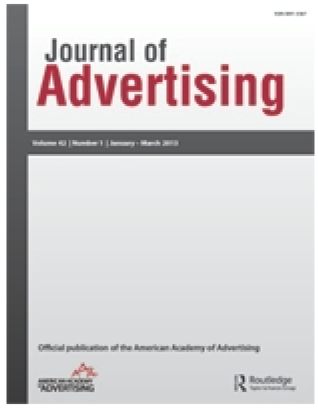

Differential Effects of Device Modalities and Exposure to Online Reviews on Online Purchasing: A Field Study

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Larry Olanrewaju Orimoloye, Ph.D.
Research Fellow
Centre for Risk Research, Southampton Business School, University of Southampton
Highfield, Southampton SO17 1BJ, United Kingdom
O.Orimoloye@soton.ac.uk

Angeline Close Scheinbaum, Ph.D.
Dan Duncan Professor of Sports Marketing
Associate Professor of Marketing
Wilbur O. and Ann Powers College of Business
Clemson University
Clemson, SC 29634, USA
512-788-2480; aschein@clemson.edu

Monika Kukar-Kinney, Ph.D.
Professor of Marketing
The F. Carlyle Tiller Chair in Business
102 UR Drive, Robins School of Business, University of Richmond
Richmond, VA 23173, USA
(804) 287-1880; mkukarki@richmond.edu

Tiejun Ma, Ph.D.
Associate Professor of Decision and Risk Analysis
Centre for Risk Research, Southampton Business School, University of Southampton
Highfield, Southampton SO17 1BJ, United Kingdom
+44 (0) 23 8059 8976
tiejun.ma@soton.ac.uk

Ming-Chien Sung, Ph.D.
Professor of Risk and Decision Sciences
Centre for Risk Research, Southampton Business School, University of Southampton
Highfield, Southampton SO17 1BJ, United Kingdom
+44 (0) 23 8059 8974
ms9@soton.ac.uk

Johnnie Johnson, Ph. D.
Professor of Decision and Risk Analysis

Nottingham Business School

Nottingham Trent University, Burton St.

Nottingham, NG1 4BU, UK

+44 115 848 8159; johnnie.johnson@ntu.ac.uk

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Abstract

We model the effect of online information search across mobile (smartphone and tablet) and non-mobile (PC – desktop and laptop) platforms on frequency of purchasing per online shopping session. Using clickstream data from a multinational retailer, we find that device modality drives purchase frequency, likely due to the differential ease of use of PCs, tablets, and smartphones. In particular, frequency of completed orders is highest when information search and purchase completion are highly convenient, such as when shopping via tablet. We also determine that information search in the form of reading online product reviews has no effect on mobile (while it does so on other platforms). These findings contribute to information search theory, suggesting that information search increases purchase likelihood when it is goal-directed, extensive, and easy to conduct. Thus, the broad role of digital advertising should be to make the information search process easier and more convenient for consumers in order to stimulate purchases. These findings help digital advertisers understand information search patterns across device modalities. Implications for digital advertisers on e-commerce platforms are offered.

Keywords

Mobile commerce, online consumer behavior, online information search theory, consumer reviews

The advertising literature has a demonstrated interest in digital and mobile advertising (e.g., Ahrens and Coyle 2011; De Keyzer et al. 2021; Huang et al. 2021; Lu and Du 2020; Maslowska et al. 2017; Okazaki et al. 2007; Okazaki et al. 2009). This interest is in part driven by relevance to the ever-evolving e-commerce industry. Understanding mobile media and mobile consumer behavior is paramount for digital advertisers (Ford 2017), especially advertisers on e-commerce platforms. In fact, the world's biggest advertiser is the electronic retailer Amazon—where consumers shop from their phones, tablets, and/or PCs. US consumers alone had a forecasted e-commerce spend of $933.30 billion in 2021, an annual increase of almost 18% (Davidkhanian 2021).

At the same time, advertisers are projected to invest over $167 billion on mobile advertising in the US by 2024, a vast increase from $87.3 billion in 2019 (Perrin 2020). According to the EVP of Measurement and Impact of NBC Universal, advertisers are putting a new priority on cross-platform measurement because consumers are sharing their time across a wider range of screens (Williams 2021). Hence, advertisers could benefit from understanding more about which screens consumers use for shopping – i.e., conducting information search as well as purchasing. Advertisers should find it especially valuable to understand the role that device modalities (such as a smartphone, tablet, or a PC) may play on consumer search and purchase frequency. Thus, device modality and consumer product information search (by way of reading product reviews) are two key concepts that call for deeper investigation.

Knowledge of consumer behavior across device modalities can help inform advertising spending share, which for 2022 is a projected 14.2% on PCs and 47.9% on mobile advertising (eMarketer 2018). Knowledge of online search behavior can inform specific placement of ads across devices. Thus, there is practical reason to study shopping device types as well as exposure to online product reviews, as this information can help inform digital/mobile media placements.

This industry relevance opens a need for advertising scholarship on purchase behavior across device modalities in electronic commerce (e-commerce) and more specifically mobile commerce (m-commerce). M-commerce refers to online shopping from mobile devices such as smartphones and tablets. When consumers shop from a PC, they presumably stay in a given location; yet, when shopping from a mobile device, consumers tend to move about to a higher degree and often use smaller screen sizes (de Haan et al. 2018). Consumers prefer mobile over stationary devices for online shopping (de Haan et al. 2018; Xu et al. 2017). Yet, preference for shopping via mobile devices does not necessarily translate into more buying; research also suggests that customer click-through behavior in paid search advertising varies for different devices (Lu and Du 2020). Such past work shows an importance of understanding the effect of mobile device use as well as aspects of online search behavior, which includes clicking on product reviews during the online shopping process.

Consumer online search behavior (Taneja 2020) is relevant for both advertisers and advertising scholarship. An area of keen interest to digital advertisers is sponsored search advertising and understanding consumers' shopping goals (Huang et al. 2021). Advertising scholarship has made many advances in online or digital related topics, and there are many more aspects in this space that advertisers need to understand (Liu-Thompkins 2019).

Yet, despite its economic and theoretical importance, few studies examine the relationship between device modality, information search (including exposure to online product reviews), and buying (Kannan and Li 2017). Scholarship employing e-commerce clickstream data that focuses on mobile technology for shopping is a ripe area for advertising scholarship and digital advertisers alike (Bernritter, Okazaki, and West 2021). Utilizing clickstream data across device types enables advertisers to gather information to personalize their communications and increase advertising effectiveness (Liu-Thompkins 2019). Such is similar to benefits for advertising gained by capturing information from registered customers on websites (Ahrens and Coyle 2011). Clickstream data can also advance knowledge on online information search theory, adding insights into how consumers search for information online (Browne, Pitts, and Wetherbe 2007).

Hence, our objective is to use clickstream data to explain and predict individual and joint effects of 1) consumers' online browsing across device modalities (PC, smartphone and tablet), and 2) consumers' information search behavior, more specifically, exposure to online product reviews, on the frequency of orders completed per shopping session. We suggest and find that information search behavior increases purchase frequency, especially when it is easy and convenient. This effect is driven both by device modality and by clicking on product reviews. We also develop knowledge on the moderating role of device modality as it interacts with information search in the form of online shoppers' clicking on online product reviews. The theoretical contribution is to add behavioral insights to online information search theory. We are not testing online information search theory per se but use it as a guiding lens to inform inclusion of these two search-related aspects (i.e., device modality and reading product reviews) in the proposed model. We also aim to make a contribution to advertising practitioners. In doing so, we intend to bring industry and academic research more closely together and to supply industry relevant insights. We also contribute by moving away from behavioral intentions and documenting actual online consumer behaviors.

Next, we supply a synopsis of the relevant literature. An overview of the empirical context follows. The next section entails a description of the model used, followed by results and a discussion. We conclude with implications for information search theory and digital advertisers, along with limitations and future research areas that are relevant for advertising scholarship.

LITERATURE REVIEW AND THEORY

Here, we synthesize literature on device modalities. Then, we discuss the role of device modalities in e-commerce and develop expectations for the effect of device modality on purchase frequency. Next, we review complementary studies in digital advertising and online reviews and link them with information search behavior research. This allows us to develop expectations for the main effect of reading product reviews. Last, based on the synthesized literature streams, we develop rationale for the moderating role of device modality on the effect of product reviews.

Advertising, e-commerce and device modality

Broadly, advertising research in digital advertising and online consumer behavior includes the importance of distinct types of devices or cross-platform analyses. Namely, Lu and Du (2020) used data from Google's advertising platform AdWords to examine consumers' clickstream behavior after exposure to search ads. They considered if the customer was shopping from a PC, smartphone, or tablet to see how that could impact clicking on the top search ad (Lu and Du 2020). Based on click-through behaviors on paid search advertisements, they found consumers are sensitive to position changes of the online ad (Lu and Du 2020). They also found that consumers prefer paid search advertisements that are on the top of the page (Lu and Du 2020). Similarly, Huang et al. (2021) studied online click-through behavior on a popular e-tail site in China; they found that click-through rates and conversion rates go down when the advertising position is lower. They further found that there is a moderating effect of the type of product that the consumer searches for online; specifically, experience (vs. search) products have a reduced effect of advertising position on consumer's click-through and purchase rates (Huang et al. 2021).

Complementary to advertising scholarship that has examined intention to click on digital ads (e.g., De Keyzer, Dens, and De Pelsmacker 2021), we examine click-through purchase behavior from various device modalities. Most scholarship examining purchasing using mobile devices examines one modality used in isolation (e.g., Andrews et al. 2016; Li et al. 2017; Luo et al. 2014). Two papers that focus on clickstream purchase behaviors across different device modalities are by Xu et al. (2017) and de Hann et al. (2018). First, Xu et al. (2017) examined the complementary and substitution impacts of the tablet on the smartphone and PC. They used a dataset from the e-tailer Alibaba and found that adoption of tablets enhanced Alibaba's e-commerce growth. Their study examined cross-device browsing, or where consumers browse on two different devices during a one-hour time window (Xu et al. 2017). Similarly, de Haan et al. (2018) analyzed browsing patterns across PCs, smartphones and tablets. They analyzed device switching using e-tail clickstream data. They found that the increased adoption of mobile devices significantly affects online shopping behavior, and that customers at times switch between mobile and fixed devices when shopping online. They also found that when customers switch from a mobile device to a stationary device, their conversion rate from browsing to buying is significantly higher (de Haan et al. 2018).

Device modality is linked with the process of online information search. Online information search theory is a theory from management information systems (MIS) offered by Browne et al. (2007) that explains and predicts consumers' online information search and notes that consumers start and end online searches depending on the type of task. While a shopping task can be entertainment-related, it is often goal (purchase and/or information search) driven. Device modality can be seen as an indicator of ease and convenience of online product/information search. Mobile devices such as smartphones may be more convenient for browsing, as they can be used almost anywhere due to their small size (de Haan et al. 2018). However, they are also used for shorter shopping sessions, while stationary devices are more convenient for purchase completion (de Haan et al. 2018).

The focus of the present research is on purchase completion and exposure to product reviews on various device types, rather than browsing behavior. As such, based on the above literature and the assumption that it is easier to conduct an extensive search for information as well as complete purchase on a larger, more stationary device, such as PC or tablet (vs. smartphone), we expect that both tablets (as per Xu et a. 2017) and PCs (as per de Haan et al. 2018) should be more effective in increasing purchase frequency than smartphones. However, the question of whether PCs or tablets are more effective compared to the other is still open, and we hope to also shed light on this relationship.

Reading product reviews and device modality

While our work builds on the contrasting findings about device modality from Xu at el. (2017) and de Haan et al. (2018), there is complementary advertising scholarship in the areas of mobile advertising and online reviews (e.g., Andrews et al. 2016; Bart et al. 2014; Ford 2017; Grewal and Stephen 2019; Luo et al. 2014; Okazaki et al. 2007; Okazaki et al. 2009). Research shows that product reviews positively affect purchase probability (Allard et al. 2020). Purchase probability is also influenced by product review features, with some reviews being less believable (Maslowska et al. 2017). However, *mobile* product reviews are different (Ransbotham et al. 2019); specifically, reviews posted from a mobile device drive purchase intentions due to less perceived effort and enhanced credibility (Grewal and Stephen 2019). This literature is used to further inform the model and help interpret the findings for advertising practice.

Similar to device modality, consumer behavior in the form of *reading online product reviews* is also intricately linked with the process of online information search. Specifically, reading product reviews can serve as an indicator of an extensive and involved online information search. When consumer is conducting an extensive search, they may be more committed to a purchase and closer to making the purchase decision. Existing research shows that there is an effect of product reviews on online consumer purchase intentions and behavior (Liu et al. 2020; Maslowska et al. 2017) and that exposure to product reviews ultimately results in positive consumer responses (Allard et al. 2020). We extend this reasoning to purchase behavior and suggest that *reading product reviews will positively affect frequency of orders completed*.

However, reading online product reviews and moving between different product review page when using mobile device, especially small one, such as smartphone, can be cumbersome and time-consuming, and may be ineffective in helping the customer make the final purchase decision. As such, it is important to address the following research question: *How does device modality interact with the information search in the form of reading online product reviews in order to influence the frequency of purchasing?*

Consumers use smartphones for convenience and shorter shopping sessions (de Haan et al. 2018), rather than for conducting extensive product research and information search, such as reading customer reviews. Consumer exposure to mobile advertising and user generated content (such as consumer reviews) does not work the same as it does for nonmobile online media (Grewal and Stephen 2019; Melumad et al. 2019). While there is a growing literature on product reviews in advertising (e.g., Allard et al. 2020; Maslowska et al. 2017; Ransbotham et al. 2019), there is little other evidence for the effect of product reviews on frequency of orders completed for different devices using behavioral data.

Based on the information search literature pertaining to online product reviews (Allard et al. 2020; Liu et al. 2020; Maslowska et al. 2017) and works on device modality (de Haan et al. 2018; Xu et a. 2017), we anticipate that information search in the form of reading online product reviews, which represents goal-directed and involved search behavior, will be most effective in stimulating higher frequency of purchase completion when conducted on a stationary device with the largest screen size, therefore, a PC, in comparison with mobile devices. Such devices are also more fitting for longer, more involved and complex shopping sessions. Tablet should follow, while searching through online product reviews should be least effective in stimulating purchase completion when conducted on smartphone.

Table 1 synthesizes the relevant literature on e-commerce/mobile consumer behavior and device modalities that employs field study data. These papers each consider mobile consumer behavior as relevant to online shopping, and many consider either multiple types of devices and/or consumer reviews. Each of them in the table are featured because they rely on field data and have a focal area or dependent variable that is relevant to advertisers or e-tailers.

[Table 1]

Next is an overview of the methods, data, variables, and analyses.

METHODS

Data

We use individual-level clickstream data (see Kukar-Kinney et al. 2022) to develop a model to explain consumers' search and buying behavior across device modalities. The data is from a large European (British) multi-purpose retailer with home products, sportswear/clothing, and footwear with a large multinational presence (over 500 stores worldwide). We use observations from customers who engaged in two or more sessions during the observed time period. A session is one continuous period where the customer is active on the site that begins when they enter the site and ends either when they leave the site or after being inactive for at least 30 minutes.

The data have unique device IDs which allows us to track and link a consumer identifier to the devices used on the site. We use data from registered customers because registration is necessary to place an order or complete a purchase. Registration is also important because in digital advertising, advertisers gather information based on registration on e-commerce sites in order to send customized communications (Ahrens and Coyle 2011). While the original data had over one million shopping sessions observations, the data used after removing nonregistered customers, and those who did not engage in two or more sessions during the time period leaves the final sample at 179,473 customers who engaged in 958,859 sessions in a two-week period in July-August 2018.

Addressing Endogeneity

Because there was no random assignment to the device modality (treatment), there could be self-selection bias across the device modalities. To address this, we use propensity score matching and make a control group. One, with binary logistic regression, we estimate each consumer's propensity to use a certain device modality to purchase. Two, for the matching process, each consumer in the treatment group is paired with a statistical twin from the control group who did not purchase using a particular device modality (but had the same propensity to use that device type). We match each treatment case to its nearest neighbor if two propensity scores fall within a tolerance zone. Limiting the scores to differ by no more than .001, we match 179,473 customers from the treatment customers. Three, we compute percentage reductions in bias for the matches (i.e., 91%), showing a reduction in self-selection biases. Four, we compute standardized differences in averages before and after matching. The matched sample is used in further analysis.

Variables

The variables are selected in line with the above review of the literature in advertising and marketing and online information search theory. The dependent variable is frequency of purchasing during the session. The dependent variable brings novelty to existing work, which typically focuses on if a sale was made. The two independent variables are device modality and product reviews accessed. Device modality is also examined as a potential moderator. Thus, an interaction of device modality and product reviews is included in the model.

Control variables include time spent shopping (in seconds), number of pages seen, cart value, and dummy variables denoting a visit to the website before work, during lunch, after work and during the evening. To control for any impact of user interfaces, device screen sizes are also included. Lastly, we control for variation in geographical differences by using six dummy variables to account for continents where the consumer is browsing from, with Asia as the baseline (vs. Africa, North America, South America, Europe and Australia).

Empirical Models and Analyses

To model the frequency of orders completed and a random intercept to account for customer heterogeneity at the individual level, we compare three models (Poisson regression model, the negative binomial regression model, and the zero-inflated negative binomial). We supply a web appendix for a comparison of the three models introduced (as well as MCMC parameter estimates to enhance validity). We conducted analysis using R. Based on the smallest BIC value and the Vuong test statistic, NB is the preferred model. Hence, results presented next are based on the NB model (Web Appendix).

RESULTS AND DISCUSSION

Findings

The Effect of Device Modality on Frequency of Completed Orders

Device modality has a significant effect on the frequency of orders completed. Particularly, the coefficient of frequency of completed orders on smartphones is 0.226 lower (p<.001) than for those using PC. However, for those on tablet, the estimate of the coefficient of the frequency of completed orders is significantly higher vs. PC by 0.101 (p<.001). *Thus, purchase frequency is highest when consumers shop via tablet, followed by PC, and lowest* *when shopping occurs via smartphone.* Our finding showing the strength of tablets is consistent with Xu et al. (2017) in that both show that tablets are the strongest device type for online sales. Our finding is also consistent with complementary work on purchase intentions when using mobile devices. Studies by Bart, Stephen, and Sarvary (2014) as well as Grewal and Stephen (2019) find a positive impact of mobile devices on purchase intentions. Another study about mobile devices finds a positive role of mobile devices (Lou, Andrews, Fang and Phang 2014) on purchase of a promoted movie. Despite this, our finding contradicts the finding from de Haan et al. (2018), who found that a PC has a higher conversion rate than mobile devices. Other work examining mobile devices also found a negative impact of mobile devices. Namely, Ghose, Goldfarb and Han (2013) found less clicks from a mobile device and Marz, Schubach, and Schumann (2017) and Ransbotham, Lurie, and Liu (2019) found less perceived helpfulness from mobile reviews.

In support of our finding that there is a positive effect for e-commerce conversions when tablets are used, we find that e-cart value is also highest with tablets. The average total e-cart value of shoppers shopping via tablet (£33.00 or $40.71) is higher than of those shopping via PC (£29.84 or $36.81) or smartphone (£24.24 or $29.90). Thus, we find that consumers have the highest valued e-cart when shopping on tablets and lowest when on smartphones.

The Effect of Exposure to Product Reviews on Frequency of Orders Completed

A further result concerns the impact of information search in the form of clicking on product reviews on online purchase frequency. *There is a positive main effect of exposure to product reviews on frequency of orders completed* (0.002, $p < .001$) overall. This is consistent with our expectation and in line with both Maslowska et al. (2017) and Liu et al. (2020), who showed that product reviews impact online consumer purchase intentions and behavior. Our finding also extends work by Allard et al. (2020), who found that exposure to product reviews ultimately results in positive consumer responses. As depicted in Figure 1, in addition to the significant main effect of product reviews, we also find a significant interaction effect of device modality and exposure to product reviews.

[Figure 1]

We expected that device modality will moderate the effect of searching product reviews on the frequency of orders completed, with information search of product reviews conducted on stationary devices leading to the largest positive effects. Our findings show that customers who are exposed to product reviews on PCs complete more orders than those using smartphones and tablets. Further, reading product reviews on smartphones is the least likely and does not significantly drive purchase behavior. Information search in the form of reading online product reviews has no effect on mobile (while it does so on other platforms). Thus, we supply evidence showing that viewing product reviews increases the frequency of completed online shopping orders, but primarily so for PCs.

Effects of Control Variables on Frequency of Orders Completed

The number of pages viewed has a positive relationship with frequency of purchase completion (.051, $p < .001$). Also, shopping before typical work hours (0.044, $p < .001$) and shopping during lunch hours (0.032, $p < .001$) have a positive relationship with purchase frequency, while shopping in the evening has a negative relationship (-0.051, $p < .001$). Time spent online searching for items (in seconds) is positively related with purchase frequency (0.0003, $p < .001$), while e-cart value is negatively related with it (-0.00004, $p < .01$). Last, two largest screen sizes have a significant positive effect, while smaller screen sizes have a negative or non-significant effect on purchase frequency (see Web Appendix).

Implications for Theory and Advertising Scholarship

While strengths of the work here are in the timely topic, behavioral nature of data, methodological rigor, and interest by advertisers who want to learn more about online consumer behavior, there are also contributions to theory that are useful to advertising scholars. Online information search theory (Browne et al. 2007) has traditionally been used in the MIS field more than in advertising; however, the shift towards digital and mobile advertising has sparked a need to consider modern ways to explain or predict how characteristics of online information search can impact purchasing online. A contribution to online information search theory is that device modality drives purchase frequency, and this is likely due to the differential ease of use and convenience of PCs, tablets, and smartphones when conducting extensive information search and completing purchases. An individual search tendency in the form of clicking on customer reviews further increases online purchases, but only when such behavior is easy to complete, such as on a PC. These findings contribute to information behavior research, suggesting that when information search is goal-directed, extensive, and easy to conduct, it will increase purchase frequency in e-tail. As such, a broad role of digital advertising should be to make the information search process easier and more convenient for consumers in order to stimulate purchases.

In addition to theory, one area in advertising scholarship that this work extends is in online/consumer reviews. It has been established that the features of online reviews impact consumer probability to buy and that some reviews may seem "too good to be true" or untrustworthy (Maslowska et al. 2017). Similarly, our work adds to past findings that product reviews have a positive impact (Allard et al. 2020) and that mobile product reviews are distinct (Ransbotham et al. 2019). It also adds to the finding that reviews posted from a mobile device bring higher purchase intentions (Grewal and Stephen 2019) by examining the role of visiting product reviews on actual purchase behavior.

As a further contribution to advertising scholarship, this research also adds to existing literature relevant to mobile advertising. Within advertising, the work is again complementary to the growing body of research in mobile advertising (e.g., Andrews et al. 2016; Bart et al. 2014; Ford 2017; Grewal and Stephen 2019; Luo et al. 2014; Okazaki et al. 2007; Okazaki et al. 2009) by studying the effect of device modalities on purchase frequency and by using behavioral data. We next discuss specific actions that could be undertaken by digital advertisers to maximize online purchase frequency.

Implications for Digital Advertisers

Our work brings industry and academic research more closely together and supplies advertising industry relevant insights for advertisers who are keenly interested in findings from clickstream data. These findings should lead to updated strategies with respect to advertisers' e-commerce and m-commerce media placements and integrated brand promotions in the areas of device modality and product review pages.

Device Modality

Our work confirmed a conversion gap, which is a discrepancy in browsing vs. buying via one device modality compared to another. *Advertisers can place more emphasis on the tablet, as advertising to consumers who shop from tablets may be especially effective.* This implication is based on our finding that the conversation rate is highest when consumers shop via tablets, followed by PCs and then smartphones, as well as the fact that the value of the items in the e-carts are highest for tablets. However, if the goal is to increase conversion rates of consumers shopping on PCs and smartphones, pushing other ads or promotions to those devices may be needed to stimulate their purchase completion.

Product Review Pages

Our findings further suggest that *advertisers can encourage consumers to read product reviews, especially from stationary devices* such as PCs. Taking device modality into account, there is considerable evidence that viewing product reviews increases the frequency of orders purchased. However, when consumers read the reviews from a PC, the effect of reading product reviews is intensified for conversions. The finding that reading online product reviews has no effect on mobile (while it does so on other platforms) is an unintended negative consequence of mobile technology to marketers, who are interested in conversions from browsing to buying.

Limitations and Areas of Future Research

There are limitations that set advertising scholars on a path for future research. First, we do not have data on how the e-commerce company incorporated digital advertising on their shopping platform. It would be helpful to add to our model any impact of exposure to a digital ad while shopping, and such an extension would supplement well with the advertising study by Lu and Du (2020) who analyzed clickstream behavior after exposure to search ads. Thus, we encourage advertising scholars to work with companies or ad agencies to obtain the data needed to model the extent to which exposure to digital ads while shopping impacts conversions on different devices. This opportunity is in line with a trend for advertising research to become more quantitative in nature (Chang 2017).

A second limitation is that while we used data based on a multi-national sample spanning hundreds of brands and several countries, the data do not include purchasing services online. Future research can replicate this work in the context of services or experiential goods, such as sport event tickets.

A third limitation is that we could not account for consumer trust perceptions of the reviews or other details about the product review pages. Hence, related topics for added scholarship in mobile research is examining the role of trust in digital advertising (Okazaki et al. 2007) or perceived trust or believability product reviews of varying valences (Maslowska et al. 2017; Grewal and Stephen 2019), as overly positive or negative reviews may not be very trustworthy. It would be further beneficial to examine any differential impact of reviews either written from or read from a mobile device (Ransbotham et al. 2019; Grewal and Stephen 2019). Here, we are only able to consider what type of device the consumer was exposed to the review from as it is not known what type of device the review was written from nor the details of the review contents. We encourage scholars to combine the work done here with studies on how advertisers and e-commerce sites could communicate trust of the site, products, and consumer reviews.

A last area for future research, such as seen in Okazaki et al. (2009) via mobile advertising in Japan, can more deeply examine country-based location impact of mobile e-commerce than what we controlled for. Such is important given that 61% of global advertising revenue is forecasted to be digital, and there are 114 advertisers who exceeded $1 billion for advertising investments worldwide (Ad Age 2020). Overall, information search theory development that blends online consumer behavior and e-commerce research is an exciting and ripe area for continued advertising scholarship in digital and mobile contexts.

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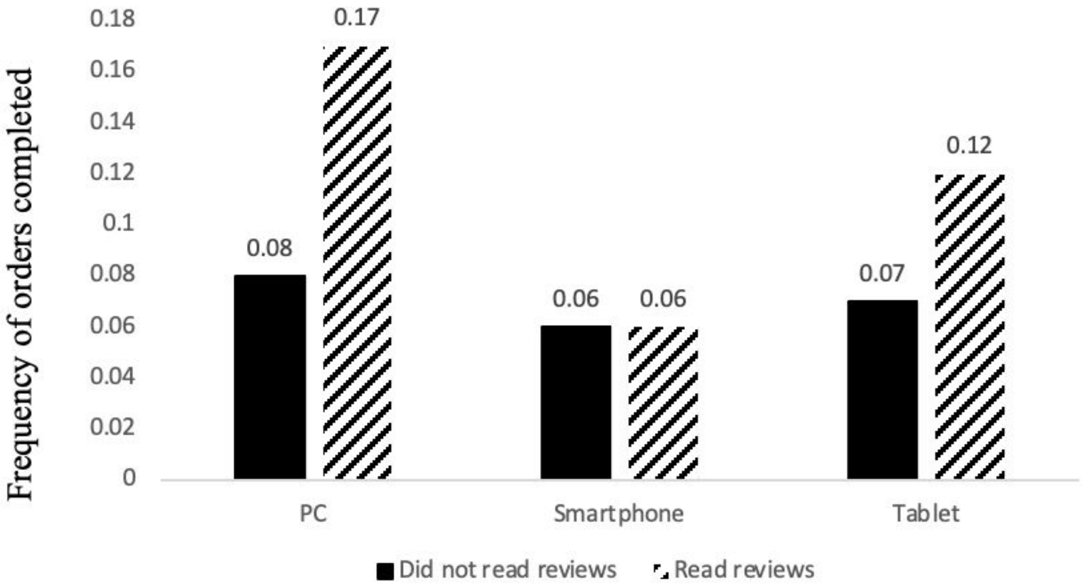
Table 1. Synthesis of Relevant Studies with Field Data in E-Commerce/M-Commerce

Source	Focal Area or DV	Considers Device Types	Considers Consumer Reviews	Key Findings
Ghose et al. (2013)	Click-behavior	Yes	No	Clicks based on brand posts can differ by two device types (mobile vs. PC).
Andrews et al. (2016)	Mobile ads	No	No	Consumers in more crowded trains are approx. 2 x more likely to make a purchase from a mobile offer (vs. those in not as crowded trains).
Li et al. (2017)	Mobile promotion	No	No	Mobile promotion effectiveness is better (& faster) in sunny weather compared to cloudy weather & is lower (& slower) when it rains.
Marz et. al (2017)	Helpfulness, value	Yes	Yes	Differences in real online reviews written on mobile vs. nonmobile devices can determine how helpful or valuable they are to customers.
Xu et al. (2017)	Tablets & e-commerce sales	Yes	No	Tablets are substitutes for computers but complements to smartphones. Tablets bring more impulse product sales & a bigger variety of types of products bought. Cross-device browsing enhances sales.
de Haan et al. (2018)	Device switching	Yes	No	When customers switch from a phone to a desktop, the sales conversion rate is higher. The effect is bigger when there is more product category risk and higher prices.
Grewal & Stephen (2019)	Purchase intentions, review perceptions	Yes	Yes	Consumers knowing a review was done on a mobile device brings higher purchase intentions/may be perceived as more trustworthy.
Melumad et al. (2019)	Emotionality	Yes	Yes	Differences in mobile (vs. nonmobile) UCG exist for content emotionality.
Ransbotham et al. (2019)	Value	Yes	Yes	Mobile reviews are more affective, less extreme, and more concrete when written via mobile devices.
Kukar-Kinney et al. (2022)	Cart abandonment	Yes	Yes	Online cart abandonment is driven by uses & gratifications: cart use, items in the cart from a past session, seeing sold-out items, visiting clearance pages, removing items from the cart, seeing reviews, and seeing many products. A convenience motivation moderates purchase, economic control, organization, & research/information motivations on online cart use.
The current research	Frequency of orders completed	Yes	Yes	The effect of reading reviews on purchase frequency is the most positive on PC, followed by tablet. Reading reviews on smartphones is not effective in stimulating purchase completion.

Figure 1. Moderating Effects: Interaction Between Visiting Product Reviews and Device Modality on Frequency of Orders Completed



Web Appendix

Details on the Analyses and Results

Poisson Regression Model with Random Effects

In the Poisson model, the frequency of orders completed per session is modelled as:

$$\text{Log } E(y_{ij} \mid u_j) = \alpha + X'_{ij}\beta + u_j \qquad (1)$$

Where y_{ij} is the observation for customer (i) in session (j) and u_j is the random effect for session (j). The two distributions are: $y \sim Pois(\lambda)$ and $u \sim N(0,\sigma^2)$. The Poisson distribution is suitable for sparse event counts; however, the conditional mean is assumed to equal the conditional variance. Thus, we also consider a negative binomial approach.

Negative Binomial Regression Model (NB) with Random Effects

The NB model allows the variance to exceed the mean. The NB distribution is:

$$\Pr(Y_i = y_i) = \frac{\Gamma(k + y_i)}{\Gamma(k) y_i} \left(\frac{k}{k+\mu}\right)^{k} \left(\frac{\mu}{k+\mu}\right)^{y_i} \qquad (2)$$

Where μ is the mean and k is the dispersion parameter. The variance of the above distribution is $\mu + \mu^2/k$, and decreasing values of k correspond to increasing dispersion levels. Here, the dispersion varies randomly among shopping sessions.

Zero-inflated Negative Binomial (ZINB) with Random Effects

Last, we consider a Zero-inflated negative binomial (ZINB) with random effects model because ZINB can handle zero-inflation and over-dispersion. It also has the ability to model the effect on probability and size. Probability is given as:

$$\Pr(Y = 0) = \pi + (1 - \pi)(1 + \alpha\mu)^{-\frac{1}{\alpha}} \qquad (3)$$

The mean is μ and α is the over-dispersion parameter.

Results of Fitted Count Regression Model (with Random Effects)

Note: Smartphone and tablet are compared to PC (the baseline).

Variables	Poisson	NB#	ZINB	MCMC Parameter estimate
(Intercept)	-2.784***	**-3.125*** **	-2.346***	-3.231
	(0.008)	**(0.172)**	(0.005)	(0.007)
Device modality (smartphone)	*-0.011****	***-0.226**** **		*-0.104*
	(0.049)	***0.012***		*(0.014)*
Device modality (tablet)	*0.124****	***0.101**** **		*0.121*
	(0.012)	**(0.011)**		*(0.005)*
Read reviews	*0.024****	***0.002**** **	*0.066****	*0.086*
	(0.002)	**(0.003)**	(0.001)	*(0.019)*
Read reviews X device modality (smartphone)	*0.012****	***0.104**** **		*0.022*
	(0.004)	**(0.010)**		*(0.011)*
Read reviews X device modality (tablet)	*-0.071****	***0.017**** **		*0.123*
	(0.001)	***(0.010)***		*(0.011)*
Control variables:				
Time spent (in seconds)	0.000***	**0.0003*** **		0.000
	(0.000)	**(0.000)**		(0.000)
E-cart value	0.000***	**-0.00004*** **	0.002***	-0.000
	(0.000)	**(0.000)**	(0.000)	(-0.000)
Visit before work	1.016***	**0.044*** **	-0.021	0.054
	(0.01)	**(0.012)**	(0.013)	(0.002)
Visit during lunch	1.615***	**0.032*** **	0.016	0.091
	(0.012)	**(0.011)**	(0.012)	(0.004)
Visit after work	2.455***	**0.004**	0.014	0.317
	(0.002)	**(0.013)**	(0.010)	(0.008)
Visit during evening	0.748***	**-0.051*** **	-0.065***	-0.371
	(0.004)	**(0.003)**	(0.006)	(0.019)
Pages viewed	0.004***	**0.051*** **		0.015
	(0.000)	**(0.000)**		(0.007)
Screen size '360x640'	-0.023***	**-0.214*** **		-0.008
	(0.017)	**(0.012)**		(0.002)
Screen size '768x1024'	0.417***	**1.326*** **		0.514
	(0.156)	**(0.104)**		(0.127)
Screen size '320x568'	-0.012	**0.014**		-0.011
	(0.016)	**(0.010)**		(0.002)
Screen size '1366x768'	0.436***	**1.019**		0.429
	(0.151)	**(0.104)*** **		(0.132)
Screen size '414x736'	-0.073***	**-0.040*** **		-0.073
	(0.016)	**(0.021)**		(0.004)
Africa	-1.014**	**-1.328*** **		-1.442
	(0.371)	**(0.411)**		(0.241)
North America	-1.934**	**-1.712***		-0.821
	(0.352)	**(0.314)**		(0.421)
South America	-0.604	**-0.711**		-0.437
	(0.307)	**(0.160)**		(0.121)
Europe	0.217	**0.105**		0.562
	(0.132)	**(0.276)**		(0.212)
Australia	-1.214***	**-1.131*** *		-2.173
	(0.304)	**(0.372)**		(0.821)
Time dummies	Included	**Included**	Included	Included
(Intercept)			-3.133***	
			(0.043)	
Read reviews			-0.110***	
			(0.011)	
Cart quantity			0.155***	
			(0.003)	
E-cart value			0.009***	
			(0.000)	

Visit before work			-0.031 (0.053)	
Visit during lunch			0.022 (0.024)	
Visit after work			-0.032 (0.0)	
Visit during evening			-0.103*** (0.029)	
Observations	179,473	**179,473**	179,473	
Number of parameters	23	**23**	20	
Log Likelihood	-162,219	**-103,501**	-210,011	
AIC	224,745	**166,168**	236,261	
BIC	265,128	**123,187**	349,909	
$\sum \hat{f}_i(0)$	77,062	**77,886**	94,405	

Significant levels for variables * p<0.05, ** p<0.01, *** p<0.001.
Key effects (device modality, product reviews, their interactions) are shown in italics at the top of the table.
[#] Negative binomial (NB) is in **bold** as the preferred model.