

articles

How to Keep Them Coming Back: Lessons for SMEs Focused on Growth and Sustainability

Jumana (Jay) Black, Ph.D.¹^a, Angeline Close Scheinbaum, Ph.D.²^b, Dana E. Harrison, Ph.D.^{3c}, Joseph F. Hair Jr., Ph.D.⁴^d

¹ Marketing, Texas A&M University – Texarkana, ² Department of Marketing, Clemson University, ³ East Tennessee State University, ⁴ University of South Alabama

Keywords: clickstream analysis, customer sessions, high-consideration products, returning customers, purchase behavior, exponential growth, customer retention

<https://doi.org/10.53703/001c.157790>

Journal of Small Business Strategy

Vol. 36, Issue 2, 2026

Most online retailers focus their budgets on customer acquisition, overlooking the long-term value of repeat business. Customer retention can help small and medium-sized enterprises (SMEs) compete in high-consideration categories by providing a solid foundation for a steady path to growth. In this study, we tested the difference in customer value between new and returning visitors by examining web interaction data from 126,335 unique customers of a US-based online alcohol retailer over the course of 12 months. Guided by Cognitive Appraisal Theory, we used session accumulation as the construct through which we could compare customer type. The results revealed that purchase likelihood increased about three times from the first to the sixth session, and later sessions were more predictive of purchase than earlier sessions. We also found that returning users had a significantly higher baseline conversion rate than new customers, as well as a significantly larger increase in conversion with each additional session. Critically, the value premium for returning users was driven by purchase frequency, which was 4.22 times higher than for new customers, rather than by transaction size, which was only 18% higher. As a result, purchase frequency accounted for most of the revenue. For SMEs operating on modest budgets, there is an opportunity cost and a potential advantage in shifting from acquisition to retention.

Introduction

Most businesses spend more than half of their allocated budgets on customer acquisition (Optimove, 2023; Weinstein, 2002), rather than investing in long-term relationships with existing customers. Small firms typically cannot outspend enterprise competitors in attracting new customers; they must find alternative paths for growth. This study examines one such path: the drivers of customer retention accumulating over visits. Our research was prompted by an earlier study on the relationship between device type and online conversion, which found a fourfold

conversion advantage for returning users over new customers (Black, 2024). This large gap between new and returning customers belies traditional views of how customer value accrues. As such, this research explores how customer value differs by customer type using web interaction data from an online alcohol retailer operating in 42 U.S. states.

Alcohol retailers, like others in high-consideration e-commerce verticals, share characteristics such as long consideration cycles (Gupta et al., 2023) and barriers to conversion due to trust issues (Meriç & Yıldırım, 2021). Customers buying alcohol online face a few barriers to purchase, including age verification, privacy, and social stigmas.

^a JBlack@tamut.edu
Texarkana, TX USA
Corresponding author

^b aschein@clemson.edu
Clemson, SC USA

^c HARRISONDL@mail.etsu.edu
Johnson City, TN USA

^d jhair@southalabama.edu
Mobile, AL USA

Notable differences emerge between new customer conversion rates (1.76%) and repeat customer conversion rates (7.41%). Repeat visitors make up 23% of our traffic but account for 60% of our revenue. Many conventional methods that attempt to gauge online metrics assume linearity with session effects. Put simply, all visits are treated equally. However, our findings suggest otherwise. Sessions taken towards the end of a session chain (sessions 3–6) had greater value than sessions 1 and 2. We utilize Cognitive Appraisal Theory (Lazarus, 1991) to help explain why. Cognitive Appraisal Theory suggests that satisfied customers of an e-commerce platform will move from primary appraisals (“Is this website trustworthy? Is purchasing from this site safe?”) to secondary appraisals (“What products would suit my needs at this moment? Do they have any sales?”). Consumers often use different devices, which leads them to appraise at different phases of the purchase funnel. Smartphones are used for discovery and browsing at the beginning of the funnel, whereas consumers use a desktop for the latter stages, conducting thorough assessments of their decisions and making the purchase (Han et al., 2022). Mobile sessions are better thought of as trust-building, where desktop sessions drive conversion. Each device offers a distinctive role in the conversion journey.

In this study, we draw on clickstream data from 126,335 verified customers to test whether session effects compound differentially for new and returning users and quantify how the value premium compounds over the course of the customer journey.

Literature Review and Hypotheses Development

Digital Touchpoints and Customer Journey

Online shoppers go through multiple touchpoints, from their initial search through to placing the order (Court et al., 2009). Online businesses analyze clickstream data to examine page visits, session frequency, and product interactions to predict conversions (Bucklin & Sismeiro, 2003; Moe, 2003) and improve website functionality.

Existing research generally assumes homogeneous effects on different consumer groups. High-consideration categories make this assumption untenable. Purchase barriers in these categories change customer behavior and decisions. When customers view the shopping experience as exceeding their threshold, they will conduct additional searches (Dowling & Staelin, 1994; Ha, 2002). In an online context, additional searches become repeat visits, longer browsing time, and taking longer to purchase. These digital touchpoints and brand experience help identify where the shopper is on their customer journey (Lemon & Verhoef, 2016). In higher-barrier-to-entry categories, new and returning users’ conversion rates differ sharply.

Cognitive Appraisal Theory in Digital Contexts

Cognitive Appraisal Theory offers a way to understand how people perceive certain situations and how they respond (Lazarus, 1991; Lazarus & Folkman, 1984). The framework can be applied to e-commerce to gain insights

into customer types. For example, new customers must build appraisals of an online business from the ground up without prior experience. They must use exploratory interactions and design cues to build evaluative frameworks in a cognitively demanding process that generates uncertainty. Repeat users, however, visit e-commerce businesses with pre-established appraisals formed through prior interactions, resulting in highly dissimilar psychological starting points in the customer journey. This idea is consistent with the perspective of Cognitive Appraisal Theory, which holds that the same behavior can reflect different psychological processes. A new user browsing through pages of an e-commerce business is likely exploring and learning about the goods offered by the business. For a returning visitor, however, spending the same amount of time browsing despite established knowledge may indicate difficulty making that decision, arising not from unfamiliarity or a lack of knowledge, but from a lack of understanding of the trade-offs involved in purchasing the product. This indecision creates a form of choice complexity similar to what is traditionally conceived in choice overload research (Chernev et al., 2015).

Bagozzi et al. (1999) distinguish between outcome-desire avoidance appraisals (i.e., negative outcome predictions) and outcome-desire pursuit appraisals (i.e., positive outcome predictions). For online shoppers, this framework suggests that new customers may feel apprehensive, expecting a negative outcome. Conversely, repeat customers with positive experiences may progress to outcome-desire appraisals, expecting successful transactions and feeling approach-oriented emotions. Each session may result in reappraisal, in which experiences that do not confirm negative expectations gradually shift customers from avoidance to an approach orientation.

Trust Barriers in Regulated Commerce

Categories with a wide range of purchase barriers present useful contexts for investigating customer behavior. There are several regulatory barriers that exist in alcohol e-retailing, such as age verification, state licensing, and retail compliance (Colbert et al., 2021), as well as consumer-facing obstacles such as perceptions of risk and the challenge of establishing trust in the absence of face-to-face interaction (Harridge-March & Quinton, 2005). Customers demonstrate self-regulation in purchases of socially sensitive categories according to high-consideration market research findings. In “strategic self-rationing,” Wertenbroch (1998) observes that consumers want to restrict access to desired products and self-regulate their behavior.

In online environments, these processes are realized over longer consideration time periods, across multiple shopping episodes, and with self-timed purchase decisions. Given these challenges, trust becomes central to online alcohol commerce.

Mayer et al. (1995) define trust as the “willingness to be vulnerable based on positive expectations of another party’s actions.” Furthermore, Mayer et al. (1995) maintain there are three core dimensions to trustworthiness: ability (i.e., competence to fulfill orders), benevolence (i.e., good-

will toward the customer beyond profit motives), and integrity (i.e., adherence to acceptable business principles).

Theoretical Mechanism for Compounding Effects

In addition to cognitive appraisal and trust building, which can explain evaluative processes during customer sessions, additional theory is needed to explain why session effects might amplify rather than progressively accumulate. We lean on habit-formation research to offer such an explanation. Wood and Neal (2009) define habits as automatic, habitual responses to particular circumstances (a particular place, sound, or preceding behavior) developed through the repetition of past experiences. They are often fast and powerful but difficult to modify. Crucially, “after people have repeatedly and consistently practiced using a particular behavior to accomplish a goal, other behaviors that served the same goal become less accessible in memory” (Wood & Neal, 2009).

Critically, Mayer et al. (1995, p. 722) propose that integrity may be most important early in a relationship, while perceptions of benevolence develop over time. When this concept is applied to how consumers shop online, integrity assessments happen in early sessions as shoppers are still familiarizing themselves (e.g., Is this vendor legitimate?). Later sessions, by contrast, as shoppers become familiar and more comfortable with the vendor, may be dominated by benevolence evaluation (e.g., Does this vendor care about my experience?). Importantly, Mayer et al. (1995) explain that customers who accumulate positive experiences without negative incidents can reinforce perceptions of trustworthiness through a feedback loop.

According to the behavioral momentum theory, which suggests that a higher rate of reinforcement makes a response more resistant to interruption, the strength of a behavior is similar to physical momentum or mass (Nevin et al., 1983). Online purchases might also build momentum that pulls customers back to their preferred sites, even in the face of attractive substitutes. The four processes outlined above (cognitive reappraisal, trust accrual, habit formation, and behavioral momentum) should reinforce one another, increasing the impact of each subsequent session.

Hypotheses Development

Because returning visitors bring a history of positive experiences that new visitors lack, their sessions should be more predictive of conversion. We formalize these expectations in the following hypotheses.

Dependent Variable: The probability of an online purchase is an intent to buy, which is determined by the likelihood that a customer will successfully make a purchase during the current session. It is a binary variable (0,1) and is the most direct measure of e-commerce purchase conversion and consumer choice (Bucklin & Sismeiro, 2003).

Purchase completion in high-consideration categories suggests that a successful path has developed through the cultivation of trust and product testing, leading to a commitment to buy.

Independent Variables: Web sessions are sequences of user activity separated by 30-minute inactivity intervals (Bucklin & Sismeiro, 2003; Montgomery et al., 2004) with initial sessions characterized by exploratory behaviors such as those Moe (2003) identifies as “knowledge-building” visits.

Traditional statistical models typically assume a linear relationship between the number of sessions and their marginal value. However, we suggest that the effect of the number of sessions compounds exponentially through psychological processes previously described. According to Cognitive Appraisal Theory, each session provides an opportunity for reappraisal, leading customers to adopt approach behaviors rather than avoidance (Bagozzi et al., 1999). Two other psychological processes likely underpin this reappraisal: the mere exposure effect, which leads to more positive evaluations of stimuli that are more familiar (Zajonc, 1968), and behavioral momentum, which produces greater resistance to change after positive outcomes have been experienced (Craig et al., 2014; Wood & Neal, 2009). For existing e-commerce customers, having prior trust shifts the focus from vendor validation to product evaluation (Kim et al., 2009). Therefore, we hypothesize:

H1: Session count is positively associated with purchase probability.

Pageviews measure engagement, but interpretation depends on user sophistication. First-time users face a large learning curve regarding site structure, product selection and availability, and navigation path; their higher pageview counts reflect the requisite learning behavior (Moe, 2003). For return visitors, however, high pageviews may indicate poor navigation or confusion instead of quality engagement. Information foraging theory would cause us to expect frequent users to establish good navigation patterns, in which they efficiently navigate to sought-after content (Pirolli & Card, 1999). If repeat users are over-browsing when they already know the site, this behavior suggests either navigation problems or unwillingness to purchase, rather than good exploration of the site. Therefore, we posit:

H2: Pageview count is positively associated with online purchase probability.

Product detail views indicate a transition from browsing to product evaluation. New users need thorough product information to evaluate the quality of and develop trust in new products. Repeat customers, having already developed trust and category knowledge, need a less detailed examination of products. Too many product detail views during repeat visits may indicate decision complexity instead of information seeking. Choice overload studies show that when customers are presented with too many options to compare, satisfaction decreases and decision-making delays (Chernev et al., 2015; Scheibehenne et al., 2010). In high-consideration product classes where trust is the major hurdle to purchasing, detailed product scrutiny by repeat users can indicate indecision or comparative analysis instead of productive consideration. Thus, we hypothesize:

H3: Product detail views are negatively associated with online purchase probability.

This hypothesis tests whether extensive product scrutiny functions as decision avoidance once trust barriers are resolved.

Cart additions are e-commerce metrics that are frequently repurposed to measure engagement (e.g., wish lists, price shopping, and product comparison; Close & Kukar-Kinney, 2010). Cart activity for high-consideration categories can indicate deliberation processes in which consumers are developing alternatives for purchase. Cart additions by new visitors can be an exploratory process, in which they are testing the capabilities of the site and exploring alternatives without any firm purchase intent. Repeat customers who are more frequent users of the site and have purchase intent also show more intentional cart behavior. Close & Kukar-Kinney (2010) found that cart additions of repeat customers signaled purchase readiness more clearly than exploratory intent. The experiential history of these users further increases the predictive ability of their cart behavior for actual purchase intent. Therefore, we hypothesize:

H4: Cart additions are positively associated with online purchase probability.

Moderator Variable: Returning user status reframes how all customer types interact with predictors of online purchase probability. New customers use sessions, pageviews, product details, and cart additions for learning and exploration, while building trust in the platform. Returning visitors, having already established trust and familiarity, use these same behaviors for purchase evaluation rather than vendor assessment. Therefore, the user type determines the interpretation of all engagement metrics: heavy browsing signals learning for new users but uncertainty for return users, whereas multiple sessions signal trust-building for new users but purchase consideration for return users (Moe & Fader, 2004). Thus, we hypothesize:

H5: Returning user status moderates the relationships between digital engagement behaviors (e.g., sessions, pageviews, product detail views, cart additions) and the probability of an online purchase.

Control Variables: Following prior e-commerce research, we controlled for device type (De Haan et al., 2018; Kukar-Kinney et al., 2022) and day of week (Sismeiro & Bucklin, 2004). Additionally, we controlled for browser type (Safari, Chrome, etc.), urban context (via IP geolocation), month (to account for seasonality), and session length. The controls isolate the effect of session accumulation on purchase likelihood.

Methods

Data and Measures

The research consisted of clickstream data from a US online alcohol retailer in 42 states (all US states except 8 require age verification and state-specific compliance systems to sell alcohol online). The data were recorded for an entire year (January–December 2022) using Google Analytics (GA4). The logs captured all user activity on the site, tracked by user ID (a unique, anonymous ID for each user). The overall dataset consisted of 126,335 unique visitors.

Data on adding to cart were not available for 724 users (0.6% of users), making the data available for the regression models $n = 125,611$.

We identified the following variables. Purchase probability was the binary dependent variable (1 = purchased, 0 = not purchased). Our moderator classified users as new (0) or returning (1) based on GA4 cookie and user identifier tracking. Control variables were session length, device type (desktop as reference), browser type, day of week (Sunday as reference), and urban location (from IP geolocation).

Statistical Analysis

We employed logistic regression as appropriate for binary outcomes. Model 1 established baseline effects:

$$\log(P(\text{Purchase})/(1-P(\text{Purchase}))) = \beta_0 + \beta_1\text{Sessions} + \beta_2\text{Pageviews} + \beta_3\text{ProductDetails} + \beta_4\text{CartAdditions} + \beta_5\text{Returning} + \gamma\text{Controls} + \epsilon$$

To test whether session effects differed by user type, we estimated separate models for new users (Model 2) and returning users (Model 3), excluding the user type indicator. Moderation effects were assessed by testing the equality of session coefficients across subgroups. Multicollinearity was assessed using variance inflation factors (VIF). All VIFs were below 3.92 (mean VIF = 2.24), which is well below the threshold of 10 that is considered an indicator of serious multicollinearity (Hair et al., 2019). All models used robust standard errors to account for possible heteroskedasticity. Stata 19 was utilized for this analysis.

Results

Descriptive Statistics and Hypothesis Testing

[Table 2](#) presented descriptive statistics and compared purchasers and non-purchasers. Engagement differences intensified progressively across behavior metrics. For sessions, the ratio between purchasers and non-purchasers was 1.23, with purchasers averaging 1.93 sessions and non-purchasers averaging 1.57 sessions. For pageviews, the ratio between purchasers and non-purchasers was 4.08, with purchasers averaging 24.20 views and non-purchasers averaging 5.94 views. For product detail views, the ratio between purchasers and non-purchasers increased to 10.16, with purchasers averaging 21.35 views and non-purchasers averaging 2.10 views. Most dramatically, the ratio for cart additions was 8.29, with purchasers averaging 3.15 additions and non-purchasers averaging 0.38 additions, suggesting this behavior served as the strongest univariate predictor of purchasers.

Returning users comprised 22.1% of non-purchasers but 55.9% of purchasers. Mobile users dominated website traffic (63.8%) but were underrepresented among purchasers (56.9%).

[Table 3](#) showed the logistic regression results. Model 1 estimated baseline associations for all users; Models 2 and 3 presented separate analyses for new and returning users to test moderation effects.

Supporting H1, sessions demonstrated the strongest association with purchasing, with each additional session in-

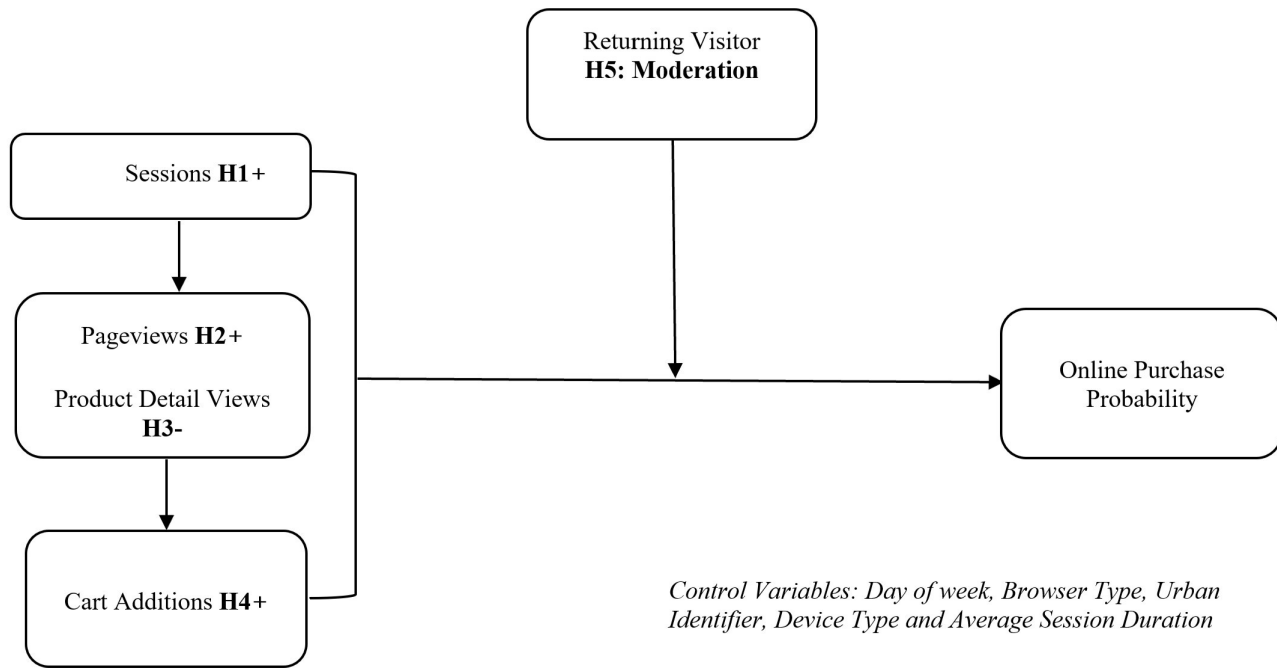


Figure 1. Online Metrics and Purchase Behavior Moderated by Returning User Status

Figure 1 models how digital metrics (sessions, pageviews, product detail views, and cart additions) affect purchase behavior. Returning user status is hypothesized to moderate these effects.

Table 1. Variable Descriptions and Summary Statistics (N = 126,335)

Variable	Description	Mean	SD	Min	Max
Dependent Variable					
Purchase Conversion	Binary indicator of purchase completion (1=purchase, 0=no purchase)	0.031	0.172	0	1
Independent Variables					
Sessions	Number of separate visits during observation period	1.58	1.08	1	6
Pageviews	Total pages accessed across all sessions	6.50	14.73	0	175
Product Detail Views	Number of individual product page views	2.69	20.59	0	3,015
Cart Additions	Items placed in shopping cart	0.46	1.83	0	20
Moderating Variable					
Returning User	User identified as returning via Google Analytics User-ID tracking	0.231	0.421	0	1
Control Variables					
Session Duration	Average seconds per session	156.75	453.63	0	4,664
Mobile	Device type: smartphone	0.635	0.481	0	1
Desktop	Device type: desktop/laptop computer	0.294	0.456	0	1
Tablet	Device type: tablet (reference category)	0.070	0.256	0	1
Chrome	Browser: Google Chrome	0.385	0.487	0	1
Safari	Browser: Apple Safari	0.493	0.500	0	1
Urban	Urban location based on IP geolocation	0.971	0.169	0	1

Note. Day-of-week dummies (Monday–Saturday) and month dummies (February–December) included as controls; Sunday and January serve as reference categories. Cart additions missing for 724 observations (0.6%); regression analyses based on n = 125,611 complete cases.

creasing the odds of purchase by 22.2%, translating into nonlinear increases in predicted purchase probability (OR = 1.222, $p < .001$). The 22.2% increase per session substantially exceeded the marginal association of pageviews (1.0%

per view) or product detail views (0.6% per view). This finding indicated that returning to the site was a greater predictor of purchasing than within-session browsing intensity. Five sessions were associated with an approximate

Table 2. Descriptive Statistics by Purchase Status

Variable	Non-Purchasers (n = 122,467)	Purchasers (n = 3,868)	Ratio
Sessions	1.57 (1.07)	1.93 (1.38)	1.23
Pageviews	5.94 (13.49)	24.20 (31.61)	4.08
Product Detail Views	2.10 (7.41)	21.35 (108.44)	10.16
Cart Additions	0.38 (1.64)	3.15 (4.33)	8.29
Returning User (%)	22.1%	55.9%	2.53
Mobile Device (%)	63.8%	56.9%	0.89

Note. Standard deviations in parentheses for continuous variables. All differences significant at $p < .001$.

Table 3. Logistic Regression Models Predicting Purchase Conversion

Variable	Model 1 (All)	Model 2 (New)	Model 3 (Returning)
Independent Variables			
Sessions	1.222*** (0.014)	1.179*** (0.022)	1.294*** (0.019)
Pageviews	1.010*** (0.001)	1.008*** (0.001)	1.012*** (0.002)
Product Detail Views	1.006** (0.002)	1.004 (0.002)	1.014*** (0.004)
Cart Additions	1.215*** (0.006)	1.229*** (0.007)	1.181*** (0.011)
Moderating Variable			
Returning User	5.964*** (0.039)	—	—
Control Variables			
Session Duration	1.0006*** (0.00003)	1.0008*** (0.00004)	1.0004*** (0.00004)
Device Type	Included	Included	Included
Browser	Included	Included	Included
Day of Week	Included	Included	Included
Urban Location	Included	Included	Included
Month (Seasonality)	Included	Included	Included
Model Fit			
N	125,611	96,590	29,021
McFadden's R^2	0.247	0.228	0.186

Note. Odds ratios reported. Robust standard errors in parentheses. ** $p < .01$. *** $p < .001$. Tablet is reference for device type; Sunday is reference for day of week; January is reference for month. Month and day-of-week dummies included.

2.2-fold increase and six sessions were associated with an approximate 2.7-fold increase in predicted purchase probability. Returning user status was strongly associated with purchase (OR = 5.964, $p < .001$), or approximately 6-fold higher odds of purchase. This association was significant after controlling for all engagement variables. A test of coefficient equality confirmed that session effects did differ significantly between new and returning users ($\chi^2 = 10.72$, $p = .001$), supporting H5. The positive difference indicated that the association between the number of sessions and purchasing was stronger for returning site visitors than new users. No other behavioral variable had a significantly differential association by user type.

The Compounding Pattern

Predicted probabilities of conversion for varying session counts revealed compounding patterns (Table 4). A new user with just one session had a purchase probability of just 0.73%. In contrast, the returning user with one session had a purchase probability of 4.17%. Purchase probability for new users increased from 0.73% (one session) to 1.95% (six sessions), a 2.69-fold multiplier. Purchase probability for returning users increased from 4.17% to 10.59%, a 2.54-fold multiplier. Both multipliers were very close and exhibited compounding, but returning users had substantially higher absolute conversion at each phase of every session. The

Table 4. Predicted Purchase Probabilities by Session Count and User Type

Sessions	New Users	Returning Users		Pred Prob	95% CI	Multiplier
	Pred Prob	95% CI	Multiplier			
1	0.73%	[0.68%, 0.77%]	1.00×	4.17%	[3.94%, 4.41%]	1.00
2	0.88%	[0.83%, 0.94%]	1.22×	5.05%	[4.79%, 5.31%]	1.21
3	1.08%	[1.00%, 1.15%]	1.49×	6.10%	[5.74%, 6.47%]	1.46
4	1.31%	[1.21%, 1.42%]	1.81×	7.36%	[6.80%, 7.91%]	1.76
5	1.60%	[1.44%, 1.76%]	2.21×	8.84%	[8.01%, 9.67%]	2.12
6	1.95%	[1.71%, 2.19%]	2.69×	10.59%	[9.40%, 11.79%]	2.54

Note. Predictions from Model 1 with covariates at means, including month controls. 95% confidence intervals calculated using delta method.

non-overlapping 95% confidence intervals indicated that the differences were statistically significant.

Marginal gains in predicted probability increased with each additional session. For returning users, moving from one to two sessions increased conversion probability by 0.88 percentage points. Moving from five to six sessions increased the conversion probability by 1.75 percentage points, about twice as large despite representing the same one-session increment. This pattern contradicts diminishing returns, suggesting sessions compound upon prior engagement.

User Type Differences

New users had a 1.76% baseline conversion rate with a 17.9% increase in odds per session (OR = 1.179). Repeat users had a 7.41% baseline conversion rate with an increase of 29.4% (OR = 1.294). The difference in session effects between groups was significant ($\chi^2 = 10.72$, $p = .001$). Seasonality was jointly significant ($\chi^2 = 746.59$, $p < .001$), with conversion highest in November–December, yet session effects remained robust after accounting for monthly variation.

Supporting H2, pageviews were positively associated with purchase ($\beta = 0.008$, $p < .001$). H3 was not supported. We predicted that product detail views would be negatively associated with purchase, but the relationship was positive ($\beta = 0.006$, $p < .001$). In high-trust situations, product information processing seemed to be an affirming rather than an avoidance activity. Product concerns were alleviated once vendor legitimacy was determined, and product examination could have solidified commitment to the purchase.

Results indicated that product detail page views were more strongly associated with purchase among returning visitors (1.4% increase in odds per view, $p < .001$) than new users (0.4% increase, not significant). Table 5 indicated that returning visitors exhibited 4.22-fold higher conversion rates than new users but only 1.18-fold higher average order value (\$295.49 vs. \$249.70). Expected value per visitor was \$21.90 for returning visitors vs. \$4.38 for new users. That 5.00-fold difference, a 400% increase, comes from variation in conversion rate, not transaction size.

Discussion

Theoretical Implications

The compounding pattern can be explained by four theoretical pillars, each addressing a different aspect. First, the compounding pattern in our data, where each visit contributes more than the previous one, is what Habit Formation Theory (Wood & Neal, 2009) would predict. As the number of sessions accrues, consumers drop alternatives from their consideration. Consequently, later sessions are more strongly associated with purchasing. Second, while Habit Formation Theory explains the change in consumers' behavior, Cognitive Appraisal Theory explains the modification of their product evaluations. At baseline, purchasing strongly favored returners because site users transitioned from avoidance mode (risk scanning) to approach mode (product choice) (Bagozzi et al., 1999). For example, customers start their purchase journey in avoidance mode (e.g., "Is this website safe?"), and as trust builds, they shift to approach mode (e.g., "Which product fits my needs?"). Trust in a site builds gradually and grows stronger as customers provide feedback about their purchasing experiences.

Third, Mayer et al.'s (1995) trust-building theory describes the feedback loop in which positive sessions prime the following ones, and customers return to the site because of their positive experiences. Consumer trust forms in early sessions, then deepens with each return, creating the compounding effect we observed in this study.

Fourth, once consumer habits are formed and they have established trust in a site, we see an increased gap in the session effect between returners and new customers, which fits behavioral momentum theory (Craig et al., 2014; Nevin et al., 1983). Once returning customers settle into a purchasing pattern, competitors struggle to disrupt it. The moderating effect of user type is strongest at the session level, not at the page-view, product-view, or cart-addition levels. Customers cross the trust threshold before navigating to the site, not while they are browsing. For online retailers, this matters; the return decision is what signals trust.

Table 5. Decomposing Customer Value: Frequency Versus Transaction Size

Metric	New Users	Returning Users	Ratio
Conversion Rate	1.76%	7.41%	4.22
Average Order Value	\$249.70	\$295.49	1.18
Expected Value per User	\$4.38	\$21.90	5.00

Note. Average order value is calculated using data from purchasers only. The expected value per user equals the conversion rate multiplied by the average order value.

Practical Implications

Across 126,335 verified customers of an SME e-commerce platform, we find that web sessions are associated with purchase probabilities exhibiting accelerated rather than linear growth. Customers who returned to the website were approximately 5 times as likely to purchase as new customers. In an industry with a continued focus on acquisition strategies (Optimove, 2023; Weinstein, 2002), a five-fold difference will be challenging to reconcile. We discuss the implications below.

First, our analysis shows that visit frequency is more valuable than higher conversion rates at the same session level. Each return visit increases the odds of purchase, making repeat-traffic strategies more valuable than push-to-buy-now approaches. Cart abandonment emails (e.g., emails sent to customers who added items to their shopping cart but didn't complete the purchase), retargeting campaigns (e.g., ads shown to previous visitors and browsers), and early loyalty enrollment are low-cost tactics that bring customers back for additional sessions. For example, a cart abandonment email sent within 24 hours of leaving items in a cart without completing the purchase can prompt a return visit. The same can be true for small incentives, such as free shipping or coupon codes, which give customers a reason to return even if they do not purchase immediately. Such incentives can be particularly effective for new customers.

Second, converting a new user to a returning user may be a high-value strategy for practitioners. The results indicate that a customer's baseline purchase probability may be expected to increase after their first visit, although the magnitude will vary by category and specialty. Given the considerable purchase likelihood advantage for returning customers and the frequency premium, SMEs should prioritize converting first-time visitors into returning customers even if it means accepting lower margins on initial purchases. Once a customer becomes a returning visitor, that is when the behavior really changes, so crossing that initial threshold is key. It's a way for small businesses to compete when they can't necessarily match big box retailers on acquisition budgets.

Third, mobile devices are often used as discovery tools. Although conversion rates are lower on mobile devices, mobile sessions build familiarity and trust before customers use desktop to complete their purchase (Han et al., 2022). Mobile design should reflect that session effects often compound across multiple devices before a purchase occurs. Retailers gain more from mobile experiences that encourage return visits than from aggressive checkout funnels. E-

commerce websites such as Shopify that offer wish list apps and allow mobile users to bookmark pages for later views are building not just visit frequency but familiarity. Rather than optimizing "buy now" buttons on mobile devices, retailers can prioritize image galleries and customer reviews that support the discover phase of the purchase journey.

Fourth, purchase frequency is a stronger predictor of value than order size. SMEs need to reallocate resources from upsell efforts into repurchase facilitations. Rather than trying to convince customers to increase order value, online retailers should determine how repeat buyers want to fulfill their repeat needs and work to make the return process faster and easier. An online merchant can send e-mails to customers notifying them when products are back in stock and provide one-click order forms specific to that customer. The fewer clicks necessary for a purchase, the higher the conversion rate for returning customers, who have already been shown more likely to convert. Thus, rather than calculating a user's average order value, SMEs should consider tracking purchases per customer per year and tailoring email messaging, loyalty, and sale calendars accordingly.

Limitations and Future Research

Our research presents a number of limitations. First, our study only used data from a single online retailer and findings may not apply to all e-commerce. Other digital retailers may have different products or services, website interface design, and user behaviors, which need a different approach to increase repeat visits. Second, since this is an observational study, we can only show associations, but not causality. Repeat visitors may have an unmeasured characteristic that is not captured by our controls and affects both repeat visits and purchase behavior. Third, the one-year observation window may miss longer-term behavioral patterns. Fourth, analyzing a single high-consideration category means we do not know whether the 22.2% compounding rate of repeat visitors is category-specific or generalizable. Future work can conduct A/B tests to examine the drivers of session frequency and test psychological mediators of the likelihood to purchase. Research should use a direct measure of trust, familiarity, and anxiety reduction as customers become more accustomed to digital platforms in these sensitive categories. In addition, future studies can explore if the rate of compounding on purchase differs for high-consideration categories or if it is a more general phenomenon signaling the accumulation of trust.

Fifth, although this research was guided by well-known theories of the construct of trust, we did not directly test

it using surveys, scales, or experiments designed to exclusively measure participants' level of trust or their cognitive appraisals of trust. Our findings are, however, consistent with the predictions of these theories. Future research could include survey measures of perceived trust, familiarity, or purchase confidence to validate these theoretical connections.

Conclusion

Our analysis of 126,335 verified customers of an SME e-commerce platform reveals that web sessions are associated with purchase probabilities, with accelerated rather than linear growth. Retailers not segmenting their customers and falling back on old 'one-size-fits-all' tactics may be missing out on the revenue potential that repeat visits could generate. Our findings show that the value premium for returning visitors was driven by purchase frequency, which was over 4 times higher than for new visitors, rather than by order value, which was less than 20% higher. This suggests that businesses, especially those in high-consideration categories, should place immense value on retention, which generates most of the revenue.

.....

Corresponding Author:

Jumana (Jay) Black, Ph.D.
Texas A&M University-Texarkana
7101 University Avenue
Texarkana, TX 75503

Funding

This research did not receive any specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Submitted: November 10, 2025 CDT. Accepted: February 11, 2026 CDT. Published: March 31, 2026 CDT.



This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CCBY-4.0). View this license's legal deed at <http://creativecommons.org/licenses/by/4.0> and legal code at <http://creativecommons.org/licenses/by/4.0/legalcode> for more information.

References

- Bagozzi, R. P., Gopinath, M., & Nyer, P. U. (1999). The role of emotions in marketing. *Journal of the Academy of Marketing Science*, 27(2), 184–206. <https://doi.org/10.1177/0092070399272005>
- Black, J. J. (2024). *Predictors of Online Purchase Conversions Using Clickstream Data and Sentiment Analysis* [Doctoral dissertation]. University of South Alabama.
- Bucklin, R. E., & Sismeiro, C. (2003). A model of website browsing behavior estimated on clickstream data. *Journal of Marketing Research*, 40(3), 249–267. <https://doi.org/10.1509/jmkr.40.3.249.19241>
- Chernev, A., Böckenholt, U., & Goodman, J. (2015). Choice overload: A conceptual review and meta-analysis. *Journal of Consumer Psychology*, 25(2), 333–358. <https://doi.org/10.1016/j.jcps.2014.08.002>
- Close, A. G., & Kukar-Kinney, M. (2010). Beyond buying: Motivations behind consumers' online shopping cart use. *Journal of Business Research*, 63(9–10), 986–992. <https://doi.org/10.1016/j.jbusres.2009.01.022>
- Colbert, S., Wilkinson, C., Thornton, L., Feng, X., & Richmond, R. (2021). Online alcohol sales and home delivery: an international policy review and systematic literature review. *Health Policy*, 125(9), 1222–1237. <https://doi.org/10.1016/j.healthpol.2021.07.005>
- Court, D., Elzinga, D., Mulder, S., & Vetvik, O. J. (2009, June 1). *The consumer decision journey*. McKinsey & Company. <https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/the-consumer-decision-journey>
- Craig, A. R., Nevin, J. A., & Odum, A. L. (2014). Behavioral momentum and resistance to change. In F. K. McSweeney & E. S. Murphy (Eds.), *The Wiley Blackwell handbook of operant and classical conditioning* (pp. 249–274). Wiley. <https://doi.org/10.1002/9781118468135.ch11>
- De Haan, E., Kannan, P. K., Verhoef, P. C., & Wiesel, T. (2018). Device switching in online purchasing: Examining the strategic contingencies. *Journal of Marketing*, 82(5), 1–19. <https://doi.org/10.1509/jm.17.0113>
- Dowling, G. R., & Staelin, R. (1994). A model of perceived risk and intended risk-handling activity. *Journal of Consumer Research*, 21(1), 119–134. <https://doi.org/10.1086/209386>
- Gupta, O. P., Gaurav, R., & Jaiswal, M. K. (2023). Understanding the decision-making process in consumer buying behaviour: An insight. *Shodh Drishti*, 14(1.1), 245–250.
- Ha, H. Y. (2002). The effects of consumer risk perception on pre-purchase information in online auctions: Brand, word-of-mouth, and customized information. *Journal of Computer-Mediated Communication*, 8(1), JCMC813. <https://doi.org/10.1111/j.1083-6101.2002.tb00160.x>
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
- Han, S., Han, J. K., Im, I., Jung, S. I., & Lee, J. W. (2022). Mapping consumer's cross-device usage for online search: Mobile-vs. PC-based search in the purchase decision process. *Journal of Business Research*, 142, 387–399. <https://doi.org/10.1016/j.jbusres.2021.12.051>
- Harridge-March, S., & Quinton, S. (2005). Initiation of trust and management of risk in on-line retailing: UK on-line wine market. *International Journal of Wine Marketing*, 17(2), 5–20. <https://doi.org/10.1108/eb008785>
- Kim, D. J., Ferrin, D. L., & Rao, H. R. (2009). Trust and satisfaction, two stepping stones for successful e-commerce relationships: A longitudinal exploration. *Information Systems Research*, 20(2), 237–257. <https://doi.org/10.1287/isre.1080.0188>
- Kukar-Kinney, M., Scheinbaum, A. C., Orimoloye, L. O., Carlson, J. R., & He, H. (2022). A model of online shopping cart abandonment: Evidence from e-tail clickstream data. *Journal of the Academy of Marketing Science*, 50(5), 961–980. <https://doi.org/10.1007/s11747-022-00857-8>
- Lazarus, R. S. (1991). *Emotion and adaptation*. Oxford University Press. <https://doi.org/10.1093/oso/9780195069945.001.0001>
- Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer.
- Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, 80(6), 69–96. <https://doi.org/10.1509/jm.15.0420>
- Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, 20(3), 709–734. <https://doi.org/10.2307/258792>
- Meriç, G., & Yıldırım, F. (2021). The role of customer experience for re-visit and purchase intention: A case study of Amazon. *International Journal of Commerce and Finance*, 7(1), 92–108.
- Moe, W. W. (2003). Buying, searching, or browsing: Differentiating between online shoppers using in-store navigational clickstream. *Journal of Consumer Psychology*, 13(1–2), 29–39. <https://doi.org/10.1207/S15327663JCP13-1>
- Moe, W. W., & Fader, P. S. (2004). Dynamic conversion behavior at e-commerce sites. *Management Science*, 50(3), 326–335. <https://doi.org/10.1287/mnsc.1040.0153>
- Montgomery, A. L., Li, S., Srinivasan, K., & Liechty, J. C. (2004). Modeling online browsing and path analysis using clickstream data. *Marketing Science*, 23(4), 579–595. <https://doi.org/10.1287/mksc.1040.0073>

- Nevin, J. A., Mandell, C., & Atak, J. R. (1983). The analysis of behavioral momentum. *Journal of the Experimental Analysis of Behavior*, 39(1), 49–59. <https://doi.org/10.1901/jeab.1983.39-49>
- Optimove. (2023). Survey of B2C marketers reveals allocation of marketing budgets. <https://www.optimove.com/blog/a-survey-of-b2c-marketing-executives-reveals-they-allocate-most-of-their-2023-budget-to-costly-acquisition-versus-retention>
- Pirolli, P., & Card, S. (1999). Information foraging. *Psychological Review*, 106(4), 643–675. <https://doi.org/10.1037/0033-295X.106.4.643>
- Scheibehenne, B., Greifeneder, R., & Todd, P. M. (2010). Can there ever be too many options? A meta-analytic review of choice overload. *Journal of Consumer Research*, 37(3), 409–425. <https://doi.org/10.1086/651235>
- Sismeiro, C., & Bucklin, R. E. (2004). Modeling purchase behavior at an e-commerce web site: A task-completion approach. *Journal of Marketing Research*, 41(3), 306–323. <https://doi.org/10.1509/jmkr.41.3.306.35985>
- Weinstein, A. (2002). Customer retention: A usage segmentation and customer value approach. *Journal of Targeting, Measurement and Analysis for Marketing*, 10(3), 259–268. <https://doi.org/10.1057/palgrave.jt.5740051>
- Wertenbroch, K. (1998). Consumption self-control by rationing purchase quantities of virtue and vice. *Marketing Science*, 17(4), 317–337. <https://doi.org/10.1287/mksc.17.4.317>
- Wood, W., & Neal, D. T. (2009). The habitual consumer. *Journal of Consumer Psychology*, 19(4), 579–592. <https://doi.org/10.1016/j.jcps.2009.08.003>
- Zajonc, R. B. (1968). Attitudinal effects of mere exposure. *Journal of Personality and Social Psychology*, 9(2, Pt.2), 1–27. <https://doi.org/10.1037/h0025848>