Browsing Intent: A Practical Shopper Intent Signal for Ecommerce

A field study across 15 merchants on how recent browsing behavior relates to purchase outcomes

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Abstract. Existing approaches to ecommerce personalization often depend on purchase history, campaign engagement, and event-based triggers. These signals are useful, but they are limited for prospects who have not purchased yet and for shoppers whose current intent has changed since their last known action. We propose using recent browsing behavior as an intent signal for ecommerce marketing. The signal works by grouping active profiles by recent behavioral signals into high, medium, and low intent levels. We analyzed this pattern across 15 merchants and approximately 4 million active 90-day profiles, then measured purchase and repeat-purchase outcomes for each group within the same window. The pattern was directionally consistent. Shoppers with stronger intent signals were more likely to buy, generated more orders per active profile, and showed stronger repeat or multiple-order behavior. Together, these results suggest that recent browsing behavior can separate active shoppers into intent groups with meaningfully different purchase outcomes in near real time. This gives merchants a practical personalization signal they can use inside the marketing program they already have, without rebuilding around one-to-one personalization or a predictive model.

1. Introduction

Today, ecommerce merchants rely mostly on purchase history, campaign engagement, and event-based triggers to decide when to discount, when to educate, when to retarget, and when to hold back. This approach works well for many customers after they buy, when purchase history can show what they bought, when they bought, what they may find interesting, and when they may be likely to buy again. But it can miss current buying intent in cases such as prospects who have not bought yet, lapsed customers who are browsing again, and subscribers who ignore emails but keep coming back to the store. For example, a prospect may be returning to the store often and comparing products, but still look like a thin profile because they have not added to cart or purchased yet. As a result, very different prospects are often treated the same way, with the same generic messages, discounts too early, or retargeting when suppression would make more sense. At the same time, shoppers showing high intent can be missed at the moment it matters most. What is needed is a simple way to infer shopper intent in near real time from recent browsing behavior, then make that signal available to the marketing systems that already send messages, build audiences, and run campaigns. This paper tests that idea by studying recent browsing behavior as an intent signal for ecommerce marketing. The signal works by grouping active profiles into high, medium, and low intent levels based on recent behavioral signals. We then measured how often each intent group purchased or purchased again during the same 90-day window.

2. Data Set

This field study is based on prior company client work used with permission. The study covered 15 merchants and approximately 4 million active 90-day profiles over a six-month period from September 2025 through February 2026. In this paper, active profiles means email and SMS subscribers with recent browsing behavior inside the 90-day scoring window. Profiles without recent browsing behavior were not scored for this analysis. Results are presented in aggregated form to protect merchant identities and support the same high, medium, and low pattern observed across the study.

3. Methodology

For this study, a 90-day correlation analysis method was used:

1. Identify active profiles with recent browsing behavior.
2. Calculate session and profile-level behavior metrics from raw onsite events.
3. Rank each profile relative to the broader active audience.
4. Group profiles into high, medium, or low intent levels.
5. Measure purchase incidence for each intent level within the same time period.

Because these measurements were taken before activation, the findings are intended to show correlation between intent level and purchase outcomes, not lift caused by the score. The analysis also did not try to predict whether a specific shopper would buy. It tested only whether recent browsing behavior could consistently separate profiles into groups with meaningfully different purchase outcomes.

4. Browsing Intent

We define browsing intent as a practical way to estimate shopper intent from recent browsing behavior. The model produces an intent score, which is then grouped into high, medium, or low intent levels. The intent score is inferred from behavior, not observed directly. The model is heuristic and intentionally simple. It evaluates six behavioral signals over a moving 90-day window and ranks each eligible profile relative to other active profiles for that merchant. The data model combines weighted behavioral signals with relative audience ranking, so each eligible profile is evaluated in the context of the merchant's own traffic patterns rather than against a universal benchmark:

1. Recency
2. Frequency
3. Cumulative session depth
4. Pageview or product-view activity
5. Add-to-cart activity
6. Checkout-started activity

Purchase events are not part of the model, and are only used after scoring to test whether the different intent levels showed correlation with different purchase outcomes during the same time period. The intent score is normalized to preserve each merchant's traffic patterns and normal site behavior. The resulting intent level can then be made available to marketing systems as a profile property for activation. In practice, the workflow has six steps:

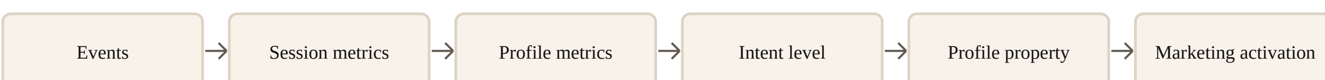

Figure 1. Event-to-activation workflow.

5. Findings

5.1 Purchase Incidence

Purchase incidence is the share of profiles in each group that bought at least once during the same 90-day window. A shopper who bought once and a shopper who bought three times both count as one converting profile. Across nearly all merchants, purchase activity became more concentrated as estimated intent moved from low to high during the same 90-day window. The high intent groups purchased approximately three times as often as low intent groups. One merchant did not show a pronounced difference in purchase incidence between intent levels during a promotional period, but it still showed stronger order density and repeat-buyer concentration in the medium and high intent groups. The observed ranges were:

Intent level	Purchase incidence range
Low	4.1% to 13.0%
Medium	5.4% to 21.5%
High	13.6% to 42.6% (3.3x higher than low)

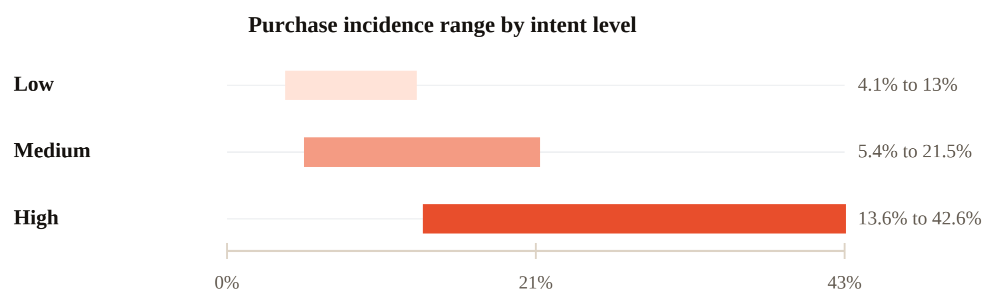

Figure 2. Purchase incidence range by intent level.

5.2 Order Density

Order density shows how much order volume was concentrated in each group relative to its size. Across all merchants, the high intent groups accounted for more order volume per active profile. For every one order per active profile in the low intent group, the high intent group generated about six to eight orders. The observed ranges were:

Intent level	Order density range
Low	0.05 to 0.15
Medium	0.11 to 0.31
High	0.40 to 0.95 (5.8x to 8x higher than low)

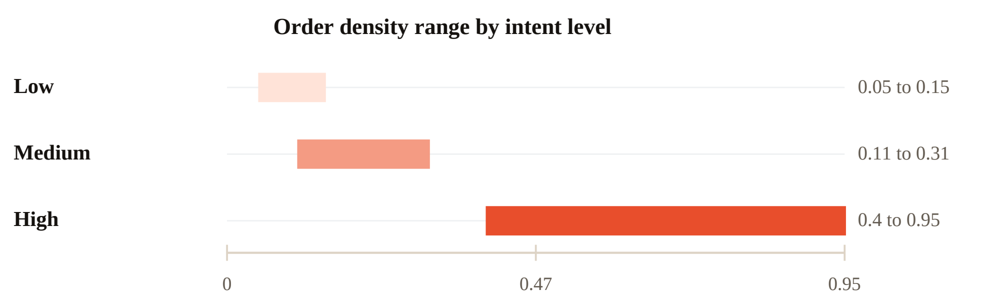

Figure 3. Order density range by intent level.

5.3 Repeat And Multiple-Order Behavior

Repeat or multiple-order incidence isolates the share of profiles who bought multiple times during the same 90-day window. Profiles with only one purchase are excluded. The study showed a strong relationship between recent browsing behavior and repeat or multiple-order behavior within the same 90-day window. The high intent groups showed repeat or multiple-order behavior at roughly five to twenty-one times the rate of the low intent groups. This study did not measure total customer value over time. The observed ranges were:

Intent level	Repeat or multiple-order incidence range
Low	0.55% to 2.7%
Medium	1.0% to 9.0%
High	5.1% to 31.0% (4.6x to 21.0x higher than low)

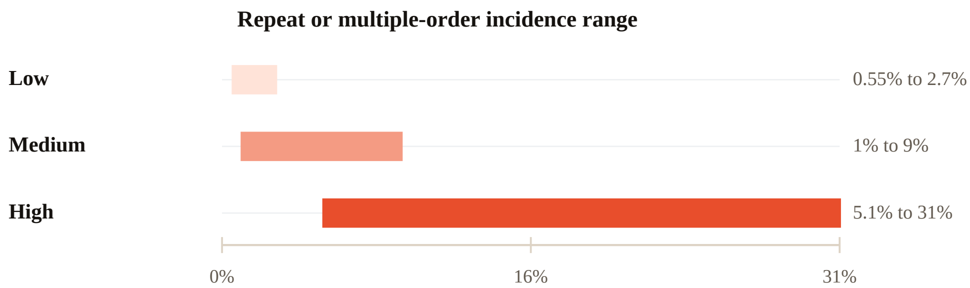

Figure 4. Repeat or multiple-order incidence range by intent level.

6. Activation Across Ecommerce Marketing

The study also explored ways the signal could be used in practice. Once merchants could separate shoppers by intent level, existing marketing automations could vary treatment for shoppers showing higher or lower intent. The clearest ideas centered on nudging prospects toward a first purchase and returning customers toward a second or third purchase, because those use cases were easier to A/B test. One idea was to treat high intent prospects as shoppers who may be closer to a decision, and therefore better suited for urgency, reassurance, and social proof. The same logic could apply after first purchase. Returning customers showing high intent may be better suited for replenishment reminders, cross-sell opportunities, or repeat purchase nudges than those showing low intent. The activation ideas that emerged during the study generally fell into the following hierarchy:

1. Nudge high intent prospects toward first purchase
2. Nudge high intent returning customers toward second or third purchase
3. Refine paid media and retargeting audiences for high and low intent shoppers
4. Reduce pressure or suppress low intent shoppers where appropriate
5. Refine segments to evaluate short-term trends and revenue opportunities
6. Refine automation conditional splits, copy and creative, timing, and offers

A practical reason these ideas were appealing was that they did not require merchants to rebuild their marketing systems or adopt a predictive model. Participating teams with strong in-house retention marketing teams found the signal relatively easy to understand, test, and apply inside existing automations and reporting workflows. The signal also gave teams more specific context for brainstorming activation ideas and generating copy variations with LLMs.

7. Activation Example

In one anonymized activation test, a merchant used intent levels to split eligible SMS subscribers inside a product-view abandonment automation, then A/B tested that version against the baseline strategy. After a clean two-week test cycle, the test showed a 74% lift in revenue per message versus control. A related cart abandonment automation test showed approximately 15% lift in revenue per message versus control. The same merchant continued to see positive relative lift during the Black Friday/Cyber Monday period, with both the product-view and cart abandonment automations generating approximately 14% more revenue than control. This was a limited-scale test on eligible SMS subscribers, not a measure of channel revenue lift. For the test, the marketing system received a custom intent level property that was added to eligible profiles and combined with customer type, such as prospect or returning customer, to create conditional splits inside the automation. High intent shoppers received more urgent messaging after viewing product pages and leaving without adding to cart, or after adding to cart and leaving without starting checkout. Low intent shoppers received softer messaging. The same offers and number of messages were used across all intent levels to stay close to the baseline strategy and reduce the number of test variables. Because intent scores only refreshed daily in this test, the team estimated that results captured only about half of the potential opportunity.

8. Limits

This was a correlation study with limited activation examples, and it does not prove that the intent signal caused a purchase. It does not assign credit to a channel, campaign, flow, ad, or message, and is not an attempt to predict whether a specific shopper would buy. This study only covers eligible subscribers with recent browsing behavior inside the 90-day window. Non-human or abnormal activity was generally less likely to rank as high intent because the scoring method emphasized commercially meaningful behavioral signals. Paid media, suppression, flash-sale, push, and broader campaign uses are presented as activation opportunities, not proven outcomes. Channel use depends on consent, eligibility, platform setup, account configuration, and data quality. Tracking quality, event setup, identity resolution, category, price point, offer strategy, creative, and execution can all affect results. References are provided as industry context only, and do not imply endorsement, partnership, certification, or validation of the data model or this study.

9. Conclusion

We have presented recent browsing behavior as a practical shopper intent signal for ecommerce marketing. Merchants often rely on purchase history, campaign engagement, and event-based triggers to personalize the customer experience. What many programs still lack is a timely signal for current shopper intent, especially before first purchase, when purchase history does not yet exist. The study showed that recent browsing behavior can help infer whether shoppers appear to be in a decision mindset or casually exploring. That signal can be used inside the marketing program a merchant already has, without rebuilding around one-to-one personalization or a predictive model. The core principle is simple. What a shopper does on the site now can inform how the merchant communicates with them minutes later. Used well, browsing intent can improve relevance for customers and outcomes for merchants.

10. Glossary

Behavioral signals: Individual shopper actions captured during browsing, such as recency, frequency, cumulative session depth, pageview or product-view activity, add-to-cart activity, and checkout-started activity.

Recent browsing behavior: The collection of behavioral signals observed over the 90-day scoring window.

Behavioral context: A structured representation of recent browsing behavior that can inform personalization.

Intent score: The model output derived from recent browsing behavior and relative audience ranking.

Intent level: A high, medium, or low category based on the intent score.

Marketing activation: The use of the intent signal in audiences, suppression, retargeting, campaigns, and lifecycle automations.

11. References

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