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Bayesian Network Evidence on Price, Electronic Word of Mouth, and Seasonality in Amazon Product Sales Performance

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Abstract. This study examines the associations of price, eWOM, and seasonal review activity with product sales performance in cross-border e-commerce. The analysis uses 3,886 products from Amazon's All Beauty category and treats sales rank as a proxy for relative sales performance. A compact Bayesian network links price level, eWOM strength, peak review season, and sales performance. Conditional probabilities are estimated with Laplace smoothing, while chi-square tests and Cramer's V assess the stability and strength of the observed associations. Products with high eWOM strength have a 48.9% posterior probability of high sales performance, compared with 19.4% for the medium group and 14.3% for the low group. Price differences are small, and seasonal differences are also limited. The strongest multi-factor combination consists of medium price, high eWOM strength, and a spring review peak, with a posterior probability of 58.7%. The results indicate that credible review activity is more closely associated with strong sales performance than price level or seasonality. The findings support a management approach that gives priority to genuine review quality, uses controlled price tests, and treats seasonal timing as supporting evidence rather than a primary decision rule.

Keywords: Bayesian network, cross-border e-commerce, eWOM, sales performance, Amazon review data

1. Introduction

Cross-border e-commerce sellers must make pricing, review-management, and inventory decisions with incomplete information. Online marketplaces display prices, ratings, review volume, review dates, and other signals, but no single signal provides a direct measure of demand. Prior research shows that online reviews can change relative sales and that negative reviews may have a stronger effect than positive reviews in some markets [1]. Consumer reviews also provide buyer-created information that can complement the seller's own product communication [2]. Their influence, however, depends on how review information is evaluated: reviewer identity disclosure can affect its credibility [3, 4], feedback-system design and context shape market trust [5], and review depth, rating extremity, and product type affect perceived helpfulness [6]. These studies clarify the role of

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particular review characteristics, but they do not provide a unified probabilistic comparison of the price, eWOM, and seasonal signals examined here. Because sellers observe these signals together, they need an interpretable basis for assessing which signals, and which combinations, are associated with a higher probability of strong sales performance.

This study analyses 3,886 products from the Amazon Review Data 2018 All Beauty subset [7]. It uses sales rank as a proxy for relative sales performance because the public data do not report actual orders, advertising expenditure, inventory, or traffic. A compact Bayesian network links price level, eWOM strength, peak review season, and sales performance. The analysis asks two questions: how does the posterior probability of high sales performance differ across combinations of price, eWOM, and season, and which factor has the strongest and most stable association with sales performance? The model estimates conditional probabilities for individual factors and their combinations, while treating the observed relationships as associations rather than causal effects. It therefore places price, review activity, and seasonality on a common probability scale and provides evidence that can inform decisions regarding pricing, review-management, and seasonal resource-allocation in cross-border e-commerce operations.

2. Literature review and research framework

2.1. Price and eWOM

Price affects purchase cost and can signal quality or brand position. Its relationship with sales performance is unlikely to be linear because different price levels serve different customer groups. Lower prices may reduce purchase barriers, whereas higher prices may be acceptable when product information and perceived value are strong. Price should therefore be examined by level rather than treated as an automatic source of better or worse performance.

eWOM reduces uncertainty by providing information from previous buyers. Review volume indicates market attention, average rating summarises evaluation, and verified-purchase information can strengthen credibility. Chevalier and Mayzlin linked online reviews with relative book sales: improved reviews were associated with higher relative sales, while one-star reviews generally had a larger effect than five-star reviews [1]. Chen and Xie described consumer reviews as part of the marketing communication mix [2], Zhu and Zhang showed that review effects vary with product and consumer characteristics [3], and Forman, Ghose, and Wiesenfeld found that identity disclosure changes how reviews relate to sales and helpfulness [4]. Together, these studies support the use of a combined measure rather than reliance on a single review statistic.

The present model uses review count and average rating to classify eWOM strength. Verified-purchase rate is reserved for a robustness test because it reflects the credibility of review activity rather than its basic scale. This separation allows the analysis to test whether the main relationship remains visible when products are divided by a second review-quality measure.

Seasonality is also relevant to online retail performance because consumer demand, search behaviour, promotional calendars, and fulfilment conditions vary over time. Using data from a large European online fashion retailer, Steinker, Hoberg, and Thonemann identify seasonality, special promotions, and public holidays as established drivers of online sales that are incorporated into forecasting approaches [8]. Yang et al. further show that product relevance in e-commerce search is time-sensitive: 39% of queries in their study were highly seasonally relevant, and incorporating seasonal relevance increased purchases in an online experiment [9]. Together, this evidence suggests that sales-related signals are not constant across calendar periods. The present study therefore treats the season containing a product's peak review month as an observable timing condition. This enables

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the subsequent research framework to compare sales-performance probabilities across seasonal conditions rather than assuming that products face the same market environment throughout the year.

2.2. Bayesian networks in marketing analysis

A Bayesian network represents variables and their conditional dependence through a directed probabilistic graph. Once evidence is available, the model estimates the posterior probability of each outcome. This structure is useful when several discrete conditions must be compared at the same time. Heckerman explains how Bayesian networks combine prior structure with data [10], and Cooper and Herskovits provide a Bayesian approach for learning probabilistic networks from observed cases [11]. Koller and Friedman give a wider treatment of inference and learning in probabilistic graphical models [12].

Prior studies also demonstrate the practical relevance of Bayesian networks in e-commerce and online-review settings. In an online shopping setting, Matsushita and Maeda use a Bayesian network to infer purchase probability from web-log and eye-movement evidence, demonstrating how observed browsing conditions can be converted into purchase-related probability estimates [13]. At the product-feedback level, Khopkar and Nikolaev develop a Bayesian network that predicts long-term product ratings from limited early ratings and information from the user base, this is relevant for online retailers because ratings are an important quality signal for promotion and inventory decisions [14]. Using 8,699 Amazon reviews, Lee, Lee, and Choeh apply a naive Bayesian network to predict review helpfulness from product, reviewer, and report better predictive performance than that of their k-nearest-neighbour and neural-network benchmarks [15]. Taken together, these studies show that Bayesian networks can integrate multiple observable commercial signals and express their relationship with a managerially relevant outcome through conditional probabilities.

These applications support the present study. Rather than predicting an individual purchase, long-term rating, or review helpfulness, the model compares the posterior probability of high relative sales performance across price level, eWOM strength, and peak review season. Theory defines the simple structure and data estimate its conditional probability table: the three factors are parent nodes and sales performance is the target node. A smaller sales-rank value indicates stronger relative performance within the category.

2.3. Research framework and hypotheses

The framework compares the posterior probability of high sales performance across individual factor levels and across selected combinations. The three parent variables are treated as observed conditions rather than as proven causes. The hypotheses concern statistical differences and association strength.

H1 proposes that the probability of high sales performance differs across different price levels. The expected direction is left open because price can reflect both affordability and perceived value.

H2 proposes a positive association between eWOM strength and high sales performance. Stronger review volume and ratings should provide more visible and favourable market information.

H3 proposes that sales-performance probabilities differ across peak review seasons. Seasonal demand, promotions, and platform traffic may produce different review and performance patterns.

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3. Research design and data processing

3.1. Data source and variable construction

The analysis uses the Amazon Review Data 2018 collection published by the McAuley Lab at the University of California San Diego [7]. The dataset's All Beauty subset contains 371,345 review records and 32,992 product metadata entries, and its recommended academic citation is Ni, Li, and McAuley [16]. Reviews are joined to metadata by the Amazon Standard Identification Number. Products are retained when price and sales rank are available and at least five reviews can be linked. These filters produce 3,886 product-level observations.

The screening rule is designed to retain product-level observations for which price, the sales-rank proxy, and eWOM indicators can be interpreted together. Products without price or sales rank are excluded because missing values prevent a complete comparison between observed conditions and sales performance. The minimum of five linked reviews is not presented as a universal cut-off. Instead, it is consistent with the 5-core construction supplied for the Amazon Review Data collection, which retains entities with at least five interactions [7]. This threshold reduces the influence of isolated feedback on product-level average-rating and review-count measures, while retaining a sufficiently broad product set for conditional-probability estimation. Finally, only records that can be matched by Amazon Standard Identification Number are kept, ensuring that every analytical observation has both review and metadata information.

Sales rank is a snapshot proxy rather than actual sales. High performance is defined as a rank of 142,171.25 or below, Medium as a rank between 142,171.25 and 588,576, and Low as a rank of 588,576 or above. Price levels use USD 9 and USD 19 cut-offs. eWOM strength is Low below a 3.5 average rating, High with at least 22 reviews and a rating of 4.0 or above, and Medium otherwise. Peak review season is product-specific: each product is assigned to the season containing the month with its highest linked review count. It is not based on a platform-wide monthly review peak. Table 1 summarises the definitions.

Table 1. Variable definitions and processing rules

Variable	Role	Definition
Sales Performance	Target node	Based on the quartiles of sales rank, products are classified as High, Medium, or Low. A smaller sales rank indicates stronger sales performance.
Price Level	Parent node	Low: ≤ \$9, Medium: \$9 < price ≤ \$19, High: > \$19.
eWOM Strength	Parent node	Low: average rating < 3.5, High: ≥ 22 reviews and average rating ≥ 4.0, Medium: all other cases.
Peak Review Season	Parent node	Product-specific season of the month with the highest linked review count, not platform-wide: Winter (Dec-Feb), Spring (Mar-May), Summer (Jun-Aug), or Autumn (Sep-Nov).

Note. All classifications are based on sample distribution and common industry thresholds, robustness of price thresholds is verified in Section 4.3.

3.2. Bayesian network structure and parameter estimation

Let P denote price level, W denote eWOM strength, S denote peak review season, and Y denote sales performance. P, W, and S are discrete parent nodes, while Y takes the states High, Medium, and Low. The joint distribution follows the factorisation in Equation 1.

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$$\mathrm{Pr(P, W, S, Y) = Pr(P)\,Pr(W)\,Pr(S)\,Pr(Y \mid P, W, S)} \tag{1}$$

Equation 1 specifies conditional dependence rather than causality. For each state combination, the conditional probability table gives the posterior distribution of Y. Laplace smoothing prevents zero probabilities in small cells, as defined in Equation 2.

$$\widehat{P}(Y = y|p, w, s) = \frac{N_{pws,y}+\alpha}{N_{pws}+K\alpha}, \quad \alpha = 1,\ K = 3 \tag{2}$$

In Equation 2, N_pws,y is the count of observations in the data used to estimate the table in class y for a combination, N_pws is its total count, K is the number of outcome classes, and alpha equals 1. Equation 3 assigns the class with the largest posterior probability.

$$\mathrm{y = y^{*},\ P(Y = y^{*} \mid p, w, s) \geq P(Y = y \mid p, w, s)} \tag{3}$$

Here, y^{*} denotes the class with the largest posterior probability among High, Medium, and Low.

Cramer's V compares the strength of association between each parent variable and sales performance. The statistic is calculated from the contingency-table chi-square value as shown in Equation 4.

$$\mathrm{V} = \sqrt{\frac{\chi^{2}}{\mathrm{nq}}} \tag{4}$$

Here, χ^{2} is the contingency-table chi-square statistic, n is the sample size, and r and c are the numbers of rows and columns.

3.3. Model validation

A fixed random seed produces a stratified 80/20 split, preserving the High, Medium, and Low class proportions in the training and test sets. Holdout accuracy is the share of test observations for which the highest posterior class matches the observed class.

$$\mathrm{Accuracy} = \frac{1}{\mathrm{n_{test}}} \sum_{\mathrm{i=1}}^{\mathrm{n_{test}}} \mathrm{I}\left(\widehat{\mathrm{y}}_{\mathrm{i}} = \mathrm{y}_{\mathrm{i}}\right) \tag{5}$$

The holdout test assesses this compact model's classification ability rather than its ability to produce a production sales forecast. The public data omit dynamic prices, advertising, inventory, traffic, and actual orders, limiting prediction and causal interpretation.

4. Empirical results and discussion

4.1. Descriptive statistics and variable distributions

The final sample contains 3,886 All Beauty products with complete price and sales-rank information and at least five reviews. Mean price is USD 21.50, above the USD 13.00 median, and the maximum is USD 999.00, indicating a right-skewed distribution. Average rating is 4.12, while the median is 4.24. Mean review count is 45.16 but the median is 12, suggesting that a small group of products receive many reviews. Mean sales rank is 412,752.58 and the median is 331,052.50. Table 2 reports the full descriptive statistics.

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Table 2. Descriptive statistics of continuous variables (N = 3,886)

Variable	Mean	Std. Dev.	Median	Min	Max
Price (USD)	21.50	44.05	13.00	0.00	999.00
Average Rating	4.12	0.64	4.24	1.00	5.00
Review Count	45.16	150.15	12.00	5.00	4,544.00
Sales Rank	412,752.58	379,309.55	331,052.50	35.00	9,549,407.00
Verified Purchase Rate (%)	90.1%	14.3%	95.3%	0.0%	100.0%

The predefined sales-performance categories are balanced, with High and Low each accounting for 25.0% of the sample and Medium accounting for 50.0%. Price levels are also broadly even: Low-priced products represent 37.9%, compared with 31.0% and 31.1% for Medium and High prices. eWOM strength is concentrated in the Medium category at 62.5%, while High and Low account for 21.9% and 15.6%, respectively. Peak review season is more evenly distributed across the year, with Spring at 29.2%, Summer at 28.2%, Winter at 24.1%, and Autumn at 18.5%. These distributions provide the descriptive context for the conditional-probability comparisons reported below.

4.2. Conditional probability results

Laplace smoothing uses alpha equal to 1 and three outcome classes. Price level produces only small differences in the posterior probability of high sales performance: 23.4% for Low, 26.8% for Medium, and 25.2% for High. The 3.4-percentage-point range offers little separation. The Medium group has a USD 14 median price versus USD 29 for the High group, its modest advantage is therefore consistent with lower purchase resistance without positioning the product at the lowest end of the market. High-price products nevertheless have a slightly higher mean rating than Medium-price products (4.27 versus 4.16) but a lower high-sales probability. Under High eWOM strength, where review signals are more comparable, the raw high-sales rate is 50.7% for Medium price and 45.6% for High price despite near-identical mean ratings (4.43 and 4.45). This is consistent with the possibility that buyers respond more strongly to favourable review signals when expenditure is moderate, but it remains an association because product quality, brand position, and category-specific benefits are unobserved.

eWOM strength separates the groups more clearly: the posterior probability of high sales performance is 48.9% for High strength, 19.4% for Medium, and 14.3% for Low. High eWOM combines review volume and favourable ratings, making prior buyer experience more visible and potentially reducing uncertainty for later buyers. However, accumulated sales may also generate additional reviews, so the direction cannot be identified. Seasonal differences are smaller: Summer, Spring, Winter, and Autumn record 27.8%, 26.3%, 22.8%, and 21.7%, respectively. Table 3 reports the single-factor estimates.

Table 3. Posterior probability of high sales performance by single factor

Conditional Variable	Level	Number of Products	Posterior Probability of High Sales Performance
Price Level	Low	1,474	23.4%
	Medium	1,203	26.8%

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Table 3. (continued)

	High	1,209	25.2%
eWOM Strength	Low	606	14.3%
	Medium	2,430	19.4%
	High	850	48.9%
Peak Review Season	Spring	1,133	26.3%
	Summer	1,097	27.8%
	Autumn	720	21.7%
	Winter	936	22.8%

Note. Posterior probabilities are estimated with Laplace smoothing ($\alpha = 1$). All three factors are statistically significant at the 0.05 level via chi-square tests.

Peak Review Season is product-specific rather than a platform-wide shopping season, so its pattern requires caution. Spring products average 51.7 reviews versus 38.2 in Summer, both seasons have a USD 13 median price and near-identical mean ratings (4.12 and 4.11). Nevertheless, Summer has the higher high-sales probability. Among High-eWOM products, the raw rate is 54.7% in Summer and 50.4% in Spring, although Summer has slightly fewer median reviews (50 versus 52). The pattern cannot therefore be attributed only to review stock or typical price, it may reflect unobserved demand, promotion timing, product mix, or life-cycle stage. Season conditions the review-sales relationship but does not establish a calendar effect.

The largest multi-factor probability is 58.7% for Medium price, High eWOM strength, and a Spring peak (53 High-sales products among 89 observations before smoothing). Its median price, median review count, and mean rating are USD 14, 53, and 4.44. The comparable Summer group records 53.7% and has similar medians, but a lower mean rating (4.40) and fewer mean reviews (123 versus 141). This is consistent with a stronger visible-review signal in Spring, but remains non-causal because sales success may itself generate more reviews.

The High-price, High-eWOM Spring group records 40.0%, 18.7 percentage points below the Medium-price Spring group, despite similar mean ratings (4.45 versus 4.44), its median price is USD 29 rather than USD 14 and its median review count is lower (45.5 versus 53). This is consistent with a stronger price-value threshold when review visibility is somewhat lower. It is not a universal high-price penalty: in Summer, the High-price, High-eWOM group reaches 56.9%, compared with 53.7% for the Medium-price equivalent, with a higher mean rating (4.49 versus 4.40) despite fewer median reviews (43 versus 52). Its probability is 16.9 percentage points higher than that of the comparable High-price Spring group, suggesting that price associations vary with demand context and product composition. Unobserved product benefits, campaign intensity, buyer demand, and inventory may explain the remaining variation. Table 4 presents the leading combinations.

Table 4. Posterior probability of high sales performance for representative multi-factor combinations

Price Level	eWOM Strength	Peak Review Season	Number of Products	Posterior Probability of High Sales Performance
Medium	High	Spring	89	58.7%
High	High	Summer	69	56.9%
Medium	High	Summer	79	53.7%

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Table 4. (continued)

Low	High	Summer	77	51.2%
Low	High	Winter	75	50.0%

4.3. Sensitivity and robustness tests

Chi-square tests identify statistically significant differences for all three factors, but the interpretation of practical strength follows the thresholds stated in the Note to Table 5: a Cramer's V below 0.10 is very weak, 0.10 to 0.30 is moderate, and a value above 0.30 is strong. eWOM strength has the largest Cramer's V at 0.237, which indicates a moderate association with sales performance. Price level records 0.051 and peak review season records 0.043, both fall in the very weak range. Accordingly, H2 receives the clearest support because eWOM has a moderate, rather than strong, practical association with sales performance. H1 and H3 are statistically supported, but their very weak effect sizes indicate limited practical separation across price levels and peak review seasons. Table 5 reports the test statistics.

Table 5. Association strength between each factor and sales performance

Factor	Chi-square Statistic	p-value	Cramer's V	Effect Strength
Price Level	20.333	< 0.001	0.051	Very weak
eWOM Strength	437.051	< 0.001	0.237	Moderate
Peak Review Season	14.259	0.027	0.043	Very weak

Note. Cramer's V measures the strength of the association: 0–0.1 = very weak, 0.1–0.3 = moderate, and >0.3 = strong.

Using alternative USD 8 and USD 20 price cut-offs gives high-sales probabilities of 23.2%, 26.6%, and 25.0% for Low, Medium, and High price. Cramer's V is 0.059, which remains in the very weak range, so the conclusion regarding price is not sensitive to the original thresholds. At the 95.3% median verified-purchase rate, High versus Low eWOM strength gives 52.3% versus 13.6% high-sales probability in the high-rate group (V = 0.254) and 46.5% versus 15.3% in the low-rate group (V = 0.225). Both remain moderate, supporting the robustness of the eWOM association.

The model correctly classified 397 of 779 products (51.0%), compared with 49.9% when every product is assigned to the majority class. This limited gain indicates that the model is more useful for comparing conditional associations than for classifying individual products.

5. Managerial implications for cross border e-commerce

5.1. Controlled pricing decisions

Price should be managed through controlled tests, rather than treated as a universal lever. Its 3.4-point probability range and V of 0.051 do not justify one fixed optimal price. Sellers should set a feasible range from cost, competition, and communicated value, then test limited changes while tracking sales rank, returns, inventory turnover, conversion, and margin where available. For a limited review base, sellers may test an introductory price, bundle, or time-limited offer while protecting margin. Strong eWOM does not imply automatic discounting, price changes should be gradual and reversed when operating metrics do not improve.

DOI: 10.54254/2754-1169/2026.BH38632

5.2. Review quality and eWOM

eWOM merits first operational priority: High eWOM has a 48.9% high-sales probability versus 14.3% for Low eWOM, and V is 0.237. Sellers should invest in conditions that make genuine customer feedback informative rather than simply increasing review volume. Sellers should improve images, specifications, usage guidance, and FAQ information, then respond to verified-buyer issues and monitor review volume, ratings, and verified-purchase rate together. They should not purchase, fabricate, incentivise, or selectively solicit positive reviews, which risks violating platform rules and undermining credibility.

5.3. Seasonal planning

Peak review season should be a monitoring signal, not an inventory or promotion rule. Its Cramer's V of 0.043 is very weak, and it reflects product-specific review activity rather than a platform-wide demand calendar. Sellers can use it to check stock cover, content, and campaign readiness, while confirming decisions with current orders, traffic, advertising, and inventory turnover.

6. Conclusion

This study used a Bayesian network to examine the association of price level, eWOM strength, and peak review season with the sales performance of 3,886 products in Amazon's All Beauty category. All three factors showed statistically significant differences, but their practical strength varied. eWOM showed the clearest association, with a Cramer's V of 0.237 in the moderate range. Price level and peak review season had Cramer's V values of 0.051 and 0.043, respectively, both in the very weak range. Products in the High eWOM group had a 48.9% posterior probability of high sales performance, compared with 14.3% in the Low group. Medium-priced products recorded the highest price-based probability at 26.8%, although the small differences across price levels indicated limited practical separation. The probabilities for Summer and Spring were slightly higher than those for Autumn and Winter, but the seasonal association was also limited. The highest multi-factor probability, 58.7%, occurred for Medium price, High eWOM strength, and a Spring review peak.

The results address both research questions. High eWOM strength appears in the strongest single-factor result and in every leading multi-factor combination, while price and season provide secondary distinctions. For cross-border e-commerce operations, genuine review quality should receive priority, price changes should be tested in controlled stages, and seasonal information should support rather than determine inventory and promotion decisions. The study remains limited by its use of sales rank as a proxy, one product category, and a public snapshot without data on orders, advertising, traffic, stock, or dynamic prices. The model identifies conditional associations and cannot establish causal effects. Future research should use authorised business data, review text, and monthly variables, then compare multiple categories and national markets. A larger design could test whether the present review-performance relationship remains stable across different product types and operating conditions.

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