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When Information is not Enough: Replenishment Uncertainty and the Value of Decision Information Use in SME Inventory Management

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Abstract

This study examines whether replenishment decision uncertainty (RDU) conditions the association between decision information use (DIU) and perceived replenishment decision effectiveness (RDE) in small and medium-sized enterprises (SMEs). Grounded in Organisational Information Processing Theory, a survey of 360 SME respondents in Selangor, Malaysia, using purposive sampling in October 2026 was analysed through standardised composite-score regression, heteroskedasticity-consistent inference and 2,500-resample percentile bootstrap intervals. DIU was positively associated with RDE at mean uncertainty ($\beta = 0.371$), and the DIU × RDU interaction was positive ($\beta = 0.115$; 95% bootstrap CI [0.017, 0.206]). Adding the interaction increased explained variance from 0.137 to 0.151 ($\Delta R^2 = 0.014$). Conditional DIU slopes were 0.256, 0.371 and 0.485 at low, average and high uncertainty. However, the RDU measure exhibited limited measurement quality (Cronbach's $\alpha = 0.662$; composite reliability = 0.683; average variance extracted = 0.433). The findings offer a cautious, decision-specific illustration of uncertainty as a statistical boundary condition rather than proof of causal inventory-performance gains. Further measurement refinement and independent operational outcomes are important for corroboration.

Keywords: Decision Information Use, Replenishment Decision Uncertainty, Inventory Replenishment, Moderation Analysis

Introduction

Inventory replenishment requires managers to select order quantities, timing and sources despite incomplete knowledge of demand and supplier lead times. Such choices are sensitive not only to what information exists, but also to whether stock records and purchasing evidence are applied when decisions are made. Research on inventory record inaccuracies demonstrates that available digital records need not mirror physical stock (DeHoratius &

Raman, 2008). In the SME context, resource-constrained firms may face additional challenges collecting and exploiting replenishment data (Teerasoponpong & Sopadang, 2022).

Information processing and business-analytics research connects data-driven practices with organisational decision effectiveness, but that evidence does not mean the information-use relationship is constant under every operating condition (Cao et al., 2015). Supply-chain studies also emphasise environmental dynamism, digital visibility and risk-management capabilities under uncertainty (Rashid et al., 2024; Tiwari et al., 2024), while meta-analytic research links analytics capabilities and operational outcomes through broader supply-chain capabilities (Raj et al., 2025). A decision-level question follows: is the observed association between actual information use and perceived replenishment effectiveness stronger, weaker or unchanged as uncertainty increases?

The distinction between information access and decision readiness is reinforced by data-quality research: fitness for purpose encompasses contextual, representational and accessibility aspects, not accuracy alone (Wang & Strong, 1996). Li and Lin (2006) examine information sharing and information quality separately in supply chains and identify supplier uncertainty as a relevant antecedent; Lem (2024) links data-analytics strategy with internal information quality in another organisational context. Together these findings motivate, but do not directly test, the behavioural and contextual constructs examined here.

Malaysian SME research illustrates the value of structured evaluation in a different managerial area: Nordin et al. (2025) examine components of paid digital advertising performance assessment. That publication is relevant to the SME decision context but is not direct evidence about replenishment uncertainty. More directly, Teerasoponpong and Sopadang (2022) propose sourcing and inventory decision support for SMEs under demand and lead-time uncertainty. The present article studies a narrower perceptual interaction, rather than claiming that uncertainty moderation in operations management is previously unknown.

The objective is to examine the conditional association between decision information use (DIU) and perceived replenishment decision effectiveness (RDE) across levels of replenishment decision uncertainty (RDU), report the interaction's incremental explanatory value, and interpret the model in light of measurement quality. The research questions are: (RQ1) Is DIU positively associated with perceived RDE? (RQ2) Does RDU moderate this relationship? (RQ3) How large is the conditional difference in slopes and what cautions limit its interpretation?

Literature Review and Hypothesis Development

Organisational information-processing theory and replenishment uncertainty

Organisational Information Processing Theory (OIPT) links task uncertainty with the demand for appropriate information-processing arrangements (Galbraith, 1974). In replenishment, variation in customer demand, uncertain supplier delivery and unexpected changes in required quantities can increase the amount and timeliness of information needed for a decision. The capacity to collect and process information may therefore matter more when operational conditions become unpredictable. Yet greater uncertainty may also diminish the

reliability of available signals; theory alone does not determine the direction of the interaction.

In digital supply chains, Rashid et al. (2024) use information-processing reasoning to examine resilience through risk-management capabilities. Tiwari et al. (2024) address visibility, digital technologies and dynamism in healthcare supply chains, while Saha and Rathore (2024) examine healthcare technologies and performance through an OIPT lens. These studies support the relevance of contingencies but operate at broader organisational or sectoral levels. None directly validates the specific DIU × RDU coefficient in the SME replenishment model.

Decision information use and perceived replenishment effectiveness

DIU denotes consultation and application of inventory, sales and supplier information when evaluating replenishment alternatives. RDE denotes a respondent's assessment of the appropriateness and timeliness of the resulting order decision. These are different constructs: information use concerns decision behaviour, whereas decision effectiveness concerns perceived results. Jonsson and Myrelid (2016) distinguish actual utilisation of shared supply-chain information from its availability and intended use. Cao et al. (2015) further provide an information-processing account connecting business analytics with decision effectiveness, although their outcome is organisational rather than a single inventory decision. Abdellatif et al. (2024) distinguish decision speed and comprehensiveness as mediating decision facets, underscoring the need not to equate information use with decision success.

Accurate records can facilitate decisions, but utilisation of available information remains a separate behavioural requirement (DeHoratius & Raman, 2008; Jonsson & Myrelid, 2016). The present study consequently expects a positive association between DIU and perceived RDE, without inferring that the same relationship establishes objective stockout reduction.

H1: Decision information use is positively associated with perceived replenishment decision effectiveness.

The moderating role of replenishment decision uncertainty

RDU refers to unpredictability associated with demand, supplier delivery and unforeseen replenishment requirements. In relatively stable environments, routines may suffice; under higher uncertainty, explicit consultation of relevant information could be more useful. Conversely, volatility may make historical records less representative of near-term decisions. OIPT provides a reason to test this contingency rather than presume a universally positive amplification (Galbraith, 1974; Rashid et al., 2024; Tiwari et al., 2024).

Moderation is represented by a multiplicative DIU × RDU term. Correct interpretation requires evaluating the conditional DIU slope at substantively meaningful moderator values, not merely reading the sign of a single coefficient (Brambor et al., 2006). Because plausible mechanisms predict opposing directions, the hypothesis is deliberately non-directional.

H2: Replenishment decision uncertainty moderates the association between decision information use and perceived replenishment decision effectiveness.

Figure 1 presents the focused conceptual model and the reported standardised coefficients. The moderator is treated as a statistical boundary condition, not as a proven cause of increased decision effectiveness.

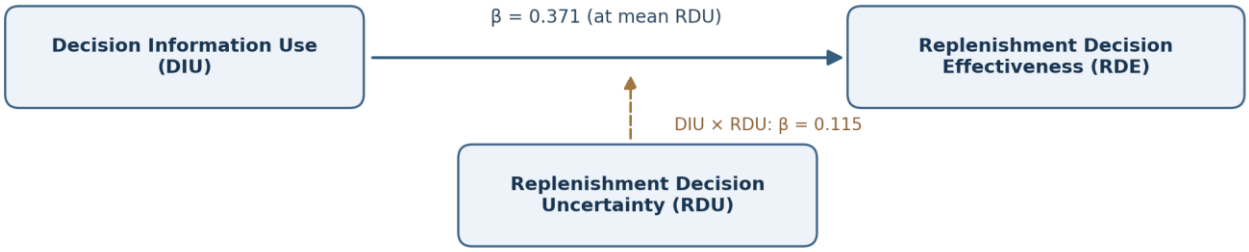


Figure 1. Focused uncertainty-moderation framework with reported composite-score coefficients

Research Methodology

Research design and analytic sample

This cross-sectional study analyses genuine survey responses from 360 SME respondents concerning inventory replenishment decisions. Data were collected in Selangor, Malaysia, using purposive sampling during October 2026. The unit of analysis is the respondent, and the model concerns self-reported decision practices and perceived effectiveness rather than independently recorded replenishment transactions. Consequently, conclusions refer to the analysed responses and should not be generalised probabilistically to all Malaysian SMEs.

The focal model comprises DIU (four five-point items), RDU (three five-point items) and perceived RDE (four five-point items). The analysis includes 360 survey records with complete responses across the 11 indicators. Construct scores are unweighted arithmetic means. The RDU specification uses three items; its content coverage is therefore narrower than an earlier four-candidate-item instrument, and item removal should not be inferred to constitute validation merely because it changes reliability statistics.

Measurement and construct diagnostics

DIU captures the reported use of inventory-related evidence, RDU combines reported demand/supply uncertainty and RDE represents perceived effectiveness. The measurement report includes Cronbach's alpha and separate one-factor maximum-likelihood estimates of composite reliability (CR) and average variance extracted (AVE). These are descriptive diagnostics, not joint confirmatory factor analysis or latent-variable PLS-SEM results. In particular, Cronbach's alpha is insufficient to establish unidimensionality or construct validity (Sijtsma, 2009).

The instrument-development literature emphasises explicit content-validity assessment before making measurement claims. Zaid and Hussin (2024) demonstrate a questionnaire-validation workflow using the Content Validity Index in the distinct domain of social-media crowdfunding; that article is a methodological precedent, not direct validation of the present inventory uncertainty scale.

Table 1 summarises the reported internal-consistency screening and descriptive statistics. The low RDU reliability is retained as an important finding rather than concealed through selective item deletion.

Table 1
Construct composition and descriptive measurement properties

Construct	Items	Cronbach's α	Mean	SD
DIU	4	0.825	3.075	0.756
RDU	3	0.662	3.061	0.710
RDE	4	0.806	3.071	0.720

RDU's reported CR (0.683) and AVE (0.433) also indicate limited preliminary measurement quality. The other two alpha coefficients exceed 0.80, but alpha alone cannot confirm dimensionality. Any interpretation of the interaction should therefore allow for attenuation, measurement overlap and possible uncertainty subdimensions (Sijtsma, 2009).

Regression specification and inference

The study uses standardised composite-score ordinary least squares regression with a main-effects baseline and a product-term model. The reported specification is $RDE = \beta_0 + \beta_1(DIU) + \beta_2(RDU) + \beta_3(DIU \times RDU) + \varepsilon$, with centred and standardised constituent composites. HC3 heteroskedasticity-consistent standard errors and 95% percentile bootstrap intervals based on 2,500 resamples are reported. The software setting and coefficient scaling should match this specification in the final analysis archive.

The conditional slope of RDE with respect to DIU is $\beta_1 + \beta_3(RDU)$. Accordingly, the reported coefficients imply 0.256 at −1 standard deviation of RDU, 0.371 at the mean and approximately 0.486 at +1 standard deviation, subject to rounding of the underlying unrounded estimates. This is a conditional association, not an identified causal effect (Brambor et al., 2006). The additional R^2 is interpreted as in-sample explanatory improvement rather than prospective prediction.

Results

Bivariate associations

Before evaluating the interaction, Table 2 displays the three bivariate Pearson correlations. This distinguishes DIU–RDE association from the weaker zero-order links involving RDU.

Table 2
Pearson correlations among focal composite measures

Construct pair	Pearson r
DIU–RDU	0.041
DIU–RDE	0.362
RDU–RDE	−0.061

The positive DIU–RDE correlation (r = 0.362) is directionally consistent with H1. The near-zero DIU–RDU correlation (r = 0.041) and small negative RDU–RDE correlation (r = −0.061) do not rule out an interaction because a conditional relationship can differ from its marginal correlations (Brambor et al., 2006).

Regression coefficients and interaction test

Table 3 reports the standardised main-effect and product-term estimates, together with HC3 inference and 95% percentile bootstrap confidence intervals. The DIU estimate is evaluated at mean RDU because the model includes an interaction.

Table 3

Moderation regression and bootstrap estimates

Term	β	HC3 SE	HC3 p	95% bootstrap CI
Intercept	−0.005	0.049	0.9235	[−0.099, 0.087]
DIU	0.371	0.048	<0.001	[0.279, 0.460]
RDU	−0.084	0.051	0.0977	[−0.185, 0.013]
DIU × RDU	0.115	0.051	0.0236	[0.017, 0.206]

The DIU coefficient is positive (β = 0.371, 95% CI [0.279, 0.460]), whereas the RDU main effect is not distinguishable from zero using the reported HC3 inference (p = 0.0977). The DIU × RDU term is positive (β = 0.115, p = 0.0236; 95% bootstrap CI [0.017, 0.206]), indicating that the fitted DIU–RDE association becomes steeper as measured uncertainty increases. This is statistical support for H2 under the specified measures, not evidence that increasing DIU causes higher inventory performance.

Incremental explanatory value

To evaluate the interaction's practical explanatory contribution, Table 4 compares the main-effects regression with the specification that adds DIU × RDU.

Table 4

In-sample explanatory power of the moderation model

Model	R^2	Adjusted R^2	ΔR^2
DIU + RDU	0.137	0.132	—
DIU + RDU + DIU × RDU	0.151	0.144	0.014

The interaction accounts for an additional 1.4 percentage points of RDE composite-score variance, increasing R^2 from 0.137 to 0.151. The total model consequently leaves 84.9% of perceived RDE variance unexplained. A statistically detectable product term is not synonymous with a large practical improvement, and ΔR^2 is an in-sample rather than out-of-sample quantity.

Conditional effects and visualisation

Table 5 presents the estimated DIU slopes at low, mean and high RDU. Reporting these conditional estimates follows methodological recommendations for interpreting interaction models (Brambor et al., 2006).

Table 5

DIU conditional slopes by replenishment uncertainty

RDU level	DIU slope	95% bootstrap CI
Low (−1 SD)	0.256	[0.123, 0.389]
Mean	0.371	[0.279, 0.460]
High (+1 SD)	0.485	[0.343, 0.610]

All three reported conditional intervals exclude zero and the estimated slope increases by approximately 0.229 between the −1 SD and +1 SD levels. Figure 2 plots the lines implied by the fitted regression equation; these are predictions from the specified model, not averages observed within three distinct SME groups.

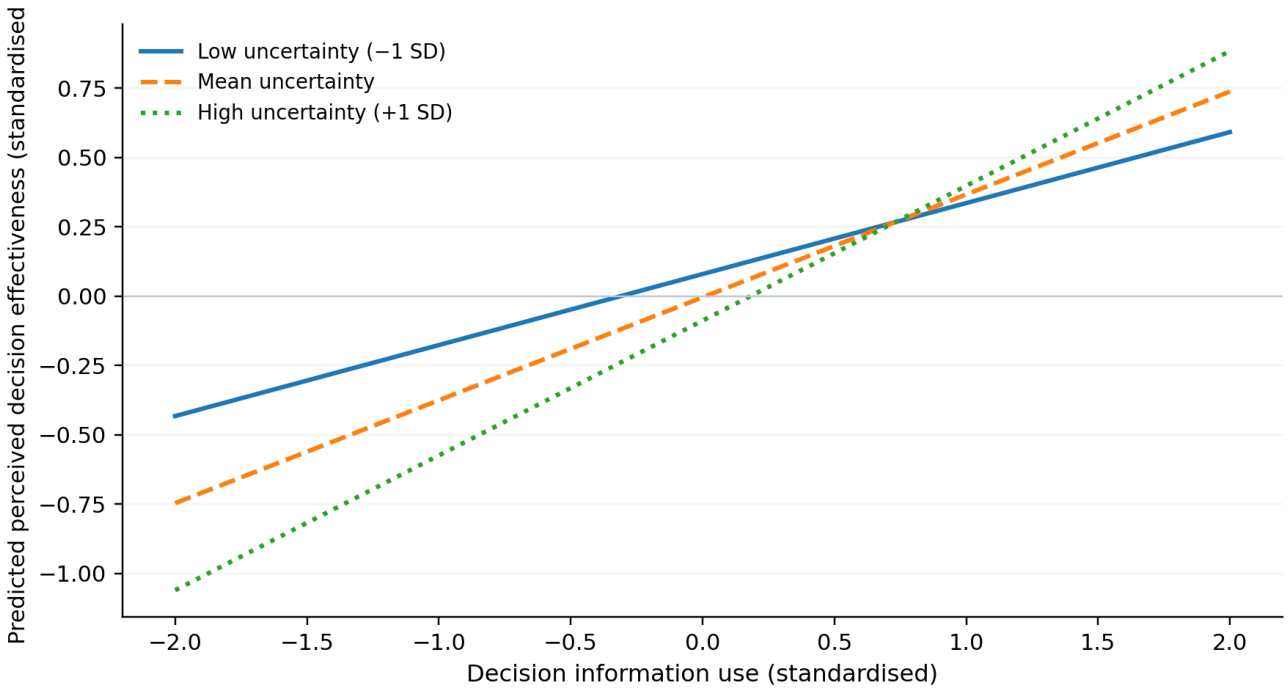


Figure 2. Model-implied DIU–RDE relationships at low, mean and high replenishment uncertainty

Figure 3 makes the uncertainty around each conditional slope explicit using the corresponding percentile confidence intervals. Its purpose is to reveal both the direction of the interaction and the precision of slope estimates.

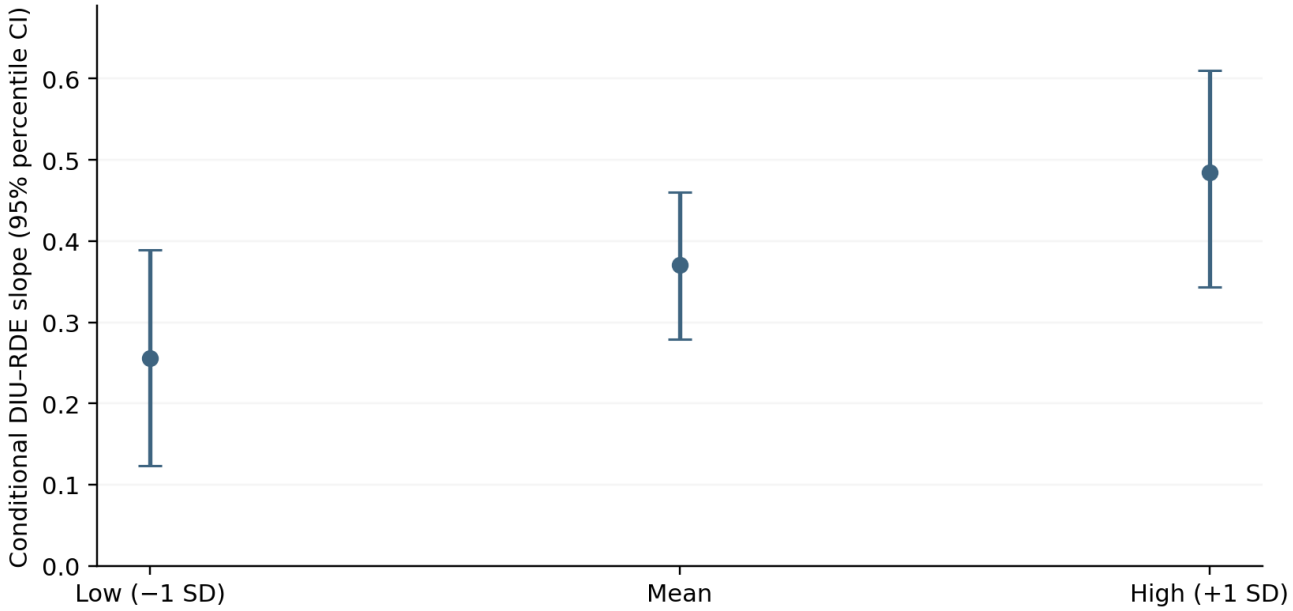


Figure 3. Conditional DIU slopes and 95% percentile bootstrap confidence intervals

Interpretive and measurement sensitivity

The positive interaction is supported by both the reported HC3 test ($p = 0.0236$) and the percentile bootstrap interval [0.017, 0.206]. Agreement between two inferential summaries does not establish robustness to item selection, omitted organisational variables, nonlinear forms or influential observations. Because RDU is the interacting variable and has $\alpha = 0.662$, CR = 0.683 and AVE = 0.433, the interaction should be interpreted as provisional with respect to measurement specification. Refitting the model with better-defined demand and supply uncertainty dimensions would be an informative next test.

Discussion

The headline result is a positive conditional DIU–RDE association that is steeper under higher reported uncertainty. It is compatible with an OIPT reading in which more demanding decisions create greater scope for deliberate information processing (Galbraith, 1974). At the same time, this pattern does not establish that uncertainty itself makes information use beneficial: managers who possess better operational routines might report greater use, stronger effectiveness and higher perceived uncertainty simultaneously. Common-source survey responses may also introduce systematic response covariance (Podsakoff et al., 2003). The result also requires careful differentiation from adjacent research. Teerasoponpong and Sopadang (2022) examine a practical decision-support system for SME sourcing under uncertain demand and lead times; the present study reports a respondent-perceived interaction rather than evaluated DSS implementation outcomes. Cao et al. (2015) relate analytics and information processing to organisational decision effectiveness, while Jonsson and Myrelid (2016) explore actual utilisation of shared supply-chain information. This manuscript combines those strands at the replenishment decision level by treating uncertainty as a moderator of the use–effectiveness relationship; it does not claim to introduce the general idea of information utilisation or contingency.

Theoretical Contribution and Relationship to Companion Manuscripts

The paper's focused contribution is the proposed and estimated boundary condition for the DIU–RDE association. It complements an upstream analysis of information governance and integration as antecedents of information quality (Paper 2), and a separate analysis of information quality, analytical capability, information use and perceived replenishment effectiveness (Paper 3). These manuscripts occupy different portions of a common information-to-decision research programme. Their shared constructs and potential sample overlap should be disclosed consistently across submissions, and article distinctiveness should rest on different research questions and analysis—not simply differently named models.

Managerial Implications

For SME inventory decision-makers, the conditional findings suggest a diagnostic approach rather than a general prescription to invest in more software. First, document the uncertainty actually encountered: demand volatility, lead-time deviations and unanticipated replenishment requirements. Second, observe the information consulted when orders are authorised. Third, compare decisions with subsequent stock outcomes to distinguish retrospective satisfaction from objective effectiveness. Such steps are consistent with the challenge of inventory-record inaccuracy (DeHoratius & Raman, 2008) and the distinction between information sharing and actual utilisation (Jonsson & Myrelid, 2016).

The positive interaction does not demonstrate savings from an intervention. A defensible next-stage evaluation would compare decision episodes using stock-position accuracy, stockout frequency, emergency ordering and realised inventory costs under different uncertainty levels. Nordin et al. (2025) provide a parallel example of structured performance assessment for Malaysian SMEs in digital advertising, but the application to inventory ordering remains a proposed diagnostic rather than an observed intervention effect.

Limitations and Future Research

Three cautions are central. First, the analysis captures concurrent perceptions and thus cannot identify the direction of influence or rule out omitted capabilities. Second, the RDU measurement properties are weak by commonly used screening conventions, and a three-item composite may combine demand- and supplier-related conditions that warrant separate constructs (Sijtsma, 2009). Third, the incremental explanatory value is modest and reflects perceived rather than independently observed inventory outcomes. Future research should use temporally separated observations, multiple information sources, validated uncertainty dimensions and prospectively recorded replenishment outcomes (Podsakoff et al., 2003; DeHoratius & Raman, 2008).

Conclusion

This study reports a positive association between decision information use and perceived replenishment decision effectiveness and a positive, modest interaction with replenishment decision uncertainty. Conditional slopes increase from 0.256 at low RDU to 0.485 at high RDU, but the interaction adds only 0.014 to explained variance. The weaker measurement diagnostics for uncertainty ($\alpha = 0.662$; CR = 0.683; AVE = 0.433) limit confidence in substantive extrapolation. The contribution is therefore a decision-level statistical account of uncertainty as a possible boundary condition, motivating better measurement and independently recorded outcomes rather than asserting causal inventory-performance gains.

Theoretical and Contextual Contributions

Theoretically, this research extends the application of Organisational Information Processing Theory from broad organisational information-processing arrangements to the specific decision of SME inventory replenishment. It shows that replenishment decision uncertainty may condition the association between decision information use and perceived decision effectiveness ($\beta = 0.115$; $\Delta R^2 = 0.014$), rather than assuming that information use has the same relationship with decision outcomes in all operating conditions. This contribution is deliberately qualified because the uncertainty measure has limited reliability and the cross-sectional analysis cannot establish causality. Contextually, the evidence from 360 SME respondents in Selangor, Malaysia, highlights the relevance of applying existing stock, sales and supplier information when demand and delivery conditions are less predictable. The findings offer a basis for local SMEs to review how replenishment decisions are made, record uncertainty and assess decisions against subsequent inventory outcomes; they do not demonstrate realised cost savings, reduced stockouts or national-level generalisability.

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