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Product engagement and identity signaling: The role of likes in social commerce for fashion products

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ABSTRACT

Motivated by a lack of understanding of user engagement with identity-relevant products, we distinguish between two mechanisms by which existing likes affect subsequent engagement: observational learning (OL) by observing the number of existing likes, and social influence (SI) by observing the likes of one's social connections. Using a novel panel dataset of 930 handbags, we find that, contrary to most OL studies, OL has a negative effect on subsequent likes, and the effect is mitigated by SI. By contrast, OL has a positive effect on clicks, and the effect diminishes as SI increases. We attribute our findings to identity signaling.

1. Introduction

"Like" is an immensely popular form of user engagement behavior in many online platforms such as social media, electronic commerce, and online user communities [1,2]. Likes are important to these platforms because they can be harnessed to generate further engagement behaviors, such as more likes and clicks. Prior research suggests that online platforms could have two ways of leveraging existing likes. First, they can leverage *observational learning* (OL) [3,4]. By displaying the number of likes that an item has received, they can signal the attractiveness of the item to users, thereby affecting their chances of engaging with it. Second, for platforms with social networking features, they can also leverage *social influence* (SI) [5,6]; when a user likes an item, the platforms can notify her online social connections, so that they may be inspired to engage with the item. While the arguments for OL and SI seem intuitive and have been successfully employed in other contexts such as software downloads [4], Amazon sales [3], and movie recommendations [7], yet, we do not know if they work the same way in identity-relevant environments, where users' engagement behaviors could hold implications for their online identities.

Examples of identity-relevant environments include social commerce websites, where users collaboratively discover, curate, and share fashion products found from other websites. Each user on social commerce websites has her own home page that lists the products she has liked or collected. She can also exploit the social networking features to connect to other users, stay updated on their activities, and interact with each other (through activities such as liking and commenting). When such a user likes a product, it reflects her fashion tastes and signals her online identity to other users in the community, including her social connections. In such an identity-relevant online environment, if she sees a product with many existing likes, would she follow others into liking the product, or would she avoid doing so (e.g., to signal her distinct taste)? Would her reaction to the number of existing likes change if her social connections also like the product? Questions like these suggest that the effects of likes on subsequent user engagement may not be the same in identity-relevant settings, thus warrant a separate investigation. Hence, we ask the following research question: *how does existing likes affect subsequent user engagement, including likes and clicks, in an identity-relevant online environment*?

Our research question is motivated by the needs of identity-relevant platforms such as social commerce websites to better harness the power of likes to maximize user engagement. For those online platforms, user engagement metrics including likes and clicks are key indicators of effectiveness and are closely associated with their online advertising revenue. Because of the identity-relevant nature of these platforms, they need to know whether they should leverage likes in the same manner as platforms that are not identity relevant. Furthermore, given these platforms can encourage OL, SI, or both, a natural question to ask is which channel of influence they should rely on, and when. These practical questions require a fundamental understanding of how existing likes affect subsequent user engagement through OL and SI, which we aim to address in this study.

We conduct our research in a leading online social commerce website for fashion, interior design, and artistic expressions, called *Polyvore*. Polyvore does not sell products but allows users to collaboratively discover and share products sold on other e-commerce

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websites. It offers a rich set of design features including displaying the number of existing likes on each product card and allowing users to follow each other's likes and creative ideas (in the form of user-generated collages, called "set"). Interestingly, this site allows users to like a product (when the product card is displayed) without clicking on the product card to see more details; conversely, users can also click on a product card to see more without liking it. This design provides us an opportunity to study clicking and liking behaviors as separate engagement events. From Polyvore, we gather data on handbags, which are widely deemed as an identity-relevant product category [8,9]. We track a random selection of 930 tote handbags for 4 months and collect data on these products and related users every other week. With this longitudinal dataset, we use a simultaneous equation model (SEM) to resolve the simultaneity between the growth of likes and clicks. We employ an instrumental variable approach with product fixed effect to estimate this model. The SEM framework is further complemented by several alternative specifications as robustness tests.

Our analyses produce several interesting insights. First, in a sharp contrast with existing literature on OL that focuses on non-identity-relevant environments, we find that the number of existing likes (OL) have a negative effect on new likes. Our finding is consistent with the identity signaling theory: due to identity-signaling concerns, people avoid liking fashion products already liked by many people from the crowd. We also find that OL has a positive effect on new clicks, which are private engagement behaviors that cannot signal identity. The contrast between our findings for likes and clicks provides evidence that identity signaling can significantly alter people's engagement behaviors. Interestingly, when a product is liked by users who have many followers, which indicates a strong social influence (SI) effect, the negative impact of OL on new likes of this product is reduced. Conversely, the positive effect of OL on new clicks is reduced. These suggest an interaction effect between OL and SI, and the pattern of interaction differs depending on whether the target engagement behavior is clicking or liking.

This research makes several contributions to the literature. First, we are among the first to show how existing likes can affect subsequent user engagement in an identity-relevant environment of social commerce. Second, our research contributes to the literature of OL by studying it in a highly identity-relevant online environment. While there is extensive research on OL, the focus has been non-identity-relevant environments. Our finding that the number of existing likes has a negative effect on subsequent likes is novel. It is a departure from the existing findings in the OL literature, which holds that people tend to follow popular choices made by the crowd. Third, we are one of the few studies that examine the interaction between OL and SI. With few exceptions [10], the prior literature has studied OL and SI separately. Our findings provide new evidence that SI attenuates the effect of OL, and the attenuation occurs with both clicks (where the OL effect is positive) and likes (where the OL effect is negative).

The rest of the paper is organized as follows. We next review the relevant literature, followed by the development of research hypotheses. We then present our empirical models, data, and findings. The final section discusses the implications of our research, its limitations, and future directions.

2. Related literature

This research intersects with the following literature streams: social commerce, OL and SI, and identity signaling. We discuss our relationship with these literature streams in turn.

2.1. Social commerce

Social commerce is a relatively new type of online platform that enables consumers to share information, experiences, and opinions about what, where and from whom to buy [11–14]. Emerged around 2005, social commerce is the convergence of social networking, user-generated content, and e-commerce [15,16]. Social commerce sites include both special-purpose websites for fashion (e.g. Polyvore and Stylehive), interior design (e.g., Polyvore), furniture (e.g., ShopStyle), and general-purpose social media platforms with support for commerce activities (e.g. Facebook and Pinterest). Most social commerce sites operate as referrals to other e-commerce sites while some support transactions within the platform. From recent research it was found that Facebook is the top social commerce site worldwide, and Polyvore leads in average order value [17].

The emergence of social commerce has drawn attention from scholars in the past several years. For example, existing studies identified acceptance factors [18–20], summarized its progress [13], and proposed major design features [15,21,22]. Research studies identified factors such as reputation, market share, information quality, as antecedents of users' trust, and purchase intentions on social commerce websites [23–29]. Social commerce is also studied from marketing perspectives. For example [30], found that intention to continue using social commerce has a positive influence on brand loyalty. To our knowledge, Olbrich and Holsing [31] is the only research on social commerce that uses objective archival data. Their study examined the roles of user-generated tags, high ratings, and idea boards in driving traffic to other e-commerce websites, whereas we focus on the role of existing likes in driving subsequent engagement.

There are very few empirical studies of likes in identity-relevant environments. Few existing studies seem to concentrate on Facebook, which is a highly identity-relevant social networking website. Kabadayi and Price [32] studied factors affecting consumers' liking behavior on Facebook brand pages using an online survey. They suggested that personality traits affect individuals' mode of interaction, which in turn determines if they like and/or comment on a post in a brand's Facebook page. There are also studies of likes on Facebook fan pages. Cvijikj and Michahelles [33] showed that posts with entertaining and informative content cause highest level of engagement (likes). Sabate et al. [34] demonstrated that inclusions of images and videos raise the impact of a post in terms of likes. Unlike these studies, we are interested in how existing likes impact subsequent user engagement in terms of clicks and likes.

2.2. Observational learning and social influence

Observational learning (OL), first proposed by Bandura [35], refers to the phenomenon that individuals' behavior is impacted by their observation of the behavior of others because of the information contained therein [36]. One widely used example of OL is restaurant selection. Observational learning occurs when consumers' choice of restaurants is significantly influenced by how crowded the restaurants are (i.e., they learn by observing the aggregate behaviors of others), especially when they are unfamiliar with the restaurants. Bandura's [35] OL theory is part of the broader social learning theory that includes mechanisms by which individuals learn from each other, with or without direct communications [35]. The notion of OL is later formalized in the economics literature by Banerjee [37] and Bikhchandani et al. [38], as information cascades: people infer the private information of the individuals before them by observing their behaviors, and such inferences lead them to choose the behavior same as that of the individuals before them. Because OL often leads to the copying of prior behaviors, it is also referred to as herding, although there are multiple mechanisms for herding, and not all of them are informational or based on observation of prior behaviors [39].

OL has been studied in numerous settings in Information Systems, Marketing, and other disciplines, and it is beyond our scope to offer a comprehensive review. Instead, we provide a few examples of such studies that support the OL idea in online platforms. Duan et al. [4] found that software's weekly rank and a total number of downloads has a positive impact on the download share of the software in the subsequent period. Simonsohn and Ariely [40] found that on eBay bidders seem not to draw rational inferences from earlier bids, whereas Zhang and Liu [41] showed that lenders on online peer-to-peer lending platform Prosper draw inferences on loan quality from prior bids and behave rationally. Liu et al. [42] also found observational learning between lenders of online peer-to-peer lending platforms. We note that most extant OL studies assume OL leads to herding, although the concept allows different inferences to be drawn. To our knowledge, the literature has not considered OL in identity-relevant settings.

The research on SI is concerned with how social interactions influence consumers' decisions. Different from OL, SI requires a *communication channel* between the influencer and the influenced, and an actual communication for the influence to occur [7,6]. Over the last decade, due to the emergence of social media, there has been an explosion of research on SI in the fields of Information Systems and Marketing. For example, Susarla et al. [43] found that social interactions influence on which videos become successful on YouTube. Aral and Walker [7] used a large-scale field experiment on Facebook to show that the strength of social influence is moderated by tie strength and structural embeddedness. Zeng and Wei [44] found the users' online social relations on Flickr influence their cultural outputs in the form of user-generated photography. Chen et al. [45] found that artists' broadcasting activities on MySpace have a significant effect on music sales.

It is worth noting that the term SI is often used interchangeably with word-of-mouth (WOM). Traditional WOM is defined as the one-to-one and face-to-face exchange of information about a product or service [46]. Recently, it has also been broadened to electronic WOM, which captures the information exchange through broadcast online channels such as product reviews on e-commerce platforms [47,48]. Our notion of SI emphasizes the interpersonal information exchange between socially connected individuals, rather than the broadcasting way of information exchange.

While there is no doubt that OL and SI each play an important role in disseminating user-generated content and products, there is little understanding of the interaction between the two. A brief literature review of recent empirical studies on OL and SI (see Table 1) reveals that a few studies examined OL and SI together on social media platforms, but not their interaction [43,10]. Li and Wu [49] found that the existing sales on Groupon (i.e., OL) have a positive impact on the sales of the next period, and Facebook likes and Twitter tweets of on a Groupon deal (i.e. SI) also benefit sales. In their study, SI and OL occurred on different platforms and they did not investigate the interaction between the two mechanisms.

2.3. Identity signaling

Identity-signaling model [8,9,52] suggests that consumers often make choices that diverge from those of others to ensure that they effectively communicate their desired identities and to avoid signaling undesired identities to others. Possessions (e.g., clothing), attitudes, behaviors (e.g., vocabulary used), and other cultural references can all be used to communicate identities [53–55]. In product domains, certain products more often serve as symbols of identity (e.g., car brands or fashion items) than others (e.g., tools). Research in marketing literature showed that consumers are more likely to diverge from majorities, or members of other social groups [8,9,52]. If a taste is adopted by majorities or out-group, it may lose its value as signals of desirable identities [56].

The identity signaling theory should be distinguished from the optimal distinctiveness theory (ODT), which also explains divergence behaviors. The ODT literature argues that when people feel overly similar to others, they strive to differentiate themselves [57]. While both ODT and identity signaling would predict divergence, they have different implications: ODT suggests that people differentiate to reduce their own internal uncertainty about who they are [58]. By contrast, identity signaling is about communicating an (divergent) identity to others. Such external divergence needs not be accompanied by internal differentiation. An example given by Berger and Heath [9] can illustrate this point: "Jocks would not want others to see them listening to music that geeks have adopted, but if they really liked a geek-adopted artist, they might continue to listen secretly in private."

As online social communication becomes an indispensable part of human lives, identity signaling has been frequently observed in online communities [59]. For instance, Zhang and Zubcsek [60] suggested that users' investment in online content generation serves as an observable signal and can be used to infer their true types (e.g., intrinsic enjoyment, prosocial attitude, or high skill levels). Zeng and Wei [44] examined users on Flickr and suggested that photos can represent uploaders' social identity, as defined by their interests, tastes, and capabilities. Liao [61] found that Second Life fashion bloggers continually construct and deconstruct their identities through virtual fashion play.

3. Hypotheses development

In this section, we focus on developing an understanding of how user engagement with identity relevant products in the forms of likes and clicks can be affected by existing likes.

We first note that identity signaling is a strong force in social commerce environments. Prior literature in offline consumer choices has already established that individuals signal their identity through the products they choose [53,62]. We similarly argue that identity signaling plays a significant role in online social commerce. Social commerce sites provide a strong foundation for online representations of individual identities. In our research context, similar to other typical social media websites, each user has a profile that contains identity-relevant information about this user [63], such as the products one likes or collects and the kinds of users one follows. Moreover, most products on social commerce platforms are highly identity relevant. Fashion, interior design, and art products tend to convey taste and identity [8,9]. Finally, users of the platform are self-selected fashion enthusiasts who care much about their identities. Taken together, social commerce platforms encourage users to develop and celebrate their online identities and provide many tools for doing so.

The main form of identity signaling on social commerce platforms is through liking products. Public endorsement activities such as liking are expressions of product fondness. Through the products they like, users can signal to others (followers and bystanders) their preferences and tastes. However, not all activities on social commerce platforms signal identities. A click reflects a user's interest in a product, but because it is not a publicly observable behavior, it does not convey identity information. Below, we discuss how existing likes affect subsequent likes and clicks through observational learning and social influence.

3.1. The number of existing likes as an observational learning signal

The identity signaling perspective holds important implications for the liking behavior. The identity signal theory suggests that people have a need to be associated with certain social status, and such needs for status are met when individuals signal their identity by converging to their reference groups, and diverging from the majority and out-group choices [8]. For example, when Volkswagen Santana became the popular choice of suburban nouveaux riches, Shanghai residents avoided purchasing it [64]. In the fashion domain, people distinguish themselves by deviating from the popular choices [38]. Applying the identity signaling argument, when a product is liked by more people from the crowd (which are out-group members), people are less likely to like it (i.e., diverge from crowd/out-group choices), for liking it would signal an undesirable identity. Thus, we expect a higher number of existing likes as a stronger observational learning signal to have a negative

Table 1
Recent Empirical Studies on Observational Learning and Social Influence.

Study	Research Method	Product	Dependent Variable	Operationalization of OL	Operationalization of SI	Major Findings
[4]	Panel fixed estimation on one-month *software download* data from CNET	Software	Share of software download in each individual category	Suggested three drives of herd behavior, i.e., information cascade, network effect, and WOM effect. Information cascade is the focus of this study; it is captured as WEEKLYRANK. Network effect is captured by TOTALDOWNLOADS.	N/A	Choices of software products exhibit distinct jumps and drops, as predicted by the informational cascades theory. User reviews have no impact on user adoption of the most popular product, while having an increasingly positive impact on the adoption of lower ranking products.
[3]	A natural experimental setting resulting from information policy shifts at *Amazon*	Digital cameras	Amazon sales rank	The OL section is presented under the "What do customers ultimately buy after viewing this item?" section. For each camera in our sample, we collected the purchase percentage data for all listed cameras in this section	N/A	Negative WOM is more influential than positive WOM, positive OL information significantly increases sales, but negative OL information has no effect.
[43]	A panel data of video and user information collected from YouTube over two months	YouTube videos	The difference of the number of clicks to the video between t and t − 1	The total number of clicks to the video	The video creator's network centrality in his subscriber network and friend network	The number of subscribers/friends of a video creator on YouTube has a positive impact on the rate of video diffusion.
[50]	A longitudinal online experiment with two surveys conducted at the adoptive and post-adoptive stage	An online wiki system	Several variables in the SEM model, such as Intention to Use, Intention to Discontinue, Satisfaction	OL means a person follows others when adopting a technology. Two messages are provided to treatment groups. 1) A message stating that PBwiki had been adopted by a large number of users. 2) a short list of some well-known organizations that had adopted PBwiki	N/A	Herd behavior has a significant influence on user technology adoption. Imitation can help reduce post-adoption regret.
[10]	Choice data from a two-stage conjoint choice experiment: a pre-influence and a post-influence stage. Analyzed with a discrete-time Markov chain model	Choose a bundle of university sports paraphernalia and a Bluetooth headset from four bundles.	Participants' choices in 12 conjoint choice tasks	Percentage of choices for each of the four product bundles	The name of participants' classmates who choose a certain bundle	Experts exert asymmetrically greater influence on a technology-related product; popular individuals exert greater influence on a fashion-related product. In addition, we find choices made by early decision makers to be more influential than choices made later for the technology-related product.
[51]	A panel analysis of detailed usage of KMS for seven months	Knowledge Management System (KMS)	Individual monthly KMS use	N/A	Prior KMS usage of each reference group (subordinates, superiors, peers, and extended professional population)	Strong evidence of bottom-up social influence across hierarchical levels, but not top-down or peer levels.
[7]	Cox proportional hazard model on data collected from a large-scale field experiment on Facebook	An application allows users to share information and opinions about movies, actors, etc.	The hazard of a peer (of an existing application user) adopting the application	N/A	The number of adoption notifications received by an adopter's peer.	The strength of social influence is moderated by tie strength and structural embeddedness
[42]	Conditional logit on a dataset of community members and connections, listings, biddings, and repayments for 18 months	Bid on a peer-to-peer loan	A binary variable indicating lender's bidding decision	The number of prior bids. The number of prior bids from the lender's strong-tie/weak-tie/online friends.	N/A	A potential lender is more likely to bid on a listing as the number of prior bids on the listing increases, and is more likely to bid on a listing if a prior bid on the listing is by an offline friend rather than by an online friend of the lender.
[49]	A panel data of Groupon deals and associated Facebook likes and Twitter tweets	Groupon deals	The new sales of a Groupon deal	The existing sales of a Groupon deal	Facebook likes and Twitter tweets	The existing sales, Facebook likes and Twitter tweets have positive impacts on the sales of a Groupon deal

effect on subsequent likes. Therefore, we hypothesize that,

H1. The number of existing likes as an observation learning signal has a negative impact on subsequent likes received by a product.

Unlike likes, clicks are private behaviors. When a user clicks on a product link to see more details, the click event does not leave a digital trace for other users to draw inferences about the focal user's identity. In other words, clicks provide users a space for exploration without worrying about identity signaling. When a user observes a product liked by many others, her expected value/desirability of the product is high, which motivates her to check it out. She may also use the opportunity to find out what out-group members like. Overall, we expect a higher number of existing likes as a stronger observational learning signal to increase subsequent clicks on the product.

H2. The number of existing likes as an observational learning signal has a positive impact on subsequent clicks received by a product.

3.2. The moderating role of social influence

When a platform has a significant social networking function, existing likes can also affect user behaviors through social influence; that is, existing likes can also influence subsequent user engagement through liker's social connections. We are especially interested in how social influence moderates observational learning. The specific setting for such an interaction to occur is as follows: when a person sees a product through social connections (e.g., by receiving updates on friend likes or browsing friends' likes), she is subject to social influence by the social connections, along with observational learning (i.e., the number of existing likes).

While the identity signaling theory stresses divergence from out-group, it also suggests conformity with in-group members. When most other IT engineers wear jeans to work, an IT engineer may do the same so as to not be seen as an outsider. Such convergence behaviors can also be explained by normative social influence [65,66]. When a product liked by out-group members is also liked by in-group members, a user can infer that liking the product is acceptable to other in-group members and will not undermine their common identity. Moreover, the fact that the product is liked by many users suggests that the product may be highly desirable. Thus, overall, one may expect that a high level of social influence can reduce the negative effect of observational learning on subsequent likes.

H3. Social influence attenuates the negative impact of observational learning on subsequent likes

Like the effect of OL on clicks, the social influence generated by likes of social connections can also increase a user's expectancy about the value/desirability of a product, and motivate clicks. When there is a high level of SI (which happens when likers have many social connections), users can form a high value expectation from their social connections; hence, by the law of diminishing returns, a unit increase in OL would have less impact on increasing users' value expectation, than when SI is low. In other words, the positive effect of OL on clicks is reduced by SI. Thus, we hypothesize a negative interaction between the observational learning and social influence effects of existing likes on new clicks,

H4. Social influence attenuates the positive impact of observational learning on subsequent clicks

4. Research context

Our research site is Polyvore, a leading US social commerce site dedicated to fashion, interior design and artistic expressions. We studied a dozen social commerce sites and chose Polyvore because of its popularity, robust design, and availability of detailed data. Polyvore was founded in 2007. As of August 2015, the website had over 20 million monthly unique visitors [67,68].[1] Polyvore provides users a suite of tools for curating products (e.g., like a product, create product collections and idea boards, like/comment idea boards, etc.) and following each other. Each registered user has a profile page, which has information about a user's tenure on Polyvore, such as a self-description, a summary of her activities and social networks, and tabs on user's activities such as likes, idea boards, and collections. Once a user starts to follow another user, she automatically gets updates on that user's activities.

Polyvore does not sell products but provides a link to a third-party site where users can buy them, which we call *source*. The website maintains a massive product repository and users can contribute to the repository by clipping a product from an external source. For third-party sites who have an affiliate program with Polyvore, Polyvore gets a commission cut on transactions originated from Polyvore [69].

When users browse pages on Polyvore (e.g., products, idea boards, and user profile pages), related products appear as product cards, which consists of a clickable product picture, the product name, the sales price (and the original price before discount, if any), the source, and the number of likes (Fig. 1). The product card allows a user to like the product through a heart-shaped like button and to click the product picture to view a product detail page (Fig. 2). The product details page contains additional information such as the product's category, a product description, idea boards and collections that feature the product, and related products ("similar" or "people also liked"). The product detail page provides tools for a user to like the product (through a heart-shaped like button), create an idea board using the product, and collect the product.

A product gets a "click" when a user clicks on a product card to view product detail. We consider a click as a private engagement behavior because other users cannot find out who have clicked on what, and there is no ostensible display of total clicks.[2] By contrast, we consider a "like" as a public engagement behavior because one can find out another user's likes through that user's profile page, or get social-network updates if she follows that user. It is worth noting that, on Polyvore, a click can occur without a like, and vice versa. This is because there is a "like" button on product cards that allows a user to like a product without clicking.

5. Research method

We collect a random sample of 930 tote handbags from the website. While any product could theoretically be used to infer identity, we choose handbags for two reasons. First, fashion products, of which the color and style are symbolic, are particularly well suited for inferring identity [8]. Handbags have been studied as a typical identity relevant product by prior studies [70,71]. Second, unlike other fashion products such as clothing, handbags are not a strongly seasonal product.

With permission, we collected data from Polyvore on a biweekly basis for 8 consecutive periods (each period is a two-week interval) from September 2013 to Jan 2014. For each handbag, we collected product information (price, brand, category, discount, and age on the website), and users' engagement with the product, including clicks and likes. We additionally collected information about users who liked the products.

[1] In August 2015, the website was acquired by Yahoo with $200 million in cash. (Source: Alba, D. 2015. "Yahoo Snags Social Commerce Site Polyvore." from http://www.wired.com/2015/07/yahoo-buys-social-commerce-site-polyvore/).

[2] We accidentally found out about the total number of total clicks because the website released a new mobile app that showed the number of total clicks in one of the obscure areas folded by default. Based on the number of app downloads and how the clicks were displayed, we believe users were not generally aware of total clicks during the period of this study.

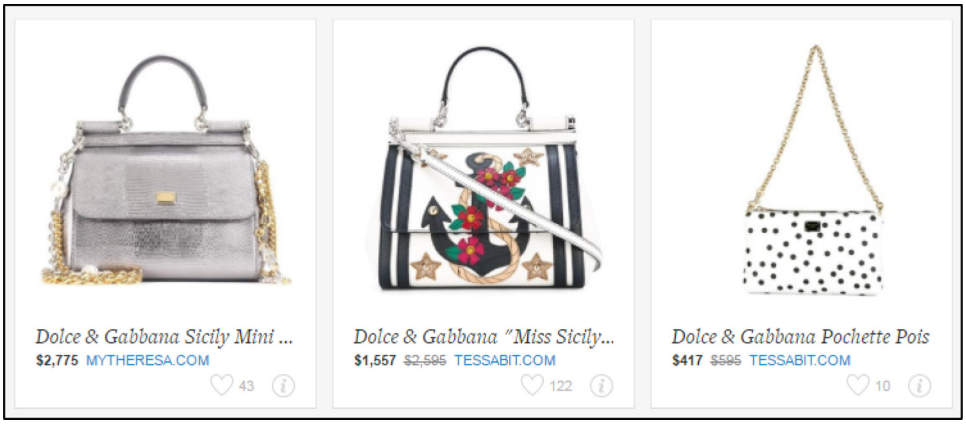

Fig. 1. Product Cards.

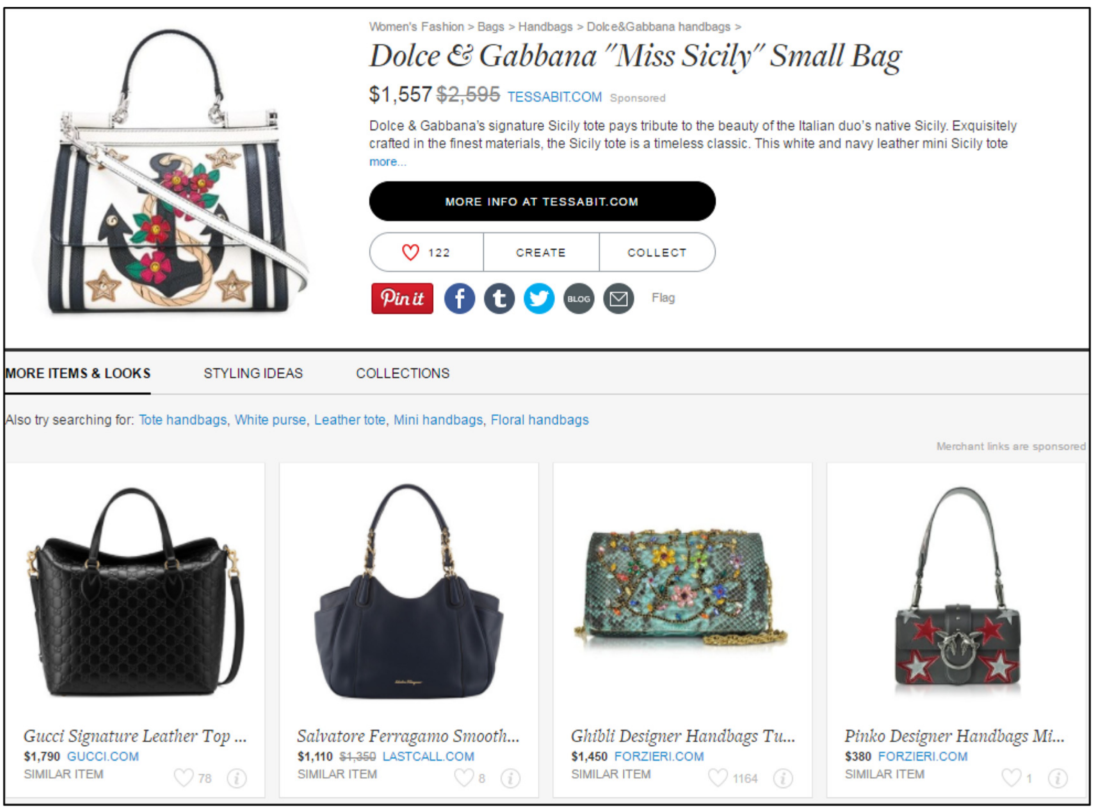

Fig. 2. A Product Detail Page.

5.1. Variables

5.1.1. Clicks and likes

As we have mentioned earlier, a click is registered when a user clicks on a product card to view details about this product. A like is registered when a user likes a product on the product card or detail page. We define $logNewClicks_{it}$ as the log number of new clicks of product i from time $t-1$ to t,[3] and $logNewLikes_{it}$ as the log number of new likes of product i from time $t-1$ to t.

5.1.2. Observational learning

Observational learning is triggered when a user observes a signal about other users' aggregate behaviors. In our context, the signal for observational learning is the number existing likes displayed on the product card/detail page. Following prior research [49,41], we use log number of existing likes at time $t-1$ to capture the observational learning effect received by product i at time $t-1$:

$$logOL_{it-1} = \log(Likes_{it-1} + 1)$$

5.1.3. Social influence

In the context we study, whenever a user likes a product, all of her followers are updated about this event and thus subject to social influence. A new like can simultaneously generate an observational learning effect (the number of existing likes increases by 1) and a social influence effect. To separate the two effects, we note that, unlike observational learning, social influence propagates through social ties, a product liked by a user who has more followers is expected to receive a stronger social influence effect because more users are reached. Taking advantage of this observation, we use the number of followers of a

[3] We use log transformed variables whenever their distributions are skewed.

product's new likers to identify the effect of social influence. That is, we use $logSI_{it-1}$, the log total number of followers of those who liked product i from time $t-2$ to $t-1$, to capture the amount of social influence received by product i from time $t-2$ to $t-1$:

$$logSI_{it-1} = \log\left(\sum_{j=1}^{NewLikes_{it-1}} LikerFollowers_{jt-1} + 1\right)$$

where $NewLikes_{it-1}$ is the number of new likes that product i received from time $t-2$ to $t-1$ and $LikerFollowers_{jt-1}$ is the number of followers that liker j had at time $t-1$.

5.2. Model for likes

We model $logNewLikes_{it}$ as a function of observational learning ($logOL_{it-1}$), social influence ($logSI_{it-1}$), and their interaction ($logOL_{it-1}$ $*logSI_{it-1}$) as follows:

$$logNewLikes_{it} = \alpha_i + \beta_1 \ logOL_{it-1} + \beta_2 \ logSI_{it-1} + \beta_3 \ logOL_{it-1} * logSI_{it-1} + \lambda \ Controls + \varepsilon_{it} \quad (1)$$

where *Controls* is a set of control variables explained below, and ε_{it} is an i.i.d random disturbance term.

We use several variables as controls. First, the number of new likes and new clicks vary naturally over time as part of the product diffusion process. This dynamic process can be captured by the popular Bass diffusion model. Following prior literature [4,49], we include both a linear component, the log product age ($logAge_{it}$), and a nonlinear component, the squared log product age ($logAge\_SQ_{it}$), as explanatory variables to capture the effect of Bass diffusion.

Several other factors could also influence the number of new likes, including the number of idea boards ($logIdeaBoards_{it-1}$) and product collections ($logCollections_{it-1}$) that feature product i at time $t-1$, the sales price of the product ($logPrice_{it-1}$) at time $t-1$, and the discount rate ($Discount_{it-1}$) at time $t-1$. To absorb common temporal shocks and site-wide promotions, we also include period dummies as controls.

5.3. Model for clicks

Similar to the model for likes, we specify the model for clicks as:

$$logNewClicks_{it} = \gamma_i + \delta_1 \ logOL_{it-1} + \delta_2 \ logSI_{it-1} + \delta_3 \ logOL_{it-1} * logSI_{it-1} + \phi \ Controls + \mu_{it}, \quad (2)$$

where *Controls* is a set of control variables including $logIdeaBoards_{it-1}$, $logCollections_{it-1}$, $logPrice_{it-1}$, $Discount_{it-1}$, $logAge_{it-1}$, $logAge\_SQ_{it-1}$, and *Period* dummies, and $\mu_{it}$is an i.i.d random disturbance term.

To capture the unobserved co-variation between clicks and likes, we combine the two equations to build a simultaneous equation model (SEM). Specifically, we assume the error terms of the clicks and likes equations are correlated and follow the Multivariate Normal distribution with mean zero in the following way.

$$[\varepsilon_{it}, \mu_{it}] \sim \text{MVN}(0, \Sigma), \quad (3)$$

where Σ is a covariance matrix.

5.4. Estimation strategies

We use several estimation strategies. First, the interaction term in the Likes model makes it difficult to interpret the estimated model coefficients. To make the model more interpretable, we center $logSI_{it-1}$ by subtracting the mean from its value, so that β_1 can be interpreted as the average partial effect of $logOL_{it-1}$ [72]. We apply the same approach to the Clicks model.

Second, Eqs. (1) and (2) form a system of regressions. Following Wooldridge [72], we take two steps to estimate this SEM model with panel dataset. (1) To eliminate the unobserved time-invariant product heterogeneity, we apply a product fixed effects transformation to the equations. (2) We then adopt an instrumental variable (IV) approach to take care of the endogeneity between clicks and likes in the transformed model. Specifically, we use the product stock information, $soldout_{it-1}$ (i.e., whether the product is sold out at time $t-1$) as an instrument for $logNewLikes_{it}$. It is chosen for the following reasons. On Polyvore.com, when a product goes out of stock at the source site, it is marked as "sold out" on the product detail page but not on the product card. Thus, *soldout* does not directly affect new clicks (which satisfies the exogeneity condition of IVs). On the other hand, *soldout* can still affect likes because a user can like the product after landing on the product detail page (which satisfies the relevance condition of IVs). Hence, $soldout_{it-1}$ could be a valid instrumental variable for $logNewLikes_{it}$.

Third, we apply the Huber-White adjustment in the 2SLS estimation to attain standard errors that are robust to potential heteroscedasticity in the panel dataset.

Fourth, because $logIdeaBoards_{it-1}$ and $logCollections_{it-1}$ are highly correlated with $logOL_{it-1}$, with correlation coefficients of 0.78 and 0.71, respectively, we exclude the two control variables in the main analyses, but report a robustness test result with the two variables included.

6. Results

6.1. Descriptive statistics

Table 2 provides the definitions and descriptive statistics for the variables used in the regressions (we use the original variables instead of the log-transformed ones here for easy interpretation). The average new clicks that a product received is about 454, and the average new likes is about 1. The average and maximum social influence (in terms of the number of liker followers) for a product are 3428 and 804,402, respectively. The product age ranges from 23 to 395 days, with an average of 160 days.

Table 3 presents Pearson correlation coefficients between model variables. We also conducted analyses of collinearity for the Clicks and Likes models. The average VIF is less than 2, and all VIFs are well below the suggested threshold of 10, suggesting that collinearity is not a concern.

Table 2
Variables definition and descriptive statistics (N = 7440).

Variables	Description	Mean	Std. Dev.	Min	Max
$NewClicks_{it}$	Number of clicks that product i received from time $t-1$ to t	454.24	827.39	0	33,161
$NewLikes_{it}$	Number of likes that product i received from time $t-1$ to t	0.89	3.49	0	115
OL_{it-1}	Total likes that product i received at $t-1$	23.43	84.15	0	1516
SI_{it-1}	Total number of followers of those who liked product i from $t-2$ to $t-1$	3,428.61	19,954.27	0	804,402
$Price_{it-1}$	Price of product i at $t-1$ after any discount	1,081.94	938.35	9.99	6200
$Discount_{it-1}$	Percentage price off product i at $t-1$	3.48	11.65	0.00	80.20
Age_{it}	Days elapsed at t since product i was first introduced to the platform	160.52	78.07	23	395
$IdeaBoards_{t-1}$	Number of idea boards that product i is featured in at $t-1$	5.98	20.88	0	310
$Collections_{t-1}$	Number of collections that product i is part of at $t-1$	0.91	3.41	0	61

Table 3
Pearson correlations between variables (N = 7440).

	Variables	1	2	3	4	5	6	7	8	9	10
1	$logNewClicks_{it}$	1.00									
2	$logNewLikes_{it}$	0.45***	1.00								
3	$logOL_{it-1}$	0.39***	0.58***	1.00							
4	$logOL\_SQ_{it-1}$	0.07***	0.50***	0.41***	1.00						
5	$logSI_{it-1}$	0.44***	0.53***	0.43***	0.25***	1.00					
6	$logPrice_{it-1}$	0.18***	0.14***	0.16***	0.07***	0.14***	1.00				
7	$Discount_{it-1}$	−0.06***	−0.03**	0.03**	−0.00	−0.01	−0.29***	1.00			
8	$logAge_{it-1}$	−0.17***	−0.06***	0.20***	0.04**	−0.21***	−0.01	0.14***	1.00		
9	$logAge\_SQ_{it-1}$	0.12***	0.05***	−0.14***	0.01	0.18***	−0.00	−0.03**	−0.63***	1.00	
10	$logIdeaBoards_{it-1}$	0.23***	0.52***	0.78***	0.54***	0.34***	0.07***	0.04***	0.21***	−0.11***	1.00
11	$logCollections_{t-1}$	0.25***	0.53***	0.71***	0.64***	0.34***	0.13***	0.07***	0.22***	−0.10***	0.69***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4
Results of panel fixed effect 2SLS estimation (N = 7440).

	DV = $logNewLikes_{it}$				DV = $logNewClicks_{it}$			
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
$logPrice_{it-1}$	0.033	0.043	0.009	0.011	−0.013	−0.239	0.512	0.487
	(0.048)	(0.046)	(0.045)	(0.044)	(0.741)	(0.830)	(0.403)	(0.413)
$Discount_{it-1}$	−0.000	−0.001	−0.001	−0.101	0.001	0.005	0.005	0.006
	(0.001)	(0.001)	(0.001)	(0.134)	(0.020)	(0.025)	(0.012)	(0.012)
$logAge_{it-1}$	**−0.414***	−0.010	0.191	0.059	4.629	−0.970	**−3.325***	−2.065
	(0.193)	(0.191)	(0.181)	(0.182)	(2.938)	(3.337)	(1.584)	(1.632)
$logAge\_SQ_{it-1}$	−0.056	0.081	**0.127***	0.102	0.542	−1.544	**−1.346***	**−1.147***
	(0.067)	(0.066)	(0.061)	(0.061)	(1.010)	(1.172)	(0.543)	(0.554)
$logSI_{it-1}$		**0.033*****	**0.036*****	−0.010		**−0.532*****	**−0.274*****	**0.176*****
		(0.003)	(0.003)	(0.006)		(0.077)	(0.031)	(0.051)
$logOL_{it-1}$			**−0.569*****	**−0.520*****			**6.397*****	**6.122*****
			(0.041)	(0.041)			(0.335)	(0.341)
$logOL_{it-1} * logSI_{it-1}$				**0.017*****				**−0.175*****
				(0.002)				(0.022)
Soldout	**−0.168*****	**−0.144*****	**−0.259*****	**−0.249*****				
	(0.015)	(0.015)	(0.017)	(0.017)				
$logNewLikes_{it}$					**15.448*****	**17.722*****	**8.828*****	**9.220*****
					(1.374)	(1.789)	(0.569)	(0.607)
R-squared	0.051	0.088	0.132	0.150	0.267	0.281	0.371	0.371

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Period dummies are included for all models. The Huber-White adjustment was used to obtain robust standard errors.

6.2. Findings

Table 4 presents the results of panel data fixed-effect 2SLS estimation for the Likes and Clicks models. We start from the base models with only the control variables. We then add the variables for observational learning, social influence, and their interaction sequentially. In this way, we can get an idea of the explanatory power of the main variables. The findings are qualitatively similar across different model specifications. For ease of interpretation, we mainly discuss the results reported in column 4 and column 8.

In the Likes model, the coefficient of $logOL_{it-1}$ is negative, that is, a product's number of existing likes has a negative impact on subsequent likes received by the product. Therefore, H1 is supported. The coefficient for the interaction term is positive ($p < 0.001$), indicating that the negative impact of OL on subsequent likes reduces as SI increases. Thus, H3 is supported.

Next, in the Clicks model, the coefficients of $logOL_{it-1}$ is positive ($p < 0.001$), indicating that the observational learning signal has a positive effect on subsequent clicks. Therefore, H2 is supported. We find a negative coefficient for the interaction term ($p < 0.001$), which suggests a diminished marginal effect of OL on clicks as SI increases. Therefore, H4 is supported.

Neither product price nor discount rate has any effect on new likes or new clicks. This is likely because users of Polyvore are mainly interested in product discovery and curation, not necessarily purchases. Thus, their engagement behaviors are not very sensitive to price or discount rate changes. In addition, when a product is marked as sold out, it is less likely to be liked by users on the social commerce website. We note that the coefficient of SI on clicks has changed from negative in the two models without the interaction term (columns 6 and 7), to positive in the full model (column 8). This change reflects the fact that the coefficient of SI carries different meanings between the models without the interaction term and the full model. It suggests that, despite the effect of SI on clicks is positive in the absence of OL (column 8, the main SI term), its effect turns negative quickly as OL increases because of the negative interaction with OL (column 8, the interaction term). As a result, on average, the effect of SI on clicks is negative for all possible values of $logOL_{it-1}$ (columns 6 and 7). Overall, this suggests that OL is a dominant driver for new clicks and SI can drive new clicks when a product has very few accumulate likes.

7. Further analysis and robustness checks

In this part, we start by extending the main analyses to gain more insights into the OL effects. We then conduct several robustness analyses. The results of these robustness checks are largely consistent with the main analyses.

7.1. How do the effects of OL on likes and clicks change with product popularity?

Extending our main analyses, we argue that the marginal effect of

Table 5
Results of Robustness Check.

	$DV = logNewLikes_{it}$					$DV = logNewClicks_{it}$				
	OLS	NB[1]	2SLS_1	2SLS_2	PVAR[2]	OLS	NB[1]	2SLS_1	2SLS_2	PVAR[2]
$logPrice_{it-1}$	0.011	0.075	0.010	0.011		**1.053*****	**0.105*****	0.480	0.486	
	(0.043)	(0.080)	(0.044)	(0.044)		(0.259)	(0.017)	(0.414)	(0.418)	
$Discount_{it-1}$	−0.001	0.003	−0.001	−0.001	−0.055	−0.000	**−0.007*****	0.006	0.009	0.174
	(0.001)	(0.006)	(0.001)	(0.001)	(0.032)	(0.007)	(0.001)	(0.012)	(0.012)	(0.128)
$logAge_{it-1}$	0.059	0.342	0.081	0.179	0.046	−0.233	**−0.124****	−2.173	−3.081	**−1.018*****
	(0.193)	(0.203)	(0.181)	(0.178)	(0.039)	(1.005)	(0.042)	(1.630)	(1.650)	(0.252)
$logAge\_SQ_{it-1}$	0.102	**0.513*****	0.109	**0.139***	0.038	0.278	**0.129*****	**−1.183***	**−1.476****	**−0.635*****
	(0.065)	(0.085)	(0.061)	(0.059)	(0.033)	(0.337)	(0.031)	(0.554)	(0.556)	(0.133)
$logSI_{it-1}$	−0.010	**0.036***	−0.010	−0.008	**−0.048***	**0.069*****	**0.080*****	**0.173*****	**0.161****	**0.130*****
	(0.006)	(0.018)	(0.006)	(0.006)	(0.019)	(0.017)	(0.008)	(0.052)	(0.052)	(0.035)
$logOL_{it-1}$	**−0.520*****	**−0.270*****	**−0.505*****	**−0.635*****	**−0.951*****	**3.069*****	**0.389*****	**6.097*****	**7.201*****	0.632
	(0.048)	(0.070)	(0.041)	(0.057)	(0.280)	(0.166)	(0.015)	(0.336)	(0.510)	(1.003)
$logOL_{it-1} * logSI_{it-1}$	**0.017*****	**0.022*****	**0.017*****	**0.017*****	**0.032*****	−0.004	**−0.009*****	**−0.174*****	**−0.176*****	**−0.027***
	(0.002)	(0.006)	(0.002)	(0.002)	(0.006)	(0.006)	(0.002)	(0.022)	(0.022)	(0.011)
$Soldout_{it}$			**−0.248*****	**−0.242*****						
			(0.017)	(0.017)						
$logIdeaBoards_{it-1}$			−0.045					−0.094		
			(0.034)					(0.302)		
$logCollections_{it-1}$			−0.029					0.357		
			(0.064)					(0.569)		
$logOL\_SQ_{it-1}$				**−0.127*****					**1.058*****	
				(0.022)					(0.204)	
$logNewLikes_{it-1}$					**−0.057***					**−0.153****
					(0.026)					(0.055)
$logNewClicks_{it-1}$					−0.012					**0.871*****
					(0.019)					(0.080)
R-squared	0.371	–	0.374	0.373	–	0.119	–	0.151	0.163	–
N	7440	7440	7440	7440	5580	7440	7440	7440	7440	5580

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The Huber-White adjustment was used to obtain robust standard errors.
Note: 1. In the Negative binomial models, we use the raw clicks and likes instead of log form. 2. We do not include $logPrice_{it-1}$ in the PVAR estimation for its occurrence with *Discount* causes the estimation to be unstable.

OL may not be the same for popular and unpopular products. One possible argument is that for identity-relevant engagement behaviors such as likes, when a product is popular, as indicated by a large number of existing likes, people who are driven by their needs for distinct identity are more likely to display a divergence tendency (by not liking it), especially because the existing likes accrue from out-group users. By contrast, the clicking behavior does not suffer from similar identity concerns; the effect of OL on clicks could strengthen with product popularity because OL signals become much stronger when there are many existing likes, and people tend to converge onto a "star" product when identity is not an issue.

To test the aforementioned ideas, we include a square-term $logOL\_SQ_{it-1}$ (so that one *logOL* in the square term can be interpreted as product popularity), and re-estimate our models for Likes and Clicks. Results from Table 5 (the "2SLS_2" columns) show that the coefficient of $logOL\_SQ_{it-1}$ in the Likes model is negative ($p < 0.001$), confirming our intuition that the divergence tendency in the liking behavior is stronger for more popular products. The coefficient of $logOL\_SQ_{it-1}$ in the Clicks model is positive ($p < 0.001$), confirming out intuition that the convergence tendency in clicks is stronger for more popular products. We note that this finding also validates our initial argument that identity signaling can change the way people react to OL signals.

7.2. Robustness checks

As a robustness test, we also estimate the Likes and Clicks models with OLS. Although OLS is not the best linear estimator when there is co-variation between the two dependent variables, it should still provide a good approximation and suffer from fewer estimation challenges than more advanced models. Because our dependent variables (before the log transformation) are count variables, we also estimate a negative binomial (NB) regression for raw counts of clicks and likes. Both OLS and NB estimations yield similar results as our main analysis (Table 5, columns OLS and NB), suggesting that our findings are robust to our model choice.

One may be concerned whether including $logIdeaBoards_{it}$ and $logCollections_{it}$ as control variables can significantly alter our results. Recall that we exclude these two variables in the main analysis out of concerns about their high correlations with OL. To address this concern, we report the results with the two variables included. As seen Table 5 (columns 2SLS_1), the main results remain quite similar.

To further address the concern that $logNewLikes_{it}$ and $logNewClicks_{it}$ may be jointly endogenous, we also estimate a Panel Vector Auto-Regression (PVAR) model [73], as an alternative to the SEM model in our main analysis. The PVAR approach to deal with simultaneity has a few benefits. First, it treats the two variables ($logNewLikes_{it}$ and $logNewClicks_{it}$) as jointly endogenous and assesses the nature of bidirectional causality between them. Second, it allows for lagged effects within and across time series, which is suitable for modeling the dynamic relationships between clicks and likes [45,74]. To use this model, we let each dependent variable, $logNewLikes_{it}$ and $logNewClicks_{it}$, to be a linear function of its own past values and the past value of the other dependent variable. Our PVAR model is specified as below:

$$y_{it} = \begin{pmatrix} logNewLikes_{it} \\ logNewClicks_{it} \end{pmatrix} = \sum_{s=1}^{p} \Phi_s \cdot \begin{pmatrix} logNewLikes_{it-s} \\ logNewClicks_{it-s} \end{pmatrix} + \beta_1 logOL_{it-1} + \beta_2 logSI_{it-1} + \beta_3 logOL_{it-1} \cdot logSI_{it-1} + \lambda Controls + f_i + \varepsilon_{it}, \tag{4}$$

where $y_{it} = (logNewLikes_{it}, logNewClicks_{it})'$ is a two-element column vector for product i at time t; Φ_s' represent 2×2 matrices of slope coefficients for endogenous variables; p is the number of lags, which is set to be one in our case according to the lag selection criteria; *Controls* is a set of exogenous variables including $Discount_{it-1}$, $logAge_{it-1}$, $logAge\_SQ_{it-1}$,; $f_i = (f_{1i}, f_{2i})'$ is a column vector of unobserved product fixed effects; $\varepsilon_{it} = (\varepsilon_{1,i,t}, \varepsilon_{2,i,t})'$ is a two-element vector of errors.

The PVAR analysis are carried out as follows. We first conduct two types of unit root tests, Harris-Tzavalis test [75] and Im-Pesaran-Shin test [76], to verify the absence of unit roots in our panel data. Both tests indicate that there is no unit root in our panel. We then conduct a lag order selection procedure for PVAR. Based on the overall coefficient of determination (CD), which captures the proportion of variation explained, we determine that a lag length of 1 is optimal. After that, we perform a Helmert transformation on both the endogenous and exogenous variables, which ensures the orthogonality between the forward-differenced variables and their lagged values [73]. Those lagged regressors are used as instruments for the forward-differenced variables. Finally, the system GMM estimator is employed to allow for error correlation across equations [74].

Overall, the PVAR findings are mostly consistent with our main estimations (Table 5, the “PVAR” columns). One exception is that the effect of OL on subsequent clicks is no longer significant. There could be two explanations. First, we note that in the PVAR model, the effect of the new variable $logNewClicks_{it-1}$ is strongly positive. It is possible that the effect of OL on new clicks is fast-acting such that it is absorbed by $logNewClicks_{it-1}$ when the latter is included. A finer time interval (recall our time interval is two weeks) would allow us to test this conjecture, but unfortunately, our data do not allow it. Second, the reduced sample size (from 7440 to 5580) might have also contributed to the lack of significance. The PVAR model discards the first period to calculate the lagged variables, which is costly because we have a relatively short panel of 8 periods.

8. Discussion and concluding remarks

Motivated by a lack of understanding of user engagement with identity relevant products, we examine how existing likes can engender new likes and clicks at a fashion-focused social commerce website. We distinguish two mechanisms by which existing likes may affect users' subsequent engagement: observational learning (OL) by observing the number of existing likes, and social influence (SI) by receiving latest likes from users' social connections. Furthermore, we distinguish between private (“clicks”) and public (“likes”) engagement behaviors.

While most OL literature predicts that people copy other's behavior, we find an opposite effect when it comes to liking a fashion product – users avoid liking a fashion product when the product has already received many likes. Interestingly, this “divergence” behavior is attenuated by SI, in that users are less likely to avoid liking the product when some of their social connections like the product. We explain these findings as a result of identity signaling – in identity relevant contexts, people diverge from “out-group” behaviors (likes by the “crowd”), but conform to in-group behaviors (likes by their social connections), to effectively communicate their identities.

Indeed, when the engagement behavior is not identity revealing, as in the case of private clicks, we observe a very different relationship. We find an increase in the number of existing likes has a positive impact on clicks received by a product, and SI attenuates the positive effect, indicating a substitution effect between OL and SI for clicks.

While our analysis focuses on likes and clicks in social commerce, our findings may have implications for other types of private and public engagement activities such as up-votes, saves, and Twitter mentions, and for a larger variety of online social platforms (such as digital content distribution and online communities). Further, we discuss the implications of our findings for academic and industry audiences.

8.1. Theoretical contribution

This study contributes to a few literature streams. First, we contribute to the literature on likes by systematically documenting how existing likes affect future clicks and likes in identity-relevant environments.

Second, we contribute to the OL literature in a few ways. The extant OL literature almost always predicts convergence, i.e., subsequent individuals will copy the behaviors of those before them as a result of observing aggregate behaviors. We demonstrate the boundary of this “convergence effect” of OL: when the behavior is identity relevant, OL could lead to divergence behaviors. We believe this finding will become increasingly relevant as more online behaviors such as likes and shares become increasingly identifiable thus could be identity relevant.

To our knowledge, this is one of the few studies that have systematically examined how SI moderates OL in an online social platform. We find SI can attenuate both the positive effect of OL (in the case of clicks) and the negative effect of OL (in the case of likes). Prior literature has treated OL and SI as two independent processes (e.g., [43,10]), and we add to the literature by suggesting that the two actually interact with each other.

Third, we offer a new theoretical perspective and empirical evidence on why likes and clicks should be treated very differently in identity-relevant environments, although both represent user engagement [77]. Drawing from the identity signaling theory, we propose and find evidence that displaying the number of existing likes can promote new clicks but discourage new likes; we further show that both effects are stronger for more popular products, which are consistent with the identity signaling theory. Our findings highlight the private nature of clicks and the public, identity-signaling nature of likes. While our findings are derived in the context of identity-relevant products, we believe this distinction could have broader implications as the identity-signaling nature of likes can turn many objects into an identity domain.

Finally, we demonstrate the value of the identity-signaling model on studying user interactions on social platforms and empirically validate the differences between the identity-signaling model and other theories that predict divergence behaviors, such as the optimal distinctiveness theory. Rather than focusing on internal drives to be different from others, the model of identity-signaling emphasizes the social process of communication, i.e., external benefit. Accordingly, we find a negative impact of OL on likes, but not on clicks.

8.2. Managerial implications

Our findings have several managerial implications. First, our findings provide insights on how likes can be best leveraged as a user-engagement tool. Likes can be both used as an observational learning signal and as social media content to be shared on social networks. Our results show that the latter channel is more important for generating more likes. This implies that in identity relevant domains, online platforms should focus on building social networks to facilitate the effect to SI. This also implies that, it is a lot more helpful to get influential users (with a large number of followers) to like a product than to get non-influential users; our results show that the latter can even backfire. Because of this, platform designers should not blindly remind users aggregate behaviors; instead, they should provide users information on behaviors of their “in-groups”.

Second, our findings on the distinction between clicks and likes in identity-relevant domains hold important implications on how marketers should measure and design their campaigns in identity-relevant domains. In digital marketing, it is traditionally believed that likes are a more premium form of engagement than clicks. Our findings suggest that this is not true in identity relevant domains. Clicks capture the private interests in an item; a lack of likes does not imply consumers are not interested in the product. Likes are a form of public endorsements, but they could be just for the “image” and do not necessarily mean that consumers have an intrinsic interest in the product. Thus, clicks and likes can each capture unique motivations of consumers not found in the other. Marketers must keep both in their basket of campaign performance and design different campaigns according to the clicks/likes pattern. For example, a campaign yielding many clicks but few likes suggest that the product may be more practical than glamorous, thus the marketer should rely more on OL for promoting the product.

Conversely, a product with many likes but relatively few clicks suggest that the product is a sought-after identity signaling symbol; marketers should rely more on the SI channel for promoting the product.

8.3. Limitation and future research

Readers should be aware of certain limitations of our study. Our study is conducted in a specific context of handbags; while we argue that our results can apply to other products on the website, the generalizability of our finding is still to be tested. We infer the underlying mechanisms of influence using proxies such as the number of existing likes and the number of liker followers at the product level; further studies with more direct measures of OL and SI and at the individual level are needed to ascertain the exact mechanisms and rule out potential confounds. While this paper focuses on engagement outcomes in the forms of clicks and likes, which are crucial for online platforms and marketers, we do leave out an important class of outcomes related to purchases. Industry reports show that social commerce websites are also important drivers of sales. Additional research focuses on associating engagement with purchases would be complementary and important.

As avenues for future research, one interesting direction is to extend the study to products that are not traditionally thought of being symbolic (e.g., hair-styling tools, baby clothing). We conjecture that our insights extend beyond symbolic consumption because the very action of liking (or other forms of endorsing) a product publicly may turn the behavior into an identity relevant domain. In a similar vein, one could also test our findings in domains beyond social commerce to test the boundary of the identity signaling effects. In this study, we have only incorporated likers' numbers of social connections when calculating the magnitude of social influence received by each product. Apart from likers' social connections, other differences of likers (such as their level of involvement, network centrality, and expertise) may also affect the level of social influence generated. Future research could further explore these heterogeneities.

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