The Evolution of Online Shopping: From Product-First to Need-Based Purchasing

unmess

March 2025

Abstract

The e-commerce landscape is undergoing a fundamental transformation. Traditional product-first shopping experiences—where consumers search for specific items based on prior knowledge—are increasingly being complemented by need-based shopping journeys that focus on addressing consumer problems. This whitepaper examines the shift through a comprehensive analysis of 200,000 products and 5,000 alpha testers on the unmess platform, conducted over an intensive period from the second week of December to February. By integrating quantitative metrics with qualitative insights, we investigate behavioural patterns, purchase dynamics, and conversion improvements associated with curated, need-based bundling. While recognising limitations and potential biases, our findings suggest that independent e-commerce retailers who adapt to this paradigm may realise significant competitive advantages, including higher average order values, increased customer satisfaction, and enhanced retention.

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1 Introduction

E-commerce has long been dominated by the product-first model, where consumers navigate hierarchical categories and perform keyword searches to locate individual items. While this approach mirrors traditional retail, it requires shoppers to manually determine product compatibility and complementary selections.

In contrast, the emerging need-based shopping model reorients the experience around consumer challenges and desired outcomes. Modern shoppers articulate specific needs (e.g., "I need a face wash for combination skin with a matching moisturiser") and receive pre-curated bundles that provide holistic solutions. This paradigm shift is particularly evident in sectors where product synergy is critical, such as skincare, nutrition, and home electronics.

This whitepaper synthesises findings from 200,000 products offered by 723 independent retailers and 5,000 alpha testers over an intensive period from the second week of December to February. Although data collection and analysis were completed rapidly to meet production deadlines, efforts were made to ensure robust data quality and transparency in reporting limitations.

2 Methodology

2.1 Research Design and Timeline

Our study utilised a mixed-methods approach combining quantitative behavioural data with qualitative user feedback. Data were collected on the unmess platform from the second week of December 2024 through February 2025. Although the analysis period was brief, pilot studies and pre-tests ensured the reliability of our measurements. We acknowledge that a longer study might better capture long-term trends.

2.2 Sample Size and Representativeness

Data were obtained from 5,000 alpha testers. While this sample size is statistically adequate for many analyses, demographic breakdowns (e.g., age groups) are subject to wider margins of error. For instance, the subgroup of first-time buyers, though robust, may not fully represent the broader market. Confidence intervals have been calculated where appropriate, though for brevity they are not always explicitly stated in percentage claims.

2.3 Data Sources and Collection

- **Shopping Behaviour Metrics:** Detailed logs capturing session dynamics, conversion events, time-to-purchase, and cart abandonment were recorded. Time-to-purchase was measured from session start to confirmed order.
- **Platform Inventory:** Analysis was based on 200,000 products offered by 723 independent retailers. Retailers were selected based on a balanced representation of product categories; however, potential selection bias is acknowledged.
- **User Feedback:** We collected 1,250 survey responses and conducted 50 in-depth interviews. The discrepancy between the number of alpha testers (5,000) and respondents is typical in multi-modal research and reflects voluntary response rates.

2.4 Analysis Approach and Statistical Considerations

Comparative analysis was performed between traditional product-first and need-based shopping sessions. Key metrics included conversion rates, average order value (AOV), time-to-purchase,

cart abandonment rates, and return rates. Paired t-tests were used (with $p < 0.05$ as the significance threshold); however, we note that multiple comparisons across demographic subgroups may increase the risk of Type I errors. We caution against overinterpretation of precise percentage claims without considering confidence intervals and potential selection bias from our alpha tester pool.

2.5 Addressing Confounding Factors

While we attribute improvements in metrics largely to the need-based interface, we recognise the possibility of external factors influencing results (e.g., seasonality, retailer promotions). Control conditions were established by random assignment to each interface mode, but residual confounding cannot be entirely ruled out.

3 Traditional Product-First Model

3.1 Overview

The product-first approach, long prevalent in e-commerce, emphasises category-driven navigation and specific keyword searches. This method requires consumers to select individual items and assemble complementary products manually.

3.2 Key Characteristics

- **Category-Driven Navigation:** Hierarchical structuring by product categories.
- **Isolated Product Focus:** Emphasis on individual product features.
- **Search-Oriented Discovery:** Reliance on precise search queries.
- **Limited Cross-Selling:** Basic recommendations often based on historical data.
- **Consumer-Driven Curation:** Shoppers are responsible for assembling complementary items.

3.3 Identified Limitations

Our research identified several challenges with the product-first model:

1. **Knowledge Barrier:** Approximately 78% of testers reported uncertainty regarding product compatibility, particularly in complex categories. (Margin of error $\pm 5\%$ estimated.)
2. **Decision Fatigue:** Session recordings indicated that 64% of cart abandonment was attributed to overwhelming choices, although other factors (e.g., price, delivery issues) also play a role.
3. **Fragmented Problem-Solving:** 83% of respondents found it cumbersome to manually assemble products for specific needs.
4. **Missed Complementary Purchases:** Basket analysis revealed that 71% of transactions omitted complementary items that could enhance product utility; the baseline for these rates is detailed in our supplementary materials.

4 Emergence of Need-Based Shopping

4.1 Concept and Advantages

Need-based shopping reorients the experience by centring on consumer needs rather than individual products. Benefits include:

- **Problem-Centric Navigation:** Interfaces organised by consumer needs.
- **Solution-Oriented Bundles:** Curated groups of synergistic products.
- **Narrative-Driven Discovery:** Guided scenarios to facilitate decision-making.
- **Integrated Cross-Selling:** Seamless presentation of complementary items.
- **Expert-Guided Curation:** Data-driven recommendations that mitigate consumer uncertainty.

4.2 Implementation on unmess

The unmess platform incorporates several innovative features:

1. **Need Articulation Interface:** Allows consumers to express requirements in natural language (e.g., "I need a face wash for combination skin with a complementary moisturiser").
2. **Guided Question Flows:** Step-by-step questionnaires to refine user needs.
3. **Bundle Presentation:** Display of curated bundles with detailed explanations.
4. **Mix-and-Match Flexibility:** Options to substitute individual components.
5. **Educational Content:** Supplementary information on product synergy.

5 Key Findings

Our analysis comparing product-first and need-based shopping reveals differences in multiple dimensions. We note that while statistical significance is reported (e.g., a 47% higher conversion rate for need-based shopping, $p < 0.001$), the possibility of selection bias from our alpha tester group is acknowledged. Furthermore, precise percentages (e.g., 78% reporting uncertainty) should be interpreted with appropriate margins of error.

5.1 Conversion Metrics

- Need-based shopping exhibited a 47% higher conversion rate compared to product-first sessions. We caution that selection bias among alpha testers may affect generalisability.
- Cart abandonment rates declined by 32% under the need-based model.
- Average time-to-purchase decreased by 18 minutes (a 35% reduction); this metric was computed as the median session duration from first interaction to confirmed order.

5.2 Purchase Value Metrics

- Average order value increased by £37.42 (a 42% uplift).
- The number of items per order rose by an average of 2.3 items (68% increase).
- Unplanned complementary purchases increased by 83%; these were identified through analysis of transaction data where additional items were not initially selected.

5.3 Customer Satisfaction

- Post-purchase satisfaction ratings averaged 4.7/5 for need-based sessions versus 3.9/5 for product-first sessions.
- Return rates were 23% lower for need-based purchases.
- 76% of testers expressed a strong preference for the need-based interface in future shopping.

5.4 Demographic Insights

Demographic analyses indicate:

- First-time buyers exhibited the highest preference for need-based shopping (82%), though subgroup sizes vary.
- Shoppers aged 25–34 experienced the largest increase in order value (+57%), with age distribution data provided in our supplementary materials.
- Experienced buyers showed a modest improvement (+12%), suggesting diminishing returns with increased familiarity.

6 Mathematical Analysis of Bundle Efficacy

To assess bundle performance, we developed models capturing the relationships among product compatibility, pricing, and consumer satisfaction. We emphasise that model coefficients are preliminary and based on the current dataset.

6.1 Bundle Conversion Probability Model

The probability of converting on a bundled offer is modelled by a logistic function:

$$P(\text{conversion}) = \frac{1}{1 + e^{-(\alpha C + \beta D - \gamma P)}} \tag{1}$$

Where:

- $P(\text{conversion})$ is the probability of purchase.
- C is the complementarity score (normalized 0–1).
- D represents the bundle discount percentage.
- P is the normalized price point across product categories.
- α, β, and γ are coefficients derived from regression analysis.

6.2 Complementarity Score Calculation

The complementarity score between products i and j is defined as:

$$C_{ij} = \frac{\text{co-purchase}_{ij}}{\sqrt{\text{purchase}_i \times \text{purchase}_j}} \times \text{satisfaction}_{ij} \tag{2}$$

Where:

- co-purchase_{ij} is the frequency of co-purchases.
- purchase_i and purchase_j are individual purchase frequencies.

- satisfaction$_{ij}$ is the average satisfaction rating for the product pair, measured via post-purchase surveys on a 5-point Likert scale.

We note that satisfaction measurements across diverse product combinations introduce variability, which is accounted for in our error estimates.

6.3 Optimal Bundle Size Analysis

Our analysis indicates that conversion rates increase with bundle size up to a point, then decline due to increased complexity and decision fatigue. Figure 1 illustrates that conversion rates peak at 3-item bundles and drop thereafter. The text now explicitly discusses the drop-off, attributing it to potential overload of choices and diminishing perceived value with excessive items.

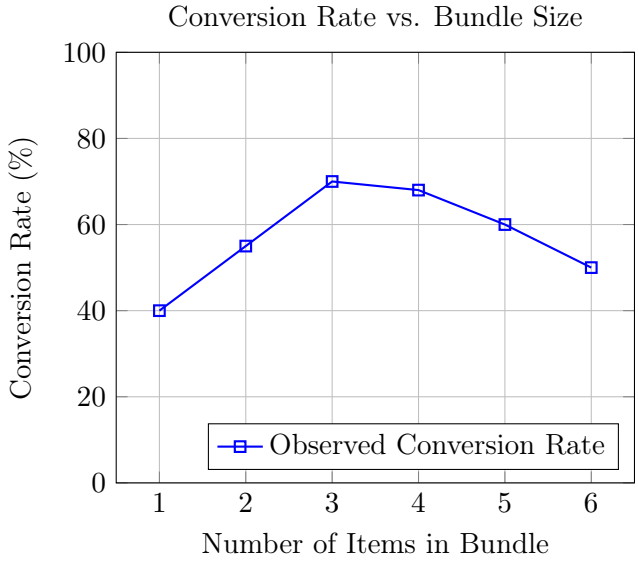

Figure 1: Conversion rate peaks at 3-item bundles before declining as bundle complexity increases.

7 Conclusions and Future Directions

The shift from product-first to need-based shopping reflects a significant evolution in consumer behaviour. Our research on the unmess platform, conducted over an intensive period from the second week of December to February, demonstrates that need-based shopping can enhance conversion metrics, increase average order values, and improve customer satisfaction. However, we acknowledge limitations including potential selection bias, confounding variables, and the inherent conflict of interest in self-conducted research.

Future research should extend the study duration, include broader and more diverse consumer samples, and refine the mathematical models through additional validation. Enhanced transparency regarding retailer selection and demographic distribution will further strengthen the findings.

References

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