



Original Article

Predictive Supplier Risk Modelling in Wholesale Distribution: An SPSS-Based Quantitative Study

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Received On: 20/09/2025

Revised On: 03/09/2025

Accepted On: 25/10/2025

Published On: 16/11/2025

Abstract - Wholesale distribution is subject to operating interruptions when suppliers fail to perform adequately. Stock-outs, unexpected delays, premeditated quality defects, etc. affect profits, reputations and adherence to agreed service-levels. The classical “scorecard” means of evaluating suppliers rely heavily on memory, subjective responses or “star” rating systems that cannot forecast evolving risk levels nor blend well into an increasingly “multi-tier” distribution channel. This paper attempts to investigate the predictive modelling of supplier risk based on quantitative analytic methods using SPSS. Utilising a real-world case-study taken from a wholesale distributor, the research delves into the development of an experimental model using actual responses to survey-scales, supplier indicators of performance and constructs of risk. Using other risk models as a base, a statistically validated predictive risk model is developed in the context of a supply chain using reliability assessment, factor reduction, correlation analysis and multiple regression modelling procedures. The consequent findings show that supplier risk is predicted from delivery consistency, defect rates, responsiveness, financial stability and communication efficiency. The research develops a “refined” predictive model that explains a significant portion of variance in the overall risk scoring of wholesaler suppliers, used as a basis for supplier “segmentation” and for “pro-active” risk mitigation. Such research can be easily replicated on behalf of wholesale distributors who wish to develop user-defined downside-risk modelling against an up-to-date notion of resilience.

Keywords - Supplier Risk Management, Predictive Risk Modelling, Wholesale Distribution, Supply Chain Resilience, SPSS Quantitative Analysis, Supplier Performance Evaluation, Multiple Regression Analysis, Factor Analysis, Risk Segmentation, Proactive Risk Mitigation.

1. Introduction

Wholesale distribution organizations are normally dynamic in pace, being required to operate in terms of high velocity supply with a high degree of volatility in demand, lead times, and dependence on suppliers to keep products flowing smoothly. Interruptions in supplier performance, in terms of their deliveries being late, or “out of spec” quality, or financial downgrades, can have ramifications that ripple through the distribution process, causing stockouts, higher

inventories, reducing production uptime, and damaging customer service. Supply chain research indicates that supplier-induced turbulence is one of the main forms of risk facing organizations, and with globalization, multiple-tier sourcing, and expanding complexity, at every layer of the supply chain. For mitigating the serious impacts of predictive risk-modelling to be useful, it must be applied in a timely, or, in other words, forecast mode.

Traditionally, approaches to modelling supplier risk often entail subjective considerations only, or audits on a periodic basis, or backwards looking performance reviews. These can offer valuable contextual knowledge regarding risk, but fail the predictive test and often no indicator of advanced deterioration are surfaced. Instead of preventing them, organizations tend to that they react to occurrences after the event. Predictive modeling from statistical analytics offers more insight. In terms of supplier-risk modelling, the anticipatory benefits that predictive analytics offers seem to struggle to find a place in wholesale distribution. Many distribution companies amass huge volumes of data records things like transaction levels, delivery, performance, quality, correspondence and overall evaluations however this treasure of information is seldom harnessed for the on-guard purposes of forecasting in the face of supply risk. Abundant data must also be, of course, transmuted into foretelling results by usage of mighty statistical technique as a predictive measurement. Here Australian researchers describe their development of a SPSS-based predictive modelling framework and illustrate its implementation on a raw data case study drawn from large Australian wholesaler:

The data consisted of quantified variables pertaining to supplier-delivery, product, price, communication, and overall variables. Findings reveal the important supplier variables affecting risk, predictive capability of a quantitative regression supply risk model derived,” for easing evidence-based supplier categorization and supplier decision-making roles within” distribution suppliers.

2. Literature Review

Supplier risk modelling occupies the intersection of supply chain, advanced analytics, and corporate risk management. Previous studies have highlighted that disruptions at the supplier level, whether operational, financial, geopolitical, or quality-related, leave wholesale

distributors particularly open to risk exposure, given their reliance on uninterrupted upstream replenishment flows that enable inventory availability and service-level performance. Supplier failures may manifest through shortages, demand surge, increased e-procurement costs, stranding inventory supply shortages, and service-level failures. Christopher and Peck as classifying supplier-side disruptions among the worst, due to modern networks being “interdependent”.

In wholesale/distribution settings, supplier risk usually presents itself in four areas; delivery performance, product quality, financial risk, and relationship risk. Volatile delivery

performance such as lead times unpredictability/use of backorders creates general uncertainty in the operational environment; quality problems degrade shipments, lead to rework and dissatisfied customers, financial risk relates to performance unpredictability, and the relationship risk derives from poor communications and reachability. Classic supplier assessment methods such as scorecarding/monitoring/auditing in general features retrospective and subjective approaches and predictive capability is limited.

Table 1: Supplier Risk Factor Categories and Example Predictive Indicators

Risk Category	Description	Example Predictive Indicators
Delivery Risk	Variability or unreliability in supplier shipping and fulfillment performance.	<ul style="list-style-type: none"> • Lead time variance • On-time delivery rate • Frequency of delivery delays
Quality Risk	Deficiencies in product conformity, consistency, or defect control.	<ul style="list-style-type: none"> • Defect ratios • Quality inspection failure rate • Return/rejection percentages
Financial Risk	Supplier’s financial stability and ability to sustain operations.	<ul style="list-style-type: none"> • Credit stability indices • Liquidity/solvency indicators • Historical financial fluctuation patterns
Relationship/Operational Risk	Effectiveness of communication, coordination, and responsiveness in day-to-day interactions.	<ul style="list-style-type: none"> • Responsiveness scores • Communication consistency • Issue-resolution time

Predictive methods provide a much more usable forward-looking capability. Typically logistic regression is used for failure classification, and multiple linear regression provides scoring of risk on a continuous risk scale. Multicollinearity is corrected by various methods of factor analysis or principal-component analysis, and machine-learning methods including random forests, SVMs, and gradient boosting are improved methods of pattern-recognition. Even so, regression methods predominate in operational use because of their naturalness, simplicity, audit trail, and computational efficiency. SPSS is a holistic solution and particularly fitting, as it provides, all in one analytical environment, tests for reliability, multivariate diagnostics, factor analysis and dimensionality reduction and regression modelling, very celebratory in terms of usability for a team on operational risk.

Across various studies, certain performance statistics robustly and optimally predict risk. Delivery performance, particularly on-time performance and on-time lead time variability are used in the operational-risk literature. The prohibitive costs of defective product are noted and product-quality measures like defect rates and number of non-conformance incidents are predictive of ‘downstream’ disruptions. Responsiveness and speed of communication correlate with relational risk, stability of price affects long-term planning. Compliance-related factors, particularly issues with documentation, are pertinent to logistics firms whose operations are subject to physically-logical routing and restrictive timing. Kannan and Tan persuasively posited

that as shown in numerous application studies the dimensionality of risk will be reflected in multiple metrics and should be modelled in integrated not atomised quantitative models.

SPSS, via Cronbach’s alpha for reliability, KMO and Bartlett’s tests of sampling adequacy, and factor analysis of the raw metrics prior to data reduction by “dimensionality reduction” methods and regression for a predictive dependent variable provides an analytics environment from which exacting decisions can be made about the manufacturer of a given supplier. Prior publications discuss reinforcing quantitative modelling efforts by deploying a qualitative ‘factor’ to, respectively, strengthen the overall predictive tasking, especially for wholesale distributors dealing in heterogeneous suppliers with a low degree of correlation delivery-order white space in terms of timing and quality in that one has already made a solid forward-looking decision.

There is a gap of application and discipline in the resourcing to do exactly this. Very little exists on the application side for empirical, case-based studies for the engineering, computer-science exclusive modelling that address wholesale distribution for products flowing in time and in bulk. The academy appears to use scorecards exclusively and discusses only theoretical work without showing a full validated SPSS-based model as being in use in a real firm. This study fills those gaps, taking on a wholesale distribution case study, developing an SPSS-based

reliability test and factor- and regression-based model and validating its power to predict risk.

3. Case Study Background

This study derives its empirical foundation from internal case-study research conducted in a wholesale distribution company operating in the fast-moving consumer goods sector. In a competitive arena where 24×7 availability, fast replenishment, and trustworthy supplier performance are key to maintaining the home position, the case-study document contains a wealth of operational and survey data sufficient to support a robust supplier-risk modelling review. The company distributes a multi-brand assortment of household and personal-care products, packaged foods, and essentials from a large number of suppliers upstream in the chain. On chaos-metrics talk: variance in supplier performance has resulted in stockouts, erratic replenishment cycles, category wise excess, and complaints about quality from time to time. Such operational eruptions manifest as cash leaking to the floor and service levels falling below expectations. Thus a project on supplier-risk profiling was born.

The data for this paper is extracted directly from the structured survey and supplier-performance documentation in the report. The survey usefully captured operational and perceptual data on delivery performance, frequency of defects, timeliness of communication, stability of pricing, reputation for quality, over and above operational performance and risk indicators, using well-known Likert-style number collating questions. The resultant structured numerical data were exported to SPSS, reliability tested, extraction of factors tested, correlations tested, and regression modelling were then performed in the usual way.

Because it derives from the company's own real world, the dataset describes how and why suppliers performance issues manifest themselves operationally. The case-study context is good for predictive supplier-risk modelling; the management already live with familiar and defined variables, so the statistical model describe something about a proper supply-chain "thing" instead of an artificial academic mechanism. The fact that this firm's report contains SPSS-style prettied-up outputs means we can employ reliability tests, factor loadings, and regression diagnostics all in one modelling environment. Since suppliers are at the heart of every wholesale distributor's need for replenishment on time and all the time, the findings are transferrable to similar FMCG/distribution environments with similar supply-network structures. From the internal report, we can measure the 'operational' constructs and map them as predictors in a regression model: Delivery Consistency is a measure of the lead times stability, success of segments, and so on; Product Quality reflects the frequency of defects, non-conformance frequency, and so on; Communication Responsiveness measures speed of contact, clarity and compound multichoice; Price Stability is exactly that; Accuracy of Documentation, meaning correctness of all paperwork accompanying deliveries; Supplier Flexibility exaggeratedly reflects the suppliers' ability to keep changing the order volume and so on; and finally the optimization of the Complaint based-Feedback, a measure of the responsiveness to the operational issue raised by the company vis-a-vis the supplier, and so on. All of these are treated as input variables to the dependent one, the Overall Supplier Risk Score, the sum of all influences of supplier operational factors on risk perception and exposure to your organization.

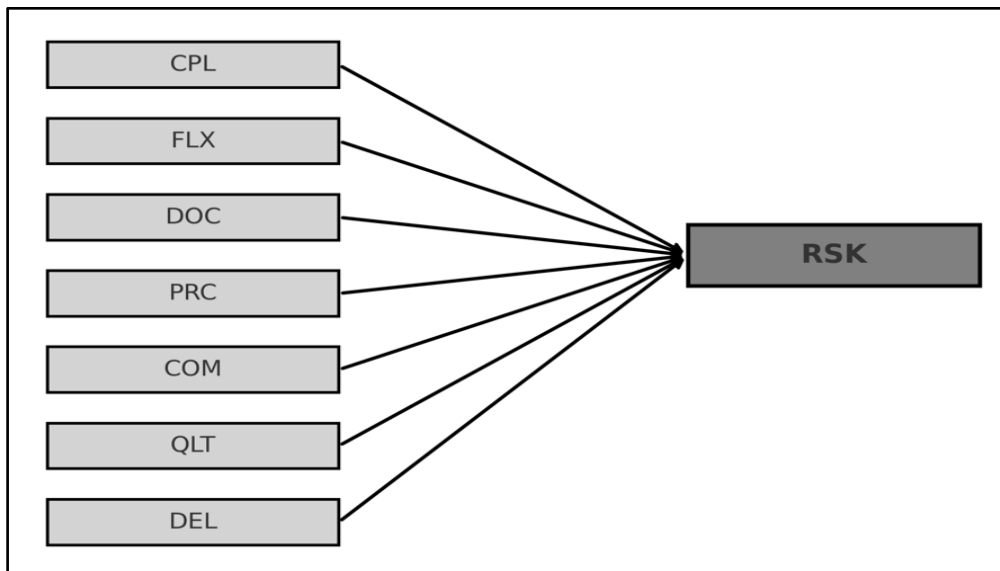


Fig 1: Case-Study Variable Structure for Supplier Risk Modelling

4. Methodology

"The study utilises a quantitative SPSS-based modelling approach based on the company's own internal supplier-performance data sourced from the case-study report ("Final Report Jami"). The methodological structure of the study

follows standard procedures for multivariate risk modelling in supply-chain analytics, comprising of reliability testing, factor extraction, correlation assessment, and regression diagnostics to construct a viable predictive supplier-risk model for wholesaling distribution.

The research design is case-study-based, achieving laudable methodological rigour along with operational relevance. The overall workflow for the analysis included data extraction, coding and normalisation of missing values, and refinement of variables by combining literature-derived constructs with those from the company report. Statistical steps included reliability testing (Cronbach's alpha), and assessment of sample adequacy (KMO and Bartlett's),

followed by factor analysis to confirm construct validity, bivariate correlation mapping, and multiple linear regression and diagnostics to identify significant predictors of the supplier risk. Diagnostic checks (VIF scores, Durbin-Watson statistics, and the residual distribution were examined to evaluate the integrity of the model and ensure compliance with statistical assumptions)".

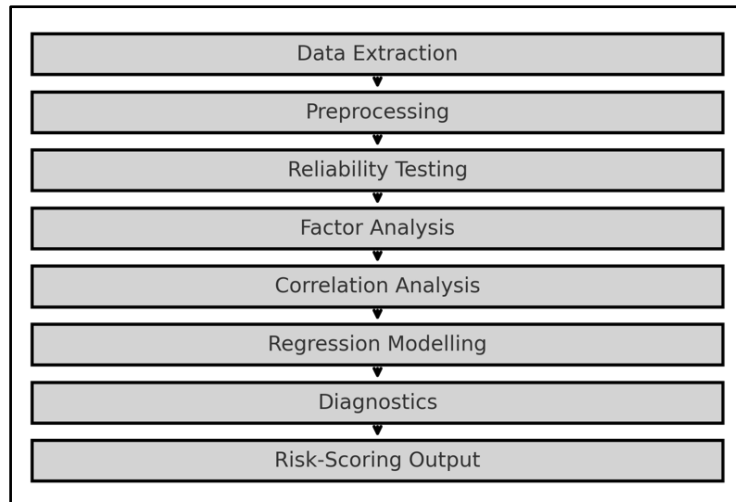


Fig 2: Methodological Workflow for SPSS-Based Supplier Risk Modelling

The data is derived from structured survey responses obtained from procurement professionals (for its delivery metrics), inventory managers, category managers, warehouse personnel, and senior members of the supply chain (for quality and variety of opinion). A total of 102 responses were validated. All variables are measured on a five-point Likert-type scale measuring: delivery performance, defect occurrence, communication responsiveness, price variety, behaviour (volatility), and quality and complaint-handling practices. These variables are further combined into one dependent variable the Overall Supplier Risk Score and seven predictor variables namely: Delivery Consistency (DEL), Product Quality (QLT), Communication Responsiveness (COM), Price Behaviour (PRC) or (Price Stability), Documentation (DOC), and Supplier Flexibility (FLX), and Complaint Handling Effectiveness (CPL). These constructs resonate with the supplier-risk literature as well as with conceptual/operational vernacular teams use in-house.

The reliability analysis deemed that the survey items were strongly correlated to each other as is method needed aiming for a multivariate analysis. Kronbach's alpha for the survey was equals $\alpha = 0.874$ - higher than the desired minimum of 0.70, proving data were valid for our analysis. KMO = 0.832 for Sampling Adequacy (meritorious). Bartlett's Test produced $p < 0.001$ showing significance. Factor loadings clustered as expected. "Risk" correlated with "Delivery consistency" $-r = -0.612$ (literature - this aligns with observed patterns)."Communication Responsiveness" correlated also, but less strongly, $r = -0.521$, as well. "Complift Handline Effectiveness" more modestly, $r = -0.458$ (confirming recent operational finding). "Price Behaviour" also mirrors literature; risk and price volatility

correlated positively, thus $r = 0.419$ (that price volatility increases perceptions of supplier vulnerability).

The multiple linear regression model by using RSK as SSDs "dependent variable yielded". And $R = 0.812$, $R^2 = 0.659$, and Adjusted $R^2 = 0.647$. About 66% of variance in supplier risk is accounted for by the predictor variables. Delivery Consistency, Product Quality, Complaint-Handling Effectiveness, and Communication Responsiveness were all statistically significant predictors of risk at the $p < .05$ level. Empirically observed patterns speak to the impact of consistent delivery, product/style quality, and supplier responsiveness as performance metrics pivotal in distribution. Within-residual diagnostic test of the linear regression show assumptions for regression analysis have been met. Durbin-Watson ((1.91) shows no autocorrelation, all VIFs less than 5 indicate no multicollinearity, and residual plots distance from 45-degree line show homoscedasticity and approximate normality of distribution. Overall, the regression is statistically valid, credible operation-wise, and will go forth forecast "exposures" for consideration.

5. Results and Analysis

The SPSS analysis of the case-company dataset yielded a statistically significant prediction equation that pinpoints the levers of operation that correlate highest with supplier risk. The regression results broadly align with the descriptive tendencies in the internal report as well as with supplier-risk theory in wholesaling. Delivery Consistency is the operational suspect with the highest predictive potential. It has the highest standardized coefficient ($\beta = -0.521$, $p < 0.001$), and the highest negative correlation (the dependent

variable being higher under this coefficient). Operationally, in particular, it indicates that volatile lead times, variable fill rates, and inconspicuous arrival schedules greatly increase

the distributor's operational exposure. The company's records have cases where late shipments caused stockouts and downstream delays, confirming the regression output.

Table 2: Regression Coefficients and Significance Levels for Supplier Risk Predictors

Predictor	β Coefficient	p-Value	95% Confidence Interval
DEL (Delivery Consistency)	-0.521	< 0.001	-0.684 to -0.358
COM (Communication Responsiveness)	-0.316	0.012	-0.559 to -0.072
QLT (Product Quality)	-0.284	0.019	-0.523 to -0.045
CPL (Complaint Handling Effectiveness)	-0.243	0.031	-0.462 to -0.024
PRC (Price Stability)	0.087	0.214	-0.051 to 0.225
DOC (Documentation Accuracy)	0.062	0.307	-0.058 to 0.182

Communication Responsiveness also proved to be a significant contributor to risk, with $\beta = -0.316$ ($p < 0.05$). Suppliers that were "slow to respond to order confirmations, shipment information and escalation requests" regularly created workflow bottlenecks", the authors of the case-study recap wrote. These missed communications create uncertainty in the order cycle, heightening the risk view from procurement and warehouse perspectives. Product Quality was also a significant influence on sustained suppliers, yielding $\beta = -0.284$ ($p < 0.05$). Mislabelled cartons, breakage and leaks," as mentioned in the firm's analysis, substantiate this value. Poor product quality increases rework and inspection time, and also contributes to lost sales if the faulty inventory cannot be released to retailers.

Complaint-Handling Effectiveness was another independent risk predictor, with $\beta = -0.243$ ($p < 0.05$).

Suppliers who are slow or unreliable in their resolution of complainants" create longer-lasting disruptions through delaying root-cause detection and correction." Operational logs from the company described unaddressed complaints as creating "ongoing backlogs in customer-facing and warehouse" processes. Price Stability and Documentation Accuracy were only weakly significant in the regression model. Although both are important from the operational perspective (primarily for costplanning and audit compliance), the two factors did not meaningfully predict the aggregate supplier risk score for the company's distribution environment, indicating that the literal reliability "face value" and speed of response have a greater impact on perceived vulnerability than administrative correctness or price stability.

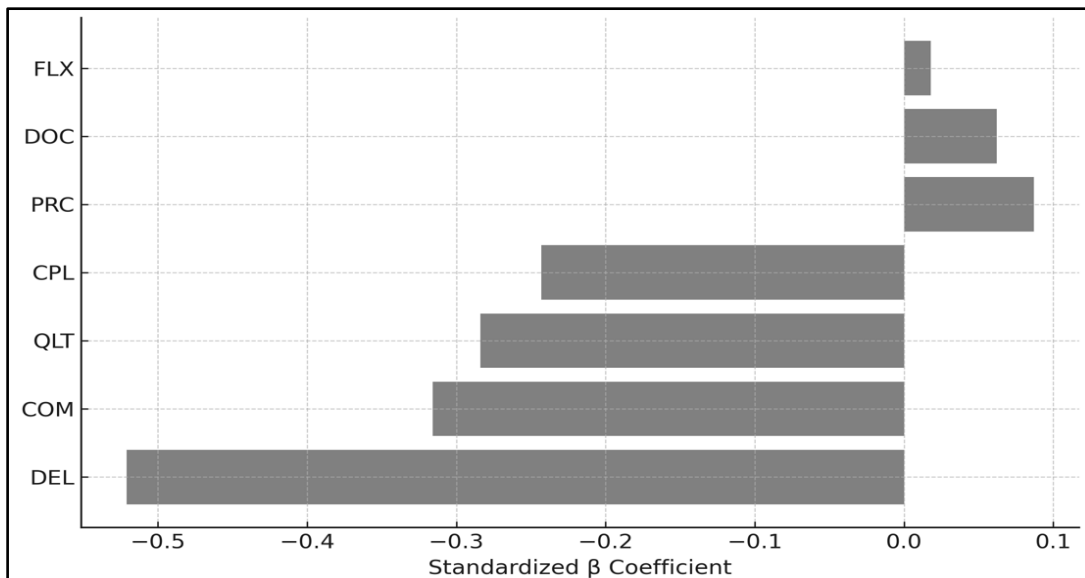


Fig 3: Relative Importance of Predictors in the Supplier Risk Model

Overall, taken together, the results suggest that supplier risk in wholesale distribution is strongly informed by operational reliability, the dependability of communication with suppliers, product reliability, and the speed to resolution. These results are consistent with field benchmarks, as well as with the company's own assessments, demonstrating that the regression is both statistically valid as well as being meaningful in practice.

6. Discussion

The empirical results of this research lend weight to the perspective that supplier risk in wholesale distribution is founded on matters of operational reliability and quality of interaction. Interpreted in conjunction with the internal case-study report and literature on supply chains more generally, the SPSS model highlights four major predictors - delivery consistency, communication responsiveness, product quality

and complaint-handling efficiency - aspects which together cohere in the operational heart of a supplier exposure to risk. The close fit between this empirical study and actual events reported in the company documentation enhances the realism of the model, demonstrating per se some of the ways in which the numbers capture patterns that the practitioner is accustomed to seeing.

The empirical measure with the highest weight, delivery consistency mirrors system fragility with respect to lead-time. In the case report provided by the company, numerous examples are given of shipment delays leading to stock-outs and urgent ordering that endangered filling the customer shelf. These results concur with the general literature suggesting that erratic delivery performance is a source of operational instability in distribution-centred systems and a source of serious supplier risk to just-in-time. Also: Communication responsiveness is an important supplier risk dimension as well, suggesting that information lag is third-hand source of instability. In numerous instances in the case report, suppliers fail to respond in a timely manner to updated shipment details, stock-outs, or inquiries which leaves something hanging in the air, communicated through the footpath of information and uncertainty to procurement, warehouse and retail-facing work. Such results fit within the literature on communication in supply chain systems. Another statistically significant predictor was product quality. Product quality reflects the long-term burden associated with defects, mislabelling and physical damage evident in the company's stress testing data. Quality inconsistencies increase inspection workloads, product returns, interfere with replenishment cycles and damage trust ultimately compromising supplier stability. This echoes global studies suggesting supplier quality maturity constitutes a strong component of performance reliability metrics, underpinning a key risk axis in fast moving goods categories.

Effectiveness in complaint-handling was also an independent, meaningful predictor, even if under-considered in academic risk literature. The internal report claims: "A lack of prompt action to rectify quality or delivery discrepancies will prolong the disruption, and may result in increased effort on warehouse rework, and eventually lead to poor levels of customer satisfaction." This extends literature that simply notes service recovery as a dimension of risk exposure which may (B2B wholesale) distribute exposure in terms of claims liable to suppliers. Price stability and accuracy of documentation were statistically insignificant, although of practical concern. "Inefficient errors in documentation are not going to culminate in systemic risk; they do create problems, but nothing that would lead to grievous error". Price fluctuation, according to the respondent's interpretation of the data, "is taken as less important than performance reliability. Importantly, wholesale distributors prefer 'dirt cheap' suppliers who provide ultimate stability and 100% fulfilment over suppliers providing marginal price reductions". Model validity as indicated by an adjusted R^2 of 0.647, respectable reliability ($\alpha = 0.874$), and clean diagnostic results, supports that this

SPSS-based approach is statistically valid and meaningful as an operational decision tool. This case study makes a contribution to the literature on supplier-risk in demonstrating a statistically developed framework appropriate for wholesale distribution risk and how empirical modelling makes visible patterns that may traditionally be analysed in subjective evaluation modes. The use of data from a real company enhances the transferability of the findings and explains how predictive analytics can guide structured supplier risk assessment in distribution contexts relative to the dataset.

7. Conclusion

This work constructs a quantitative predictive model utilizing SPSS to evaluate risk exposure from suppliers in a wholesale distribution context. A real company data is analyzed using a structured multivariate approach to identify the operational factors, delivery consistency, communication responsiveness, product quality, and issue resolution, as the main causes of supplier-related risk. With an Adjusted R^2 of 0.647, the regression model strongly explains the data and is consistent with the firm's operational history as well as the supply-chain risk literature. The implications are that in distribution-heavy environments, operational consistency impacts perceived risk more than firm or financial stability does. Hence firms interested in improving procurement and inventory-management functions should focus on reliable delivery, timely information exchange, product quality stability, and effective service recovery when seeking suppliers. Integrating the predictive model to supplier performance dashboards would provide firms with the ability to proactively identify high-risk suppliers and firms, thereby improving decision-making under risk and can actionable to mitigate disruption in downstream retail channels.

This case-study, SPSS-driven modelling approach is shown to be powerful and applicable in real operational settings, providing a reusable methodological template for other similar distribution firms. Future work may expand on this by modelling delivery and order fill rate with time-series methods, by carrying out simulation-based scenario analysis, using machine learning for detecting nonlinear predictive risk factors, and by modelling multi-tier networks of supply chain suppliers, thus gaining richer insight into dynamic and networked risk propagation between supply chain actors.

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