 2016; Wang et al., 2018; Yılmaz et al., 2020).

The relationship between sourcing and returns may differ byproduction mode. Material requirements are relatively standardized in make-to-stock systems, whereas technical conformity becomes more critical in make-to-order and engineer-to-order production. Consequently, the aggregate source construct may conceal stronger associations within particular sourcing subprocesses.

H2: The SCOR source process is significantly associated with return performance.

2.5 Make and Return Performance

Make is the stage at which customer requirements are transformed into a physical product. Quality defects, deviation from technical specifications, incorrect product configuration, or poor management of production changes can directly increase return risk. The challenge becomes greater as product customization increases because operational flexibility must be balanced with process discipline.

SCOR research has shown the contribution of Make to the overall supply chain and internal performance (Li et al., 2011; Zhou et al., 2011). In carpet production, engineer-to-order products require close coordination of color, design, yarn, and quality specifications, creating a strong rationale for expecting a relationship between Make and return performance.

H3: The SCOR Make process is significantly associated with return performance.

2.6 Deliver and Return Performance

The delivery covers the physical and informational fulfillment of customer orders. Order accuracy, lead time, product–customer matching, packaging, and shipment verification are the final control points before a potential return. In a Türkiye-based SCOR application, Yılmaz et al. (2020) identified traceability of returned products and shipment according to promised dates as important supplier-performance criteria.

For bulky products such as carpets, delivery errors create costs beyond reshipment. When reverse transportation is economically unattractive, firms may need to discount, reroute, or resell the product in another market. Thus, delivery quality is expected to be associated with the return construct.

H4: The SCOR delivery process is significantly associated with return performance.

2.7 Enable, Information Management, and Return Performance

The ability in SCOR 12.0 represents the infrastructure that allows the physical supply chain to function effectively. Its components include business rules, performance

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management, data and information management, human resources, assets, contracts, and supply chain network management. Dweekat et al. (2017) emphasized that real-time data collection and communication can strengthen supply chain control, whereas Chehbi-Gamoura et al. (2019) highlighted the role of big data analytics in shared information generation and decision-making across SCOR processes.

The contemporary relevance of these capabilities is clearer in the SCOR Digital Standard. Orchestrate now operates at Level 0 and includes performance and continuous improvement, data and technology, human resources, contracts, network design, risk, ESG, and circular supply chain management (ASCM, 2025, 2026). This evolution reinforces the view that governance and information capabilities are foundational to operational coordination rather than peripheral support functions.

From a return perspective, information errors, managerial turnover, unclear process ownership, and a lack of standardized business rules may be associated with product or shipment errors. Enable is therefore expected to show a statistically significant association with return performance.

H5: The SCOR enable process is significantly associated with return performance.

2.8 Research Gap and Conceptual Model

The literature broadly confirms that SCOR is an effective framework for supply chain performance measurement, that Plans play a central coordinating role, and that SCOR can be combined with multicriteria decision methods. Three gaps nevertheless remain. First, return is commonly examined as one component of a general performance system, whereas the strength of its associations with other SCOR processes is rarely compared directly in a single empirical model. Second, empirical evidence remains limited in highly customized manufacturing environments such as textiles and carpets. Third, comparatively few studies contrast construct-level regression patterns with managers' decision priorities and then contextualize those patterns with case-based stakeholder evidence.

Accordingly, the present study tests five process-level hypotheses in the construct-level regression. The underlying SCOR metrics are examined only as exploratory diagnostic analyses intended to identify practices that may underlie the aggregate associations; they are not treated as additional confirmatory hypothesis tests. This approach condenses the dissertation's detailed structure into a journal–article format while retaining subprocess information with appropriate inferential caution.

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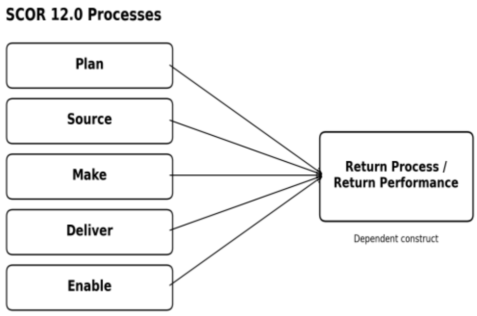

Fig. 1. Conceptual model: relationships between SCOR 12.0 processes and return performance

3 Methodology

3.1 Research Design

The study uses a sequential multimethod design in which the same research problem is examined through complementary sources of evidence. In the first stage, survey data are used to assess the measurement structure of the SCOR constructs, bivariate associations, and construct-level regression model. In the second stage, importance assessments for 28 SCOR metrics provided by 10 supply chain managers are weighted via the entropy method. In the third stage, semistructured interviews with the supply chain manager, raw-material supplier, distribution representative, and retailer of a large carpet manufacturer are used for contextual interpretation of operational mechanisms and boundary conditions.

The methods are not treated as substitutes. Multiple regression estimates statistical associations and relative coefficients; entropy weighting derives dispersion-based priorities conditional on managers' ratings; and the interviews provide contextual and illustrative evidence. The latter two stages do not statistically remove potential common-method bias from the questionnaire regression and are therefore interpreted as complementary rather than confirmatory validation.

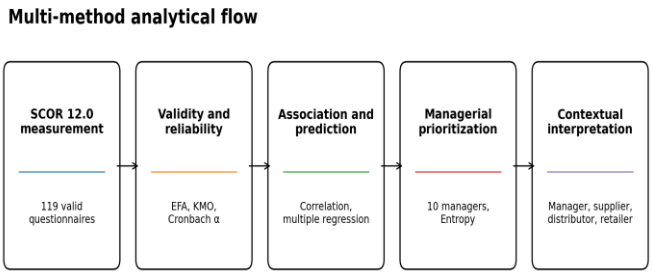

Fig. 2. Multimethod analytical flow of the study

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3.2 Population, Sample, and Data Collection

The population consists of carpet manufacturing firms operating in Gaziantep, Türkiye. During the field study, approximately 250 carpet manufacturers were identified, 170 of which were active. The questionnaire was distributed to these 170 active firms, and 125 responses were obtained. Six questionnaires were excluded because they were incomplete or carelessly completed, resulting in 119 valid observations. The final sample therefore represents approximately 70% of the active-firm population identified for the study.

The dissertation initially calculated a minimum sample size of 70 using a 95% confidence level and a 10% margin of error. Sekaran's (2003) sample size guidance, according to which 118 observations are adequate for a population of 170, was subsequently considered. The final sample of 119 meets that threshold.

After the survey stage, face-to-face evaluations were obtained from supply chain managers at 10 carpet manufacturers. Managers rated the importance of 28 SCOR level-2 metrics for return-related performance using values of 1, 3, 5, 7, and 9. These ratings formed the decision matrix for the entropy analysis.

For the qualitative stage, a large carpet manufacturer operating in the Gaziantep Organized Industrial Zone and maintaining international warehouses and sales points was examined as a case. Semistructured interviews were conducted with its supply chain manager, raw material supplier, distribution representative, and retail stakeholder. The interviews were recorded with participant permission; one participant responded by email.

3.3 Measurement Instrument and Variables

The survey consists of 28 items based on the level-2 process categories of SCOR 12.0. Plan, Source, Make, Deliver, and Enable are treated as explanatory constructs, whereas Return is the dependent construct. The plan includes the supply chain network, sourcing, production, delivery, and return planning. The source covers material sourcing for make-to-stock, make-to-order, and engineer-to-order products. Make covers the corresponding three production modes. Delivers include delivery activities for those production modes and retail products. The Enable covers business rules, performance, data and information, human resources, assets, contracts, and network management. The six return items cover defective, maintenance-related, and excess-product returns associated with sourcing and delivery.

All the items were evaluated on a five-point Likert-type scale, and the construct scores used in the regression were calculated as the arithmetic mean of the items assigned to each construct. The dependent variable is therefore a perception-based composite rather than an observed return count or return rate. The archived materials available for this revision do not preserve the verbatim wording of the six Return items or the exact endpoint labels of the original response scale; these details are therefore not reconstructed from memory. Accordingly, the return variable is referred to conservatively as the perception-based return construct, and the sign of a regression coefficient is interpreted only as the direction of association with the composite score, not as direct

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evidence of a change in actual return frequency or objectively measured return-management effectiveness.

Table 1. Research Variables and Measurement Coverage

Construct	Main coverage	Items
Plan	Network, sourcing, production, delivery, and return planning	5
Source	Sourcing for make-to-stock, make-to-order, and engineer-to-order products	3
Make	Make-to-stock, make-to-order, and engineer-to-order production	3
Deliver	Delivery for production types and retail products	4
Return	Defective, maintenance-related, and excess-product returns from sourcing and delivery	6
Enable	Business rules, performance, data-information, HR, assets, contracts, and network management	7

Note. Total number of items = 28. The measurement structure is based on the SCOR Model 12.0 process categories. The construct scores were calculated as item means. Because the archived revision materials do not contain verbatim return-item wording or response anchors, the return construct is interpreted as a perception-based composite and not as an observed return rate.

3.4 Validity, Reliability, and Statistical Analysis

The data were analyzed in SPSS. Skewness and kurtosis were first inspected, using ±1.5 as the acceptable range for approximate normality (Tabachnick & Fidell, 2013). Exploratory factor analysis with varimax rotation was then used to assess construct structure. Sampling adequacy was evaluated with the Kaiser–Meyer–Olkin (KMO) statistic and Bartlett's test of sphericity; KMO values of .60 or above and Bartlett p values below .05 were treated as acceptable. A minimum factor loading of .50 was used (Hair et al., 1998).

Internal consistency was assessed via Cronbach's alpha. Values of .70 or above were treated as strong reliability, whereas the source scale's alpha of .638 was interpreted as moderate reliability and is acknowledged as a limitation (Taber, 2018). Pearson correlations were used to evaluate bivariate associations. The five main hypotheses were tested via multiple linear regression on the basis of mean construct scores, with Return as the dependent variable and Plan, Source, Make, Deliver, and Enable as predictors. Item-level regressions were subsequently reviewed only as exploratory diagnostic analyses. No formal familywise error or false discovery rate adjustment was incorporated into the original item-level analysis; therefore, the reported item-level p values are explicitly treated as unadjusted and hypothesis generating. As a conservative sensitivity

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benchmark, .05/28 yields $\alpha \approx .0018$; only item-level associations reported at $p < .001$ necessarily satisfy that benchmark. Because the design is cross-sectional and perception-based, all regression coefficients are interpreted as associations rather than causal effects.

Common-method variance is a further concern because the predictor and outcome constructs in the survey component were collected from the same respondents, through the same questionnaire, and at the same measurement occasion. The original research design did not include a dedicated marker variable, temporal separation, a latent-method-factor model, or other statistical diagnostic that can now be reconstructed from the archived results. Common-method bias therefore cannot be ruled out (Podsakoff et al., 2003; Fuller et al., 2016). The relatively strong correlations and high model R^2 values are interpreted with this possibility in mind. The entropy and interview stages involve methodologically distinct evidence, but they are not statistical controls for common-method variance in the survey model.

3.5 Entropy Analysis and Qualitative Interviews

The entropy method derives criterion weights from the degree of differentiation observed in a decision matrix. Greater variation increases a criterion's discriminating contribution, whereas more homogeneous evaluations increase entropy and reduce the criterion's relative weight (Shannon, 1948; Shemshadi et al., 2011). In this study, however, the underlying decision matrix consists of subjective importance ratings from 10 supply chain managers using values of 1, 3, 5, 7, and 9. The resulting values are therefore described as entropy-derived or dispersion-based weights rather than as objectively measured importance. The ratings were normalized, entropy values (E_j) were calculated, divergence was obtained as $D_j = 1 - E_j$, and final criterion weights (V_j) were derived. The criterion weights were then aggregated within the six SCOR process groups. Because the groups contain unequal numbers of indicators, an additional sensitivity comparison divides each aggregate process weight by the number of indicators in that process. This mean-weight-per-indicator comparison reduces the mechanical influence of the group size but is a sensitivity check rather than a re-estimation of the original entropy model. Given the 10-manager panel and the absence of resampling or leave-one-out analyses, the rankings are interpreted as indicative priorities within this panel rather than stable population-level estimates.

The semistructured interview component was designed as a contextual case-based inquiry rather than as a standalone qualitative study intended to achieve theoretical saturation or statistical generalization. The interview guide covered predefined operational topics, including supplier and retailer integration, reliability, responsiveness, flexibility, operating cost, return procedures, make-to-stock and make-to-order production, information sharing, delivery accuracy, and the potential use of process-reference systems such as SCOR. The interview material was reviewed descriptively and organized around these predefined topics to identify explanations, qualifications, and illustrative examples relevant to the quantitative patterns. A formal multicoder thematic coding procedure and a systematic negative-case search were not part of the original design.

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The qualitative evidence is therefore treated as contextual and interpretive rather than as independent confirmation of the survey results.

4 Findings

4.1 Descriptive Statistics and Distributional Properties

Table 2 reports the means, standard deviations, skewness, and kurtosis values. All skewness and kurtosis statistics fall within ±1.5, indicating acceptable distributional properties for the parametric analyses used in the study. The highest mean is observed for Make (4.014), whereas the lowest mean belongs to Return (2.513).

Table 2. Descriptive Statistics

Variable	Mean	Median	SD	Skewness	Kurtosis
Plan	3.800	4.400	1.170	-0.806	-1.030
Source	3.272	3.333	0.577	0.287	0.670
Make	4.014	4.333	1.021	-1.293	0.500
Deliver	3.853	4.250	1.030	-0.809	-0.679
Enable	3.511	3.714	1.064	-0.340	-1.152
Return	2.513	2.000	1.176	0.811	0.959

Note. ±1.5 was used as the acceptable range for approximate normality.

4.2 Validity and Reliability of the Measurement Model

As reported in Table 3, the KMO values are .897 for Plan, .634 for Source, .714 for Make, .797 for Deliver, .926 for Return, and .906 for Enable. Bartlett's test of sphericity is significant at $p < .001$ for every construct. The factor loadings range from .901-0.935 for Plan, .708-0.808 for Source, .857-0.931 for Make, .661-0.843 for Deliver, .793-0.874 for Return, and .768-0.904 for Enable. These results support the suitability of the data for exploratory factor analysis.

Reliability is strong for Plan (α = .951), Make (α = .891), Deliver (α = .909), Return (α = .959), and Enable (α = .935). The source shows lower internal consistency (α = .638). The latter may reflect greater heterogeneity among sourcing activities and may partly contribute to the weaker aggregate source result in the main regression; however, this interpretation should be treated as a possibility rather than a demonstrated explanation.

Table 3. Factor Analysis and Reliability Results

Construct	KMO	Cronbach α	Variance explained (%)	Factor-loading range
Plan	.897	.951	83.95	.901-.935
Source	.634	.638	58.15	.708-.808
Make	.714	.891	82.21	.857-.931
Deliver	.797	.909	78.90	.661-.843
Return	.926	.959	83.10	.793-.874

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Enable	.906	.935	72.30	.768-.904

Note. Bartlett's test of sphericity is significant at $p < .001$ for all the constructs.

4.3 Correlation analysis

The correlation analysis shows that Return is significantly and negatively associated with all five explanatory SCOR processes (Table 4). The strongest relationship is between Plan and Return ($r = -.839$), followed by Enable and Return ($r = -.781$) and Make and Return ($r = -.626$). Source ($r = -.431$) and Deliver ($r = -.430$) display smaller but still statistically significant relationships. High correlations among some explanatory constructs—especially Plan and Enable ($r = .810$) and Make and Deliver ($r = .757$)—are consistent with the integrated nature of SCOR processes, but they also warrant caution when interpreting regression coefficients. Because all six survey constructs were measured via the same questionnaire and occasion, shared method variance may also contribute to the observed correlation magnitudes.

Table 4. Correlations among SCOR Processes

Variable	**P**	**S**	**M**	**D**	**E**	**R**
Plan (P)	1					
Source (S)	.356**	1				
Make (M)	.617**	.546**	1			
Deliver (D)	.474**	.495**	.757**	1		
Enable (E)	.810**	.461**	.636**	.550**	1	
Return (R)	-.839**	-.431**	-.626**	-.430**	-.781**	1

Note. ** $p < .001$.

4.4 Main Regression Model and Hypothesis Tests

As presented in Table 5, the multiple linear regression model including plan, source, make, delivery, and enable is statistically significant ($R = .870$; $R^2 = .757$; adjusted $R^2 = .747$; $p < .001$) and accounts for 75.7% of the sample variance in the return construct. Given the conceptual interdependence among SCOR processes and the common measurement context, this relatively high R^2 should not be interpreted as evidence of causal determination and may partly reflect shared method variance.

When standardized coefficients are compared, Plan is clearly the strongest predictor ($\beta = -.559$; $p < .001$). Enable ($\beta = -.253$; $p = .004$), Make ($\beta = -.200$; $p = .017$), and Deliver ($\beta = -.170$; $p = .021$) are also statistically significant. Source is negative but not statistically significant ($\beta = -.091$; $p = .115$). Accordingly, H1, H3, H4, and H5 are supported, whereas H2 is not supported at the aggregate process level.

The negative coefficients must be interpreted in light of the measurement design. Return is a perception-based composite rather than an observed count or rate of returned products. The coefficients therefore indicate inverse associations with the Return composite as coded in the original study. Because the archived materials available for this

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revision do not preserve the verbatim return-item wording or response anchors, the analysis does not assign a stronger substantive meaning—such as a quantified reduction in actual returns or an increase in objective return-management effectiveness—to a lower composite score.

Table 5. Multiple Regression Results for SCOR Processes and Returns

Variable	B	SE	β	t	p	Hypothesis
Constant	6.409	.325	-	19.719	<.001	-
Plan	-.562	.083	-.559	-6.802	<.001	H1 supported
Source	-.185	.116	-.091	-1.589	.115	H2 not supported
Make	-.230	.095	-.200	-2.426	.017	H3 supported
Deliver	-.194	.083	-.170	-2.343	.021	H4 supported
Enable	-.279	.095	-.253	-2.945	.004	H5 supported

Model summary: $R = .870$; $R^2 = .757$; adjusted $R^2 = .747$; model $p < .001$.

4.5 Exploratory Item-Level Regression Findings

As presented in Table 6, the item-level regressions are treated as exploratory diagnostics rather than confirmatory hypothesis tests. Within Plan, Delivery Planning is nominally significant ($\beta = -.377$; $p = .002$), suggesting a possible association with the coordination of timing, quantity, and shipment arrangements before the product reaches the customer. Because the item-level p values are unadjusted for multiple testing, this result should not be interpreted as independent confirmatory evidence.

Although aggregate source is not significant in the main model, two sourcing subprocesses are nominally significant: material sourcing for make-to-order products ($\beta = -.195$; $p = .041$) and material sourcing for engineer-to-order products ($\beta = -.306$; $p = .002$). Material sourcing for make-to-stock products is not significant. These patterns are hypothesis-generating and suggest that sourcing may merit closer examination as product-specific requirements increase; however, they require replication under a design that formally controls multiplicity.

Within Make, engineer-to-order production shows a comparatively large nominal association ($\beta = -.546$; $p < .001$). Within Deliver, retail product delivery is nominally significant ($\beta = -.422$; $p = .006$). Within Enable, supply chain data and information management have the largest absolute item-level coefficient ($\beta = -.668$; $p < .001$), whereas human resource management is nominally significant ($\beta = -.191$; $p = .021$). Using 28 comparisons as a conservative Bonferroni family gives $\alpha \approx .0018$; only the two associations reported at $p < .001$ necessarily clear that benchmark. Accordingly, all item-level results are interpreted as exploratory, with particular attention given to the two strongest signals rather than as a set of independently confirmed subprocess effects.

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Table 6. Exploratory Item-Level Associations with Return

Main process	Subprocess	B	β	p
Plan	Delivery planning	-.319	-.377	.002
Source	Material sourcing for make-to-order products	-.326	-.195	.041
Source	Material sourcing for engineer-to-order products	-.424	-.306	.002
Make	Engineer-to-order production	-.528	-.546	<.001
Deliver	Retail product delivery	-.391	-.422	.006
Enable	Supply chain data and information management	-.585	-.668	<.001
Enable	Human resource management	-.170	-.191	.021

Note. Only nominally significant subprocess associations at $p < .05$ are shown. The p values are unadjusted for multiple comparisons and should be interpreted as exploratory rather than confirmatory. A conservative Bonferroni benchmark using 28 comparisons is $\alpha \approx .0018$.

4.6 Managerial Prioritization through Entropy Analysis

Table 7 presents the entropy-derived process priorities and the indicator-count sensitivity analysis. Entropy analysis uses a different logic from regression by deriving dispersion-based relative weights from the 10 managers' importance ratings of 28 SCOR metrics. At the individual criterion level, source planning ranks first, and return planning ranks second; maintenance-related returns in sourcing and human resource management are also among the more heavily weighted criteria. These are entropy-derived priorities conditional on this expert panel, not objective population-level importance estimates.

When criterion weights are summed within the six SCOR processes, plan ranks first (.3354), followed by make (.1679), delivery (.1400), enable (.1349), source (.1260), and return (.0959). Because the processes contain unequal numbers of indicators, a sensitivity comparison was calculated by dividing each aggregate weight by its indicator count. The resulting mean weights per indicator are .06708 for Plan, .05598 for Make, .04200 for Source, .03499 for Deliver, .01927 for Enable, and .01598 for Return, producing the ranking Plan, Make, Source, Deliver, Enable, Return. Thus, the plan remains first under both specifications, but the ordering of the intermediate processes changes. The agreement between a plan's construct-level regression prominence and its first-place entropy ranking is therefore treated as supplementary cross-method convergence, not as independent confirmation.

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Table 7. Entropy-Derived Process Priorities and Indicator-Count Sensitivity Analysis

Agg. rank	SCOR process	Aggregate weight	n	Mean weight/indicator	Normalized rank
1	Plan	.335379	5	.06708	1
2	Make	.167925	3	.05598	2
3	Deliver	.139954	4	.03499	4
4	Enable	.134907	7	.01927	5
5	Source	.125986	3	.04200	3
6	Return	.095850	6	.01598	6

Note. The aggregate weights are derived from the importance ratings of 28 metrics by 10 supply chain managers. The mean weight per indicator = aggregate process weight/number of indicators. The normalized ranking is a sensitivity check for unequal process sizes, not a re-estimation of the entropy model.

4.7 Contextual Evidence from the Case Interviews

The case interviews provide contextual observations rather than an independent qualitative test of the statistical results. The large carpet manufacturer had not yet fully implemented a formal supply chain process-reference model, although management reported efforts toward greater standardization. Domestic-supplier integration was described as relatively strong, whereas international-supplier integration was more difficult. Long relationships with some core suppliers—exceeding 20 years—were viewed as valuable for continuity but were also described as potentially restricting product-development flexibility. These observations qualify a purely confirmatory reading of the case evidence by showing both strengths and constraints that are not represented directly in the regression model. These interview observations and their relationship to the quantitative findings are summarized in Table 8.

Managerial turnover was reported to disrupt information flows and customer communication, affecting responsiveness and reliability. The company had experienced incorrect-product and incorrect-quantity shipments and introduced a preshipment packing-list verification process with customers. These observations are contextually consistent with the construct-level Deliver association and with the exploratory Delivery Planning and Retail Delivery results, but they are not treated as qualitative validations of those coefficients.

Return costs were described as particularly problematic in international sales. Because reverse transportation and storage can be expensive, products are not always returned to the central facility; firms may instead redirect them to warehouses in other countries or offer discounts to customers. This provides an additional operational insight not directly tested in the regression: in some international transactions, economic recovery may involve rerouting or negotiated disposition rather than physical reverse movement.

The company predominantly favored make-to-order and engineer-to-order production because make-to-stock production exposes the firm to product value and raw material price risks. The dependence on imported raw materials and differences in technical specifications were described as challenges for production accuracy. The supplier

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interview emphasized ERP use, joint planning, R&D/product-development cooperation, and tracking material suitability for production lines. These observations provide contextual convergence with the exploratory engineer-to-order and data-information signals while remaining case-specific and descriptive. Table 8 summarizes the main interview observations and their relationship to the quantitative findings.

Table 8. Contextual Interview Observations in Relation to Quantitative Findings

Interview theme	Field observation	Relationship to quantitative evidence
Planning and coordination	Frequent managerial turnover disrupted information flows and planning and contributed to incorrect-product and incorrect-quantity shipments.	Provides contextual evidence relevant to the Plan construct-level association; the item-level Delivery Planning result remains exploratory.
Data and information management	ERP use, information sharing, joint planning, and pre-shipment packing-list verification were reported as mechanisms supporting planning, information visibility, and shipment accuracy.	Provides operational context for the exploratory Data and Information Management association rather than independent confirmation of the coefficient.
Supplier integration and dependence	Domestic supplier integration was described as relatively strong, whereas international integration was more difficult; long-term supplier dependence could also constrain product-development flexibility.	Provides a qualifying perspective not directly represented in the regression model.
Customized production	The firm preferred order-based and engineering-based production rather than make-to-stock production, while supplier and material requirements varied according to customer and market specifications.	Provides case-specific operational context for the exploratory Engineer-to-Order Production finding rather than independent validation of the item-level coefficient.
Delivery accuracy	Incorrect-product and incorrect-quantity shipments had occurred, and a preshipment packing-list verification procedure with customers was introduced to address these problems.	Provides contextual evidence relevant to the Deliver construct-level association; the Retail Delivery item-level result remains exploratory.
Cost of returns	Because international reverse transportation and storage were costly, products were sometimes redirected between foreign	Provides an additional operational mechanism not directly tested in the regression model.

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	markets/warehouses or discounts were offered instead of physically returning them to the central facility.	

Note. The interview observations are used for contextual interpretation. They were organized descriptively around predefined interview topics; no formal multicoder thematic coding or systematic negative-case analysis was conducted. Convergence with quantitative findings is therefore supplementary rather than confirmatory.

5 Conclusion And Discussion

This study examined the associations between SCOR processes and the perception-based return construct in the Gaziantep carpet manufacturing industry. Product returns should not be viewed solely as a reverse logistics issue located within the return process; the survey results show substantial associations with upstream processes and organizational capabilities. The construct-level regression accounts for 75.7% of the sample variance in Return, with Plan showing the largest standardized coefficient. Within the separate 10-manager entropy panel, Plan also receives the highest aggregate priority and remains first after normalization for unequal indicator counts. This convergence is suggestive, but it is interpreted cautiously because the survey is cross-sectional, common-method variance cannot be ruled out, and the entropy rankings are panel dependent.

The prominent construct-level association for Plans is consistent with previous SCOR research emphasizing the integrative role of planning across Source, Make, and Deliver activities (Lockamy & McCormack, 2004; Zhou et al., 2011). Delivery planning is nominally significant in the exploratory item-level analysis ($p = .002$), but its p value is unadjusted for multiple testing and does not satisfy the conservative .0018 benchmark used here. It should therefore be treated as a hypothesis-generating signal rather than evidence that delivery planning uniquely drives returns. Substantively, the pattern nevertheless directs attention to order quantities, delivery requirements, shipment timing, and customer specifications as plausible coordination points for future confirmatory research.

Enable is also significant at the construct level and has the second-largest standardized coefficient after Plan. In the exploratory item-level analyses, supply chain data and information management have the largest absolute coefficients ($\beta = -.668$; $p < .001$), whereas human resource management is nominally significant ($p = .021$). The data-information result is one of only two item-level associations that necessarily clears the conservative .0018 benchmark, although it remains exploratory because no formal multiplicity-adjusted analysis was available. This pattern is consistent with research emphasizing real-time information and analytics in supply chain performance (Dweekat et al., 2017; Chehbi-Gamoura et al., 2019) and with arguments that AI-enabled visibility and decision support can strengthen coordination (Güngör & Abukalloub, 2026).

The Source, Make, and Deliver findings further illustrate why construct-level and item-level evidence should be distinguished. The aggregate source is not statistically

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significant, whereas make-to-order and engineer-to-order sourcing are only nominally significant in exploratory analyses. Engineer-to-order production shows a stronger exploratory signal ($\beta = -.546$; $p < .001$) and is the second item-level association that necessarily clears the conservative .0018 benchmark. Retail delivery is nominally significant ($p = .006$) but does not meet that benchmark. These results do not establish subprocess-specific causal effects; instead, they identify customized production, specification accuracy, and final fulfillment as priorities for replication.

The interview evidence provides context, convergence, and qualifications rather than independent validation. Reports of incorrect products and quantities, managerial turnover, information-flow disruption, and preshipment verification are compatible with the quantitative patterns. Moreover, the interviews also revealed observations not captured directly by the regression, including stronger domestic than international supplier integration, possible flexibility costs of long-term supplier dependence, and the use of discounts or cross-market rerouting instead of physical international returns. Because the four stakeholders are connected to one large manufacturer and no systematic negative case sampling or multicoder thematic analysis was conducted, the qualitative stage should be read as case-based interpretation rather than confirmatory triangulation.

The study contributes to the literature in four ways. First, it treats the return construct as related to multiple SCOR processes rather than as an isolated after-sales activity. Second, the construct-level regression compares Plan, Source, Make, Deliver, and Enable within one model, with Plan showing the strongest association. Third, entropy-derived priorities provide a supplementary managerial perspective; indicator-count normalization shows that Plans remain first even though the ranking of intermediate processes changes. Fourth, the study translates the historically appropriate SCOR 12.0 measurement framework into the current SCOR Digital Standard, thereby preserving managerial relevance without implying that the two architectures are identical.

Contemporary mapping is especially important for obtaining significant and strong exploratory findings. Under SCOR DS, Plan remains a Level-1 process, and planning is explicitly executed for Order, Source, Transform, Fulfill, and Return. The former Enable activities are largely elevated into the Level-0 Orchestrate layer; therefore, the study's emphasis on data and information management corresponds most closely to Orchestrate activities for data, information, and technology, whereas human resources likewise sits within Orchestrate. Make is expanded into Transform, so the engineer-to-order production signal maps primarily to Transform but also spans the Order–Plan–Transform interface because customized production depends on accurate capture, planning, and execution of customer-specific requirements. The delivery system is separated into Order and Fulfill, with retail delivery and physical shipment control mapping primarily to Fulfill. Return remains a distinct Level-1 process linked to reverse flows, diagnosis, disposition, transform, and circular activities (ASCM, 2025, 2026).

Table 9. Mapping of Key SCOR 12.0 Findings to the Current SCOR Digital Standard

Study finding under SCOR 12.0	**Current SCOR DS correspondence**	**Contemporary managerial interpretation**

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Plan: strongest construct-level association	Plan (Level 1); particularly planning for Fulfill	Synchronize requirements, resources, customer commitments, shipment timing, and fulfillment capacity before execution.
Enable; data and information management	Orchestrate (Level 0), especially data, information, and technology	Treat data governance, information accuracy, technology integration, traceability, and process visibility as strategic orchestration capabilities.
Enable; human resource management	Orchestrate: Human Resources	Emphasize skills, accountability, continuity, and role clarity as part of supply-chain orchestration.
Engineer-to-order Make	Primarily Transform, with Order–Plan–Transform interfaces	Translate customer-specific requirements accurately into planning, materials, configuration, and production execution.
Deliver/retail product delivery	Deliver is separated into Order and Fulfill; physical delivery maps mainly to Fulfill	Strengthen order execution, picking, packing, shipping, transportation scheduling, shipment verification, and customer acceptance.
Make-to-order/engineer-to-order sourcing	Source, with interfaces to Plan and Transform	Prioritize material conformity, supplier coordination, and specification accuracy for customized products.
Return	Return	Manage reverse flows and disposition while connecting recovery decisions to Transform and circular activities.

Note. The mapping follows the current ASCM SCOR Digital Standard and official SCOR DS/SCOR 12 crosswalk (ASCM, 2025, 2026). The correspondences are functional mappings rather than strict one-to-one equivalences because SCOR DS represents a substantive architectural revision.

From a managerial perspective, return reduction should therefore be approached as a supply chain-wide and, in current SCOR DS terms, orchestrated responsibility spanning plan, order, source, transform, fulfillment, and return. Planning systems should verify customer specifications, product codes, quantities, delivery dates, and shipment information before release. Orchestrate-related capabilities should strengthen data quality, master–data management, digital traceability, supplier–customer information integration, human–resource continuity, and standardized handovers. Customized products

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require especially strong source and transform controls, whereas order and fulfillment products should incorporate systematic order, packing, shipment, and customer acceptance verification. When international returns are unavoidable, alternative recovery options such as rerouting, reselling, reworking, or negotiated discounts may reduce economic losses. Such decisions should be evaluated in relation to logistics cost, operational efficiency, and broader sustainability considerations.

The study nevertheless has several limitations. First, the survey is cross-sectional, perception-based, and restricted to the Gaziantep carpet manufacturing sector; the regression findings are therefore associations rather than causal effects. Second, all predictor and outcome constructs were measured from the same respondents, questionnaires, scale formats, and measurement occasions. Because the original design did not include a dedicated common-method diagnostic that can now be reconstructed, common-method bias cannot be ruled out and may have contributed to the strong correlations and high R^2. Third, the archived materials available for this revision do not preserve the verbatim Return-item wording or response anchors, so the substantive meaning of score direction cannot be reconstructed more precisely than the original composite coding permits. Fourth, the source has relatively low internal consistency (α = .638), and high correlations among some predictor constructs warrant caution regarding construct overlap and multicollinearity. Fifth, the item-level p values are unadjusted for multiple testing and must be treated as exploratory. Sixth, the entropy weights are based on subjective ratings from only 10 managers; the rankings may be sensitive to panel composition and rating dispersion, although the plan remains first after indicator-count normalization. Finally, the qualitative component consists of four stakeholders connected to one large manufacturer and does not employ formal multicoder thematic coding, systematic negative-case sampling, or saturation procedures. The interview evidence therefore provides context rather than independent validation.

Future research should replicate the model across industries and use longitudinal or temporally separated designs; multiple informants; and objective indicators such as actual return rates, return costs, defect rates, delivery errors, and perfect-order fulfillment. Common-method concerns could be addressed prospectively through procedural separation, marker variables, or latent-method-factor approaches. The item-level hypotheses should be preregistered or analyzed with formal familywise error or false discovery rate controls. Larger expert panels should be subjected to bootstrap, leave-one-out, or alternative normalization sensitivity analyses. Structural equation modeling or PLS-SEM could provide a more integrated framework for modeling latent constructs and measurement error, although such approaches would represent a redesigned analytical model rather than a simple robustness correction. Qualitative extensions should sample multiple firms, use explicit coding protocols and multiple coders, actively seek negative or contradictory cases, and document thematic saturation. Future instruments should also adopt current SCOR DS terminology and examine Orchestrate, Order, Transform, Fulfill, risk, digital capabilities, and circular supply chain practices.

Overall, the results indicate that the perception-based return construct is strongly associated with upstream SCOR processes, particularly plans at the construct level. The plan also receives the highest entropy-derived priority within the 10-manager panel and remains first in the indicator-count-normalized sensitivity comparison. At the item

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level, data and information management and engineer-to-order production provide the strongest exploratory signals, but item-level inferences remain subject to multiplicity and measurement limitations. Taken together, the evidence supports a cautious shift from a purely reactive view of returns toward a preventive supply-chain perspective focused on planning, orchestration of information, customized transformation, and fulfillment control. These conclusions should be interpreted as context-specific associations and managerial priorities rather than causal estimates or universally stable rankings.

DECLARATIONS

Author Contributions

Conceptualization, D.B.T.; methodology, D.B.T.; formal analysis, D.B.T.; investigation, D.B.T.; data curation, D.B.T.; writing—original draft preparation, D.B.T.; writing—review and editing, D.B.T. and H.A.; supervision, H.A. All authors have read and approved the final version of the manuscript.

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The authors declare that there are no conflicts of interest regarding the publication of this article.

Data Availability Statement

The data are not publicly available due to privacy, ethical, or confidentiality restrictions.

Artificial Intelligence (AI) Disclosure

Grammarly was used solely for grammatical improvements in editing this manuscript. The scientific content remains the sole responsibility of the authors.

Research Ethics

The study received a favorable decision from the Hasan Kalyoncu University Social and Human Sciences Ethics Committee on March 29, 2021 (Decision No. E-804.01-2103290016). The interviews were conducted with participant permission, and relevant sessions were audio-recorded with consent.

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Informed Consent Statement

Informed consent was obtained from all participants involved in the study.

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