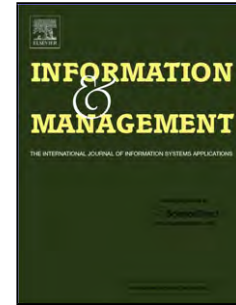


## Accepted Manuscript

Title: With a little help from my friends: Cultivating serendipity in online shopping environments

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PII: S0378-7206(17)30375-0  
DOI: <https://doi.org/10.1016/j.im.2018.06.001>  
Reference: INFMAN 3083

To appear in: *INFMAN*

Received date: 5-6-2017  
Revised date: 27-5-2018  
Accepted date: 12-6-2018

Please cite this article as: Camille Grange, Izak Benbasat, Andrew Burton-Jones, With a little help from my friends: Cultivating serendipity in online shopping environments, Information and Management <https://doi.org/10.1016/j.im.2018.06.001>

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## **With a little help from my friends: Cultivating serendipity in online shopping environments**

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### **Abstract**

Many important findings and discoveries in science and everyday life are the result of serendipity, that is, the unanticipated occurrence of happy events such as the finding of valuable information. Consumers are increasingly seeking serendipity in online shopping, where information clutter and preprogramed recommendation systems can make product choice frustrating or mundane. However, it is notoriously difficult to design online shopping environments that induce it. In this study, we explore how social media affordances such as obtaining access to peer-generated content and being connected to online friends can help create the right conditions for serendipity in online shopping. We supplement this analysis with an account of two individual factors that are also likely to be instrumental in a shopping context, namely, the intensity of shoppers' information search and their aversion to risk when faced with a product choice. Our investigation relies on a conceptualization of serendipity that has two defining elements: unexpectedness and informational value. The results of an experimental study in which we manipulated an online product search environment reveal the superiority of designs that incorporate online friendships, and these results support the positive effects of search effort and risk aversion on serendipity. This study contributes by developing a theoretical framework for the analysis of serendipity and by explaining how

social commerce, that is, the integration of social media and electronic commerce, can cultivate serendipity.

**Keywords:** online information search, social commerce, serendipity, unexpectedness, informational value, disconfirmation, diagnosticity, diversity.

## INTRODUCTION

The rapid adoption of e-commerce by consumers has been fueled by the increasing number of goods available for online purchase and by the increasing availability of information on the characteristics and performance of these goods. However, this abundance of information and choice has cluttered online shopping environments. Consumers face an overwhelming number of alternatives to choose from and a profusion of information on each option, which reduce their motivation and ability to filter and evaluate products (Iyengar and Lepper 2000; Nagar and Gandotra 2016). Although product filtering and recommendation agents can lower search costs (Brynjolfsson et al. 2011), they tend to yield a narrower range of suggestions, thus making online shopping a tedious experience (Clune 2013; Darlin 2009; Herlocker et al. 2004). In addition, while powerful algorithms have enhanced the accuracy of the recommendations that shoppers obtain, such recommendations are often, by design, too predictable, which means that they overlook shoppers' desire for the good surprises that can spark their engagement and satisfaction (Adamopoulos and Tuzhilin 2014; Matt et al. 2014).

To address this concern, we explore the potential value of online shopping environments that cultivate *serendipity*, that is, the finding of unexpected but valuable product-related information. Online retailers increasingly value serendipity because it is a significant driver of consumers' decision satisfaction (Yi et al. 2017), positive affect (Matt et al. 2014), and engagement (Sun et al. 2013). The concept of serendipity is relatively nascent in the Information Systems (IS) field, but several other fields (e.g., marketing, medicine, and engineering) have long recognized the important role it has played in various scientific contexts including the discovery of gravity, penicillin, and computerization (Anguera de Sojo et al. 2013; Kubinyi 1999; Roberts 1989; Van Andel 1994).

Both consumers and vendors value serendipity, but designing for it is challenging and online environments that are successful in that regard are rare (Makri et al. 2014). Indeed, even top retailers such as Amazon struggle to create serendipity (Worstall 2013; Sung 2016). Yet recent research has sparked new hope by observing that social features such as consumer-generated product tags and lists of socially endorsed shoppers could foster serendipitous product search experiences (Yi et al. 2017). These findings have revealed an opportunity to examine the role of social features in inducing serendipity in online shopping environments.

The goal of this paper is to pursue this avenue by focusing on features associated with two fundamental characteristics of social media: (1) Users share and access consumer-generated content (CGC) such as product reviews and (2) Users are increasingly interconnected through online friendships (Hennig-Thurau et al. 2013; Kane et al. 2014). Because serendipity depends on both search environments and information seekers (Björneborn 2010; Erdelez 2000), we supplement our analysis of the effect of social design by considering two other factors: the intensity of shoppers' information search effort and their tendency to avoid uncertainty with regard to a purchase. To analyze the effects of social design (an environmental factor) as well as search effort and risk aversion (two individual factors) on serendipity, we rely on the concepts of *unexpectedness* and *informational value*. We propose expectancy disconfirmation as the key mechanism underlying unexpectedness as well as information diagnosticity and diversity as the two main drivers of informational value.

The paper makes two key contributions. First, it contributes to theory by clarifying and contextualizing the concept of serendipity in online shopping contexts. Although a few studies have identified strategies that can cultivate serendipity (Björneborn 2008; McCay-Peet and Toms 2011), these studies are mainly descriptive and inductive. Thus, the literature has offered limited theoretical foundations. The present study addresses this gap in past work by framing serendipity in terms of unexpectedness and informational value and by articulating the theoretical mechanisms associated with them. Second, it contributes by offering theory-based implications for design. It verifies the value of such design principles by offering first-hand evidence of the role of online friendships in inducing serendipity in an online shopping experience. From a practitioner's perspective, this research provides insights into how platform owners can use an understanding of key social media affordances as well

as attitudinal and behavioral differences to enhance the serendipity experienced by website visitors. Further, we define the conceptual foundations, develop the hypotheses, present the methodology, and discuss the results.

## FOUNDATIONS: THE NATURE AND DRIVERS OF SERENDIPITY

Given the lack of detailed conceptualizations of serendipity to date, our first task was to conceptualize the construct. In this section, we specify two core attributes of serendipitous experiences, namely, unexpectedness and informational value, and we present the three theoretical mechanisms that can trigger them—disconfirmation, diagnosticity, and diversity.

The term “serendipity” is attributed to Sir Horace Walpole, who is said to have created it while commenting on the fairy tale “The Three Princes of Serendip” in 1754. Walpole explains that he was struck by the fortuitous discoveries these three princes made during their travels and that he decided to use the term serendipity to refer to such accidental events one experiences (Merton 1968). Since then, interest in serendipity has developed in several fields such as the philosophy and history of science (Roberts 1989), medicine (Sojo et al. 2014), computer science (André et al. 2009), library and information science (Foster and Ford 2003), marketing (Stephen Brown 2005), entrepreneurship (Dew 2009), and information systems (Yi et al. 2017). Our review of the definitions of serendipity (Table 1) shows that despite a few specificities related to the contexts in which serendipity is being studied, two defining properties appear to be fundamental: *unexpectedness* and *value*. For example, in Table 1, the terms “surprise,” “fortunate,” and “accident” allude to unexpectedness and the terms “insight,” “happy,” “useful,” and “beneficial” allude to value.

**Table 1. Definitions of serendipity in the literature**

Source	Definition	Context
Agarwal 2015	An incident-based, unexpected discovery of information when the actor is either in a passive, nonpurposive state or in an active, purposive state, followed by a period of incubation leading to insight and value.	Models of information behavior
André et al. 2009	The finding of unexpected information (relevant to the goal or not) while engaged in any information activity, and the making of an intellectual leap of understanding with that information to arrive at an insight.	HCI/web browsing and filtering
Beale 2007	The making of fortunate discoveries by accident.	HCI/ambient intelligence

Source	Definition	Context
Cunha et al. 2010	The accidental discovery of something valuable.	Organizational learning
Foster and Ford 2003	The faculty of making happy and unexpected discoveries by accident.	HCI/collaborative filtering system
Herlocker et al. 2004	A measure of the degree to which the recommendations are presenting items that are both attractive to users and surprising to them.	Information seeking in academic research
Makri et al. 2014	Serendipity occurs when unexpected circumstances and an “aha” moment of insight result in a valuable, unanticipated outcome.	HCI/creative professionals’ information search
Makri et al. 2015	It involves encountering information that we perceive to be both useful/potentially useful and unexpected.	HCI/naturalistic information task
Sun et al. 2013	A beneficial discovery that happens in an unexpected way.	HCI/microblogging
Van Andel 1994	The art of making an unsought finding, where a finding is something “new and true (science), new and useful (technology), or new and fascinating (art)”.	Science and technology

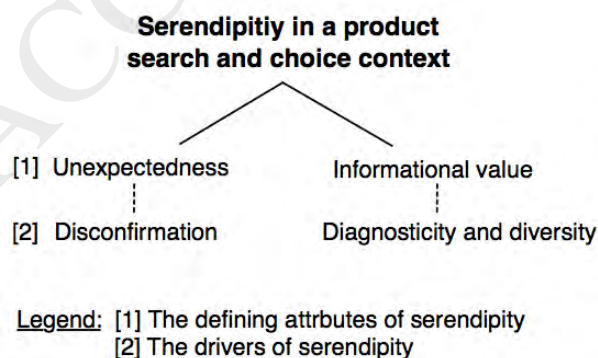
Note: HCI: Human–computer interaction.

First, serendipity involves an element of unexpectedness, that is, surprise (Barto et al. 2013). Previous studies have noted that serendipity involves “unexpected circumstances” (Makri et al. 2014) and the “finding of unexpected information” (André et al. 2009) and that it “happens in an unexpected way” (Sun et al. 2013). Unexpectedness relates to a key theoretical mechanism: expectancy disconfirmation (Stiensmeier-pelster et al. 1995). Expectancy disconfirmation (disconfirmation, hereafter) is the violation of a previously established mental representation. It happens when individuals experience a gap between their expectations and their observations of reality (Berlyne 1960; Oliver 1977). This mechanism is central to the expectation disconfirmation theory, which explains customer satisfaction as a function of prior expectations and disconfirmation (Oliver 1977). In the original theory, expectations are defined as probabilistic beliefs that take the form of mental representations aroused in a context, and the target of both expectation and disconfirmation is a product’s performance. Since then, the theory has been expanded to fit other targets such as the usefulness of an information system (Bhattacharjee and Premkumar 2004). In the present study’s context of online product search, we consider expectations as users’ a priori beliefs about the product-related information available for use in a shopping environment. Subsequently, we refer to disconfirmation as the cognitive discrepancy between such a priori

beliefs and the newly formed beliefs developed because of being exposed to the search environment.

Second, serendipity requires that something of value is found. Value can be specified and operationalized differently depending on the context. In this study, we consider *informational value* because effective product learning and informed decision-making rely heavily on gaining access to valuable information such as peers' opinions (Cheung and Thadani 2012; King et al. 2014). There are two dominant views about what generates informational value. The first view stresses the importance of *diagnosticity*. Diagnostic information conveys highly valid, reliable, and interpretable meaning. It is particularly valuable in a product search context because it helps customers better understand products and compare their probable performance (Herr et al. 1991; Jiang and Benbasat 2007). The second view stresses the importance of *diversity*, which refers to the heterogeneity of peer opinions and recommendations. Diversity makes it possible to escape so-called “filter bubbles” or “echo chambers,” in which one risks remaining exposed to similar viewpoints (Bakshy et al. 2015; Pariser 2011; Uzzi and Dunlap 2005). Thus, it is useful for obtaining a broader perspective on products and ultimately for making better decisions (Aral and Van Alstyne 2011; Burt 1992). In sum, diagnosticity and diversity are both important and desirable with regard to informational value, and whether one matters more than the other is dependent on context (Reagans and Zuckerman 2001). Figure 1 shows our proposed conceptualization of serendipity, which we define as the finding of unexpected and valuable product-related information.

**Figure 1. Conceptualization of serendipity for online product search and choice**



Definitions of key terms:

\* **Serendipity** is the finding of unexpected and valuable product-related information.

\*\* **Disconfirmation** is the extent to which product-related information (e.g., the result of an information search) deviates from expectations (a priori beliefs).

\*\*\* **Diagnosticity** is the extent to which product-related information is valid, reliable, and interpretable. **Diversity** is the extent of heterogeneity in product-related information.

## RESEARCH HYPOTHESES

In this section, we explain how and why the environmental and individual factors of interest in this study influence serendipity by encouraging disconfirmation, diagnosticity, and diversity. In terms of environmental factors, we focus on two key affordances of social media (accessing peer-generated content and being connected to online friends). The nascent literature on this topic suggests that inducing serendipity in online product search is not easy and that different social features may contribute to serendipity by different mechanisms. For example, Yi et al. (2017) found that websites with peer-generated product tags were associated with significantly higher levels of serendipity than websites without tags only when socially endorsed people (i.e., list of popular shoppers) were featured in these websites because the latter facilitates browsing of diverse alternatives favored by a specific set of community users. They explain that although information from socially endorsed people leads to unexpected product findings, product tags favor search coherence and relevance. In developing the hypotheses, we apply the same logic by investigating what social design affordances, in the form of accessing online friendships and exploiting peer-generated content, can affect serendipity-inducing mechanisms.

In terms of individual factors, we consider the intensity of shoppers' information search and shoppers' risk aversion. The former is relevant because serendipitous opportunities must be actively sought after. An information seeker who invests in search manifests a willingness to learn, and this ends up contributing to unexpected discoveries (Erdelez 1999, 2000). In other words, people tend to make surprising discoveries by making a purposeful search effort. A shopper's risk aversion captures an attitude that relates to a shopper's tendency to avoid uncertainty with regard to a purchase (Bao et al. 2003; Matzler et al. 2008). It is another particularly pertinent factor because the literature suggests that (1) some people hold attitudes that make them more likely to experience serendipity than others (André et al. 2009; Toms 2000) and (2) attitudes are particularly salient when they are specific to the context where their influence is studied (here, product choice).

### **The influence of social design on serendipity (H1a, H1b)**

There are two alternative means to combine social media and e-commerce features to yield social commerce environments: either by importing e-commerce functionalities into a social



media platform (e.g., incorporating a “buy button” on Facebook or Pinterest) or by designing social features into an e-commerce environment (e.g., adding the possibility to “comment” on or “recommend” products or services on Amazon or Netflix) (Huang and Benyoucef 2015). In this study, we focus on the latter, and we scrutinize three different ways of implementing it. One of them affords open access to product-related informational content that other users have created (e.g., reviews). We refer to it as the *CGC access* design type. This is the least sophisticated and most typical form of social commerce design (Gonçalves Curty and Zhang 2013). The second type enables users to access their social connections on the shopping platform and to leverage these connections in their product search (e.g., see a list of products that friends reviewed). We refer to it as the *social circle* design type. It is a more sophisticated, less prominent, social design (Huang and Benyoucef 2013). The third type is a combination of the two previous ones. It affords both an open access to all CGC and a personalized access to one’s social circle; hence, we refer to it as a *hybrid* design. We explain next why a social circle design should create *more* serendipity compared to a CGC design (H1a), and why it should induce *less* serendipity than a hybrid design (H1b). The hypotheses are based on an analysis of the unique properties of each of the three product search environments with regard to their potential for triggering unexpectedness and for producing informational value (Table 2).

**Table 2. Salience of the drivers of serendipity in each type of social design**

		Theoretical drivers of serendipity		
Social design	Associated hypotheses	<i>Disconfirmation</i>	<i>Diagnosticity</i>	<i>Diversity</i>
<i>CGC access</i>	H1a	low	low	high (AWT)
<i>Social circle</i>		high (SPF)	high (FSI)	low
<i>Hybrid</i>	H1b	high (SPF)	high (FSI)	high (AWT)

Note: The key rationale for our evaluation of salience is summarized in brackets, and it is explained in more detail in the text below. SPF: social product filtering; FSI: familiar sources of information; AWT: access to weak ties.

We expect a social circle design to yield more serendipity compared to a CGC access design (H1a) because, as we explain next, it provides a more fertile ground for both unexpectedness and informational value.

First, a *social circle design* offers a search space that is prone to triggering the *disconfirmation* mechanism underlying unexpectedness. Online shoppers conduct two key

tasks as part of their product decision-making process: (i) they select a number of products among the whole set of alternatives and (ii) they evaluate products in this consideration subset. In a social circle design, users can select products for evaluation by exploiting social filtering. Although traditional filtering mechanisms designed into shopping websites enable selecting a subset of products based on their attributes (e.g., the type of food that is served in a restaurant, the neighborhood in which it is located), social filtering involves being exposed to products based solely on social graph information, that is, based on whether friends shared opinions about them or not (Li et al. 2013). This mechanism yields a “reality” in the form of a filtered set of product alternatives that is shaped by one’s online friendships. In other words, social filtering enables users to rely on friends’ preferences, which are external to them and cannot be easily anticipated. This is in contrast to users’ own internal preferences for certain product attributes, which are by definition familiar and anticipated. As a result, social filtering encourages users to rely on a subset of product alternatives that are unlikely to fit exactly to their expectations. This encourages the formation of a gap between users’ anticipated preferences and the set of products that will be considered for evaluation, hence the disconfirmation leading to experiencing unexpectedness (Stiensmeier-pelster et al. 1995). By contrast, a *CGC access design* does not offer social filtering; thus, users are likely to end up with a “reality” that fits more strongly with their own mental representations, a situation that does not favor disconfirmation. Note that while a level of similarity among online friends is likely to occur (McPherson et al. 2001), we do not expect that a social circle design will produce product consideration sets that fit closely to users’ a priori beliefs as a CGC design. Similarity does not imply equality; although it is likely that shoppers will value what their friends suggest because of related preferences (a point we elaborate in the next paragraph), friends are not likely to have bought or reviewed exactly the same products because they are different individuals. In sum, compared to a CGC design, a social circle design should favor exposure to product alternatives that are *less* anticipated.

Second, a social circle design should be more inclined than a CGC design to generate informational value. This is primarily because users of a social circle design can access informational content (i.e., online reviews) that is easily understandable and interpretable because it is generated by familiar others (one’s friends). Information created by familiar peers is highly *diagnostic* because friends are considered to be credible informants, and thus,

they are the source of information that is more believable (Ananthakrishnan et al. 2015), more trustworthy (Kubiszewski et al. 2011), and, in general, more useful (Sussman and Siegal 2003). Moreover, online shopping environments that appear more familiar and personalized to consumers tend to provide better perceived fit with one's informational needs (Komiak and Benbasat 2006). By contrast, a CGC design does not connect shoppers to their online friends (i.e., shoppers' social network is invisible). The authors of product reviews have a profile page, but they are unknown to shoppers, thus making it difficult for shoppers to interpret the reviews and to assess their credibility. Although a CGC design should be less conducive to diagnosticity, it has the advantage of affording access to weaker ties (i.e., nonfriends), thus promoting opinion diversity, another important driver of informational value. Because the literature has strongly established the prime importance of diagnosticity in product search and decision contexts (Andrews 2013; Jiang and Benbasat 2005; Pavlou and Fygenson 2006; Smith et al. 2011), diagnosticity should be the leading driver of informational value, and diversity should be a secondary factor. In sum, given the unique potential of a social circle design to induce disconfirmation as well as its higher capability to generate diagnosticity, we propose H1a.

*H1a: A social circle design generates more serendipity than a CGC design.*

We expect a *hybrid design* to yield more serendipity compared to a social circle design (H1b) because of its combination of features. The key affordances of a social circle design (reaching products through a social feed and accessing information from familiar peers) provide the most effective conditions to induce unexpectedness (by disconfirmation) and informational value (by diagnosticity)—as explained in H1a. Yet, a CGC access design affords access to weaker ties, and thus, we anticipate that a hybrid design will outperform a social circle design in terms of informational value by supporting diversity *in addition to* diagnosticity enabled by the social circle design. Research suggests that people are socially connected to others who share similarities (McPherson et al. 2001) and that variations in knowledge and behavior between people and familiar others tend to diminish with time and interactions (Kilduff and Tsai 2003). Because shoppers in hybrid environments can reach information situated further away than their direct, proximate, social ties, they are more likely to be exposed to the opinions of more unfamiliar contacts (weaker ties), who in turn are more likely to offer novel insights (Gray et al. 2011). Although being in contact with

online friends and leveraging such familiar relationships to evaluate products has benefits in terms of diagnosticity, as explained in H1a, this can encourage a tendency to remain exposed to similar opinions. A hybrid design (similar to a CGC access design) provides an unlimited access to the opinions of all other users, not only the opinions from online friends. This reduces the risk of developing a “narrow mindset” by accessing cross-cutting, more diversified, content (Bakshy et al. 2015). Therefore, a hybrid design should help users broaden their views and avoid filter bubbles, where they would risk becoming separated from information that challenges their viewpoints (Matt et al. 2014; Pariser 2011). In sum, a hybrid design should enhance serendipity by offering shoppers more opportunities to leverage diversity, hence a more complete understanding of products. Accordingly, we propose H1b.

*H1b: A hybrid design generates more serendipity than a social circle design.*

### **The influence of shoppers’ information search on serendipity (H2a and H2b)**

Products and product reviews constitute two key information entities in online product search environments. As such, they are the targets of two important search behaviors: product sampling (i.e., the number of product alternatives that a shopper decides to consider) and product review sampling (i.e., the number of product reviews that a shopper decides to consult) (Ho and Bodoff 2014). We conceptualize *breadth of product sampling* (BPS) as the extent of search invested in selecting product alternatives and *breadth of review sampling* (BRS) as the extent of search invested in evaluating selected alternatives. We predict that BPS and BRS will both have a positive influence on serendipity (H2a and H2b, respectively). As we explain next, these hypotheses are based on an analysis of how search behaviors influence the conditions that are the most likely to yield unexpectedness and informational value.

First, we anticipate that an increase in either BPS or BRS will encourage *disconfirmation*, thus unexpectedness. Indeed, the greater the exposure to different product alternatives and opinions about them, the greater the chances of finding something novel and of experiencing disconfirmation. Encountering something novel implies that little corresponding representation is found in memory. Thus, expectations end up being violated by the observation of a novel item because the latter could not have been anticipated (i.e., one

cannot expect the occurrence of something that is novel, that is, not present in one's memory schema). A stimulus is considered to be *absolutely* novel when users experience something they had never experienced before; it is *relatively* novel when it involves some level of familiarity, but the way it is presented or arranged is novel (Berlyne 1960). BRS is likely to lead to absolute novelty because while shoppers might be exposed to products in the media or elsewhere before their search task, the reviews they choose to consult are likely to be unique. BPS can produce relative novelty in addition to absolute novelty. This is because although shoppers may have never bought or consumed a particular product alternative that they are considering, it is possible that they heard about it in the past. Thus, shoppers may consider a product as a result of recognizing certain aspects (e.g., its name in the case of restaurants). In sum, an increase in BPS and BRS encourages shoppers' exposure to new product alternatives (for the former) and new product opinions (for the latter); hence the disconfirmation (leading to unexpectedness).

Second, we expect that an increase in either BPS or BRS will encourage *diagnosticity* and *diversity*, thus informational value. BPS and BRS represent amounts of evidence collected by shoppers during their product choice task. Therefore, greater levels of BPS and BRS should induce diagnosticity by offering a more comprehensive view of the choice set and a more accurate understanding of the potential performance of each alternative. In parallel, search efforts should also promote diversity. Each additional unit of BPS broadens the set of product choice options, and each additional unit of BRS expands the number of unique opinions of peers that one can use to evaluate the option. These arguments lead to H2a and H2b.

*H2a: Breadth of product sampling positively influences serendipity*

*H2b: Breadth of review sampling positively influences serendipity*

### **The influence of shoppers' risk aversion on serendipity (H2c)**

We expect serendipity to be more likely when shoppers are more risk averse. The rationale behind this hypothesis is twofold. First, we anticipate that an increase in risk aversion encourages *disconfirmation*, thus unexpectedness. Shoppers who are risk averse wish to reduce the level of uncertainty surrounding a product decision, and thus, they tend to

entertain the habit of remaining in their comfort zone concerning product consideration and choice (Bao et al. 2003). In other words, they are likely to have well-formed, rigid beliefs (i.e., expectations) regarding the preferred characteristics of the type of products among which they shall choose. In such cases, the expectations shoppers hold constitute strong anchors against which to compare reality in the form of lists of product alternatives. Therefore, shoppers who are more risk averse are more inclined to experience and perceive gaps between their existing cognitive frames and the information to which they are exposed during product search; thus, they are more likely to experience disconfirmation (Stiensmeierpelster et al. 1995). Second, we expect that an increase in risk aversion will increase *diagnosticity*, thus informational value. Although risk averse shoppers are not likely to actively look for novelty and diversity (as they convey uncertainty), they are likely to be highly attentive to the product-related information they encounter during a decision-making task (Shimp and Bearden 1982). As a result, they should be more capable of making faithful and valid interpretations about the information they access. We explained earlier that serendipity involves active learning. Because attention is an important facilitator of learning, when being attentive, the chances of learning also increase. In fact, “being observant” is a strategy that users can employ to encourage serendipity (Makri et al. 2014). Another way of putting it is that more risk-averse shoppers are likely to work more mindfully toward reducing the uncertainty surrounding a decision, paying more attention when interpreting peers’ opinions and assessing the validity of their claims. This makes them better positioned to experience highly diagnostic product search. These arguments lead to H2c.

*H2c: Risk aversion positively influences serendipity*

Table 3 summarizes how the aforementioned individual factors contribute to serendipity.

**Table 3. Salience of the drivers of serendipity for each individual variable**

Individual variables	Associated hypotheses	Theoretical drivers of serendipity		
		Disconfirmation	Diagnosticity	Diversity
<i>Breadth of product sampling</i>	<b>H2a</b>	high (novelty)	high (completeness)	high (broadening)
<i>Breadth of review sampling</i>	<b>H2b</b>	high (novelty)	high (completeness)	high (broadening)
<i>Risk aversion</i>	<b>H2c</b>	high (rigidity of prior beliefs)	high (attention)	low

Note: The key rationale for our evaluation of salience is summarized in brackets, and it is explained in more detail in the text above.

## RESEARCH METHOD

### Design of the experimental website

A between-subjects experimental design was chosen to test the hypotheses. We developed a website, which afforded searching for restaurants<sup>1</sup> among 287 alternatives in the city in which our university was located. We manipulated the website to create three versions corresponding to the three experimental conditions. The first condition corresponded to a website designed with *access to CGC*. The website included basic filtering features that enabled searching restaurants “by location” and “by cuisine.” Each restaurant page presented some general information about the restaurant (cuisine, location, brief description, address, map, and picture of store front) and included the reviews written by other users. Subjects could click on reviewers’ name and reach their profile page, but no social network information was made accessible (similar to how several retailers including Amazon.com design their product and reviewer pages). In addition to the basic product filtering and presentation features designed in the CGC access condition, subjects in the *social circle* and *hybrid* conditions could traverse relational ties by using a list of friends. They could also consult a social feed, a typical content access mechanism in online networks that took the form of a list of restaurants reviewed by friends (Ellison and boyd 2013) (Indratmo and Vassileva 2012). *The social circle* and *hybrid* conditions differed in that the former restricted users from reading reviews from nonfriends and from navigating the full network further away than their friends, whereas the latter did not.

### Sampling

We recruited subjects using a panel of individuals (restaurant goers) that we created for the purpose of the research. The panel was assembled by advertising the study in a variety of ways such as posting printed ads in major thoroughfares and sending emails to lists at our university and asking personalities who regularly tweeted about dining options in the city to promote participating in the panel. This process yielded a panel of 352 individuals who had

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<sup>1</sup> We chose this context because shoppers often rely on others’ opinions when searching for experiential products such as restaurants (Huang et al. 2009).

completed a preliminary task consisting in writing reviews about restaurants they had visited in the city in which our university was located. The review task yielded a large amount of CGC (more than 30,000 tags, 3,000 recommendations, 5,000 ratings, and 750 open comments). A key characteristic of this pool of research participants was that their Facebook friendship connections had been recorded: we had asked participants to log in to the panel website using a Facebook app developed for this purpose, which enabled us to recreate an underlying social network. Panel members had, on average, 4.3 friends in the panel, ranging from none to 25<sup>2</sup>. They were aged between 19 and 65 years (mean age of 28 years), and 52% were nonstudents.

We used stratified random sampling to obtain three groups of subjects balanced in terms of their network size (i.e., number of friends), the key variable determining the extent of informational content (i.e., reviews) available through subjects' social circle. This method ensures that a representative subset of the sample can be obtained without modifying a social environment (Gray et al. 2011). For instance, even if only a subset of subjects from the whole panel conducts the task, the information of the whole network can remain available to them (it only varies depending on their experimental treatment). Thus, we divided the panel members in six strata: one with all isolates (i.e., unconnected users); three with subjects with one, two, and three friends, respectively; a fourth one with subjects with four to five friends; a fifth one with subjects with six to eleven friends; and a final stratum with subjects with  $\geq 12$  friends. All members were assigned to one of these strata. We drew members from the strata until we reached balanced groups and a sample size that would allow us to meaningfully test our model.

For the results of our study to have meaningful practical implications, we felt that they should have at least a medium effect size (Aguinis et al. 2010). To detect a medium effect size of  $f^2=.15$  at a power level of 0.80, a multiple regression test with four independent variables requires  $n=84$  (Faul et al. 2007). With this goal in mind, we used the stratified random sampling approach mentioned above to select and contact 146 of the 352 panel members to ask them to participate in the main study. To maximize response rate, we sent

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<sup>2</sup> In building the panel, we had incorporated some mechanisms that would induce such connectedness (e.g., friend referral, social ads).



weekly reminder emails for a month (per Hoddinott and Bass 1986). Because 39 of them did not answer our call to participate and 10 provided unreliable answers, this yielded  $n=97$  for the main study. The 97 were randomly assigned to the three experimental groups. During this process, seven isolates were assigned to the two groups including social circle features. We did not include them in our final analysis because, without any “friends,” they would not experience the expected affordances. This led to a final sample size of  $n=90$ , with group sample sizes of  $n=28$  (CGC access),  $n=31$  (social circle), and  $n=31$  (hybrid). Randomization was effective, as there were no significant differences between groups on gender ( $\chi^2_{(2, N=89)} = 0.54, p = 0.76$ ), age ( $F_{(2, 89)} = 1.9, p = 0.16$ ), occupation ( $\chi^2_{(2, N=89)} = 0.57, p = 0.75$ ), number of Facebook friends ( $F_{(2, 89)} = 0.82, p = 0.45$ ), eating out frequency ( $F_{(2, 89)} = 0.65, p = 0.53$ ), or network size ( $F_{(2, 89)} = 0.44, p = 0.64$ ).

## Procedures

Recruited subjects completed the study online (i.e., not in the laboratory). They were provided with a brief tutorial illustrating the features of the version of the website they were assigned to. This helped them to understand the possibilities of each site, and our manipulation checks, reported later, show that subjects did understand these possibilities correctly. After completing the tutorial, subjects were directed to the task, which involved browsing the site and filling in a “wish list” of restaurants. In contexts such as ours in which customers are asked to choose from a list of products that include some they know already (products they reviewed during the panel development stage), some consumers may focus on products they recognize, without engaging in the task (Moe 2003; Pachur et al. 2011; Todd 2007). To control for this, we first asked subjects to write down a “wish list” of restaurants they would be interested in trying out in the future. We then asked subjects to perform the main task: to select at least three restaurants that (1) they had not reviewed during the panel sign-up task procedure (we had recorded this piece of information; thus, we could design the site to prevent them from doing so), and (2) they had not included in their wish list at the start (we manually checked that this did not occur). Subjects were asked to browse the site to search for restaurants they would be interested in trying out, to add the chosen restaurants to their wish list, and to complete a questionnaire, after which they were free to leave the site. Vouchers were used as incentives and redeemable at the restaurants identified in subjects’ wish list.

## Measurement

Measurement items are shown in Table 4. *Serendipity* was measured with three items adapted from recent studies (McCay-Peet and Toms 2011; Yi et al. 2017). *Risk avoidance* was measured with items reused from Bao et al. (2003). All items were assessed along a 7-point (strongly disagree to strongly agree) scale.

BPS and BRS were measured using data collected as subjects used the website during the experimental task. BPS was operationalized as the count of unique new restaurant pages visited by subjects during the task. BRS was operationalized by a count of reviews that subjects consulted (based on their clicks on “see review” buttons) per unique new restaurant page consulted.

**Table 4. Measurement items for the study variables**

Construct	Measures
Serendipity <sup>(1)</sup>	<i>The MyTable website...</i> -Triggered unexpected encounters with restaurants that seem worth a try. -Provided some surprising yet interesting ideas of restaurants. -Delivered unexpected but useful findings about restaurants.
Risk aversion <sup>(2)</sup>	-I am very cautious about trying new/different restaurants -I would rather stick with a restaurant that I usually go to than try one I am not very sure of -I always end up going to the same restaurants I have already been rather than discovering new ones

<sup>(1)</sup> measured *after* task completion.

<sup>(2)</sup> measured *before* task completion

## DATA ANALYSIS

We analyzed the data in two steps: first by checking the validity of our manipulations and then by testing the hypotheses using a linear regression model.

### Manipulation check

Table 5 shows the descriptive statistics for the subjects’ responses to the questions (MC1 to MC4) used to test the validity of our manipulations. We used analyses of variance (ANOVAs) and post-hoc comparisons (Table 6) to examine whether the results were consistent with our predictions. All three designs enabled attribute filtering (by cuisine and location); hence, we did not expect significant difference for MC1; this was supported by the

ANOVA ( $F_{2,82} = 0.04$ ,  $p = 0.96$ ). However, we expected and found significant differences in subjects' perceptions regarding the degree to which they could reach content produced by nonfriends (MC2,  $F_{2,82} = 19.6$ ,  $p < 0.001$ ), see a list of their friends (MC3,  $F_{2,82} = 46.13$ ,  $p < 0.001$ ), and filter restaurants that their friends reviewed (MC4,  $F_{2,82} = 19.74$ ,  $p < 0.001$ ).

**Table 5. Descriptive statistics for manipulation check variables**

Variables	Treatment Groups	CGC access (N=28)		Social circle (N=30)		Hybrid (N=27)	
		Mean	STD	Mean	STD	Mean	STD
MC1: Attribute filtering		<b>5.71</b>	0.85	<b>5.63</b>	1.27	<b>5.70</b>	1.24
MC2 : CGC availability		<b>5.50</b>	1.26	3.30	1.80	<b>5.52</b>	1.50
MC3 : List of friends		3.89	1.03	<b>5.93</b>	1.08	<b>6.26</b>	0.86
MC4 : Social filtering		3.82	0.82	<b>5.47</b>	1.30	<b>5.44</b>	1.18

Notes:

-In bold: values are expected to be high.

-The items took the form of 7-point Likert scales with anchors from "1. Definitely not" to "7. Definitely yes" and introduced by the following question "Does the website make it possible to..."

MC1 (attribute filtering): Filter restaurants according to neighborhood or cuisine preferences.

MC2 (availability of content): See restaurant reviews written by people I did not know.

MC3 (list of friends): See a list of my social connections (i.e., my friends).

MC4 (social filtering): Filter restaurants to display those that my friends reviewed.

**Table 6. Post-Hoc Tests for Perceived Affordances (Manipulation Checks)**

Dependent Variable	Group (i)	Group (j)	Mean Diff. (i-j)	Std. Err.	Sig.	Expected Result?
MC1 (attribute filtering)*	CGC access	Social circle	-0.08	0.28	0.95	Yes
		Hybrid	0.01	0.28	0.99	Yes
	Social circle	Hybrid	-0.07	0.33	0.98	Yes
MC2 (CGC availability)	CGC access	Social circle	2.20	0.41	0.00	Yes
		Hybrid	-0.02	0.42	0.99	Yes
	Social circle	Hybrid	-2.22	0.41	0.00	Yes
MC3 (list of friends)*	CGC access	Social circle	-2.04	0.26	0.00	Yes
		Hybrid	-2.37	0.25	0.00	Yes
	Social circle	Hybrid	-0.33	0.27	0.42	Yes
MC4 (social filtering)*	CGC access	Social circle	-1.65	0.28	0.00	Yes
		Hybrid	-1.62	0.26	0.00	Yes
	Social circle	Hybrid	-0.02	0.33	0.99	Yes

(\*) Indicates that the Levene test for homogeneity of variances was significant, in which case we used the Games-Howell test; otherwise, we used the Tukey HSD test.

## Hypotheses testing

The scales used to measure the psychometric variables (serendipity, risk aversion) demonstrated adequate reliability (Cronbach's alpha: 0.80 and 0.89, respectively); hence, we

created single scores (averages) for these variables to be used in the analysis. Table 7 provides descriptive statistics for the study sample, and Table 8 shows the correlation matrix.

**Table 7. Descriptive statistics: mean (standard deviation)**

Variables	CGC access N=28*	Social circle N=28*	Hybrid N=27*	Total N=83
Serendipity	4.2 (1.3)	4.7 (1.3)	4.8 (0.8)	4.6 (1.1)
Breadth of product sampling	6.4 (5.1)	6.9 (6.8)	6.4 (6.9)	6.6 (6.3)
Breadth of review sampling	2.7 (2.9)	0.7 (0.7)	2.1 (3.2)	1.8 (2.6)
Risk aversion	3.8 (1.2)	3.6 (1)	3.7 (1.3)	3.7 (1.1)

\* Isolates and/or outliers removed.

**Table 8. Correlations among noncategorical variables**

	Serendipity	BPS	BRS	RA
Serendipity	-			
Breadth of product sampling (BPS)	0.27*	-		
Breadth of review sampling (BRS)	0.24*	0.10	-	
Risk aversion (RA)	0.20 <sup>t</sup>	0.07	-0.13	-

\*  $p < 0.05$ ; <sup>t</sup>  $p < 0.10$

The hypotheses were tested using the following linear regression model:

$$\text{Serendipity} = \beta_0 + \beta_1 D_{CGC} + \beta_2 D_H + \beta_3 BPS + \beta_4 D\_BRS + \beta_5 (D\_BRS * BRS) + \beta_6 RA$$

In this model,  $\beta_1$  represents the first design effect (CGC access compared to social circle) on serendipity and  $\beta_2$  the second one (hybrid compared to social circle). The  $\beta_3$  parameter stands for the effect on serendipity of each new additional product considered. Given that a fair proportion (30%) of subjects did not read any reviews during the product search task, the model accounts for a threshold effect through a dummy variable ( $D\_BRS$ ) that takes on the value zero for subjects who did not read any reviews (i.e.,  $BRS = 0$ ) and the value 1 for subjects who read at least one review (i.e.,  $BRS > 0$ ). This modeling choice helps to separate the effect that occurs when the number of reviews read by a subject for each product considered increases from zero to one ( $\beta_4$ ) from the effect of a one-unit *subsequent* increase in the number of reviews read per considered product ( $\beta_5$ ). In other words, it enables distinguishing a step function from a linear trend. Finally, the model accounts for the effect of shoppers' level of risk aversion ( $\beta_6$ ).

The regression results (Table 9) indicated a significant design effect on serendipity, and it yielded two key findings. First, subjects in the social circle condition experienced significantly more serendipity (0.86 units more, on average) than subjects in the CGC access condition ( $p < 0.01$ ), which *supported H1a*. Second, subjects in the hybrid condition did not report higher levels of serendipity than subjects in the social circle condition ( $\beta = -0.18$ , ns), and thus, *H1b was not supported*.

**Table 9. Results for the linear regression analysis on serendipity**

	$\beta$	SE	Sig.	Related hyp.	Supported?
Intercept	4.85	0.199	***		
CGC design ( $D_{CGC}$ )	-0.86	0.278	**	H1a	Yes
Hybrid design ( $D_H$ )	-0.18	0.271		H1b	No
Breadth of product sampling (BPS)	0.04	0.017	*	H2a	Yes
Breadth of review sampling (BRS)	0.16	0.049	**	H2b	Yes
Dichotomous BRS ( $D_{BRS}$ )	0.28	0.278			
Risk aversion (RA)	0.24	0.096	*	H2c	Yes

R-squared = 26.9%; Adjusted R-squared = 21%

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . SE: standard error

The results also indicated that our hypotheses regarding the influence of shoppers' search effort on serendipity were supported: both BPS ( $\beta_{BPS} = 0.04$ ,  $p < 0.05$ ) and BRS ( $\beta_{BRS} = 0.16$ ,  $p < 0.01$ ) had significantly positive effects on serendipity, thus *supporting H2a-H2b*. Further, "the first review read" had no significant effect on serendipity ( $\beta_{D_{BRS}} = 0.28$ ,  $p = 0.32$ ), thus indicating no significant threshold effect. Finally, risk aversion had a significant positive effect ( $\beta_{RA} = 0.24$ ,  $p < 0.01$ ), which *confirmed H2c*. We tested interaction effects between design and individual variables and none were significant.

## DISCUSSION

This study generated three key findings. First, the results indicated that serendipity was significantly influenced by both environmental factors (i.e., website design) and individual factors (i.e., shoppers' search behaviors and attitude toward uncertainty). Second, as hypothesized, serendipity was significantly higher when there was a social circle design than when there was a CGC access design. Third, contrary to our expectations, a hybrid design did not represent "the better of the two worlds." We also observed that the *magnitude* of the social circle design effect (as opposed to a CGC design) corresponded to users accessing

approximately five additional reviews for each considered product or to their considering 20 additional new products<sup>3</sup>. Thus, although the search effort of shoppers matters (as can be seen from the significant effects of both BPS and BRS), the design effect, which can be controlled by website owners, appears to be more important with regard to generating serendipity. The results also corroborated the hypothesized positive influence of risk aversion on serendipity, thus supporting the claim that the attitude of shoppers plays a role in cultivating serendipity. The magnitude of this effect suggests that a 2.5-point increase in risk aversion (which was measured using a 7-point scale) is needed to yield a surge in serendipity equivalent to the one created by adding the social circle features. Overall, these results reveal the unique role that the social circle of shoppers plays and the value of incorporating it—through online friendships—into online product search environments. In their study of the impact of “product tags” and “socially endorsed people,” Yi et al. (2017) stressed the difficulty of designing for serendipity. Therefore, it is quite promising to observe in the present study that such a meaningful effect results from a relatively small design change (i.e., adding the social circle design features).

### **Theoretical and practical implications**

The study offers two important theoretical implications. First, it contributes by clarifying and contextualizing the concept of serendipity in online shopping contexts. Serendipity is sometimes presented as the art of obtaining an unsought finding, where a finding is something “new and true (science), new and useful (technology), or new and fascinating (art)” (Van Andel 1994). In a shopping context, the results of our study indicate that a finding may also be something: “unexpected and informationally valuable.” In other words, our conceptualization of serendipity in a specific context improves knowledge of a construct that has remained weakly theorized to date despite its importance in several fields. The proposed conceptualization provides the theoretical groundwork necessary to guide future empirical investigations and facilitates cumulative research. This groundwork helps to clarify the what and why of serendipity. Prior works on serendipity in information searches have

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<sup>3</sup> The regression coefficient representing the social circle design effect (over a CGC design) was 0.86. It was 0.16 for breadth of review sampling (thus approximately *five* times less) and 0.04 for breadth of product sampling (thus approximately *20* times less).

mostly relied on contextually rich, qualitative, and observational studies. Although several ad hoc characteristics of serendipitous environments or serendipitous searches have been identified through such works (Björneborn 2008; Makri et al. 2014, 2015; McCay-Peet and Toms 2015), these characteristics have not been conceptualized on the basis of an overarching theoretical framework, and therefore, they have lacked an explanatory logic. The present research helps to fill this gap by using a deductive approach. We began by defining serendipity as the finding of unexpected and valuable product-related information, and then, we specified the mechanism underlying unexpectedness (disconfirmation) and the attributes driving informational value (diagnosticity and diversity).

Second, the study contributes through its implications for theory-based design by examining and verifying *how* social media affordances (CGC access and social circle design) support serendipity in online consumer decision-making. The findings indicate that the serendipity potential of social network-enabled shopping environments is higher than that of environments that have a social flavor but do not involve social embeddedness (i.e., when peer-generated content is accessible while shoppers are not formally connected to online friends). Thus, the study responds to those who have called for more research on how to obtain more value from social commerce (Hennig-Thurau et al. 2013; Wang and Zhang 2012; Yadav et al. 2013; Zhang et al. 2013). Researchers have long studied social environments and online shopping, but little research has been conducted on the ways that they intersect. Social networks, in particular, are known to afford unique information benefits such as reducing uncertainty and introducing novelty (Sundararajan et al. 2013), both of which are important in online shopping. We contribute to this literature by explaining how social commerce environments, designed with or without formalized online relationships and open access to all CGC content, offer the conditions that induce disconfirmation, diagnosticity, and diversity. Moreover, the study validates the role that information seekers have in experiencing serendipity (Erdelez 1999, 2000). Investing in search by consulting several product alternatives and reading several opinions about them contributes to serendipity and so does shoppers' attitude toward risk. However, our study shows that the design effect exceeds that of each of these individual factors.

From a practitioner's perspective, this study offers detailed insights into how practitioners

could design social shopping sites that deliver a greater value for online shoppers and explanation for why the recommended designs work. To stimulate and support serendipity, several technological advances have been proposed in past work including search engines (Rahman and Wilson 2015), microblogging (Bogers and Björneborn 2013; Kop 2012), and recommendation systems (Adamopoulos and Tuzhilin 2014; Iaquina et al. 2008). According to the results of this study, sites with social network designs appear to induce more serendipity than sites offering more mainstream social environments (i.e., ones with CGC access design), and from a vendor perspective, they represent a relatively economical means to provide shoppers with a personalized environment. Designers can use social circle designs to create opportunities for serendipity that are not “over controlling,” designs that give users a certain level of autonomy during their search experience. The rapid and broad adoption of e-commerce by consumers during the last two decades has been fueled by information availability. Because social networks are new mechanisms for creating personalized product search environments that support unexpected informational value, online vendors need to be aware that network transparency may become a more important driver of value in the future.

### **Limitations and future research**

Our study offers a theoretical framework and empirical findings that support its validity, but more work is needed to develop a finer explanation of the roles of disconfirmation, diagnosticity, and diversity. By using a direct measurement approach and more in-depth data collection and analysis methods such as process tracing (Svenson 1979; Todd and Benbasat 1987), researchers would obtain a more comprehensive understanding of how shoppers experience unexpectedness and obtain informational value. This would help to explain how social designs can trigger disconfirmation and induce the informational characteristics that facilitate serendipity. In particular, this approach could help to further investigate why we did not find support for the superiority of the hybrid design. Possible reasons include diversity not adding much in terms of informational value (compared to diagnosticity) and users not being exposed or attentive enough to diversity during search. Moreover, we have assumed that unexpectedness and informational value are of equal importance, but more studies need to be conducted to determine whether this is always the case and whether their respective importance depends on certain conditions. For example, it may depend on factors such as product type or the degree of shopper’s involvement in decisions.



It is also important to emphasize that our study focuses on one specific type of serendipity, which is sometimes referred to as foreground serendipity (Bogers and Björneborn 2013). We encourage researchers to expand this focus. Foreground serendipity confirms a person's focus and direction. Thus, it involves focusing on how to connect things together in a particular context, which is what happens with the product-related serendipity studied here. By contrast, background serendipity involves a change in focus and direction. It occurs, for example, when a person who is engaged in a specific activity encounters something that provides insight into an unrelated matter. This limitation of our study has something to do with the nature of the task that we investigated. We focused on purposive information seeking where users seek information to satisfy a specific goal; however, serendipity could manifest itself differently in nonpurposive searches where users are *not* actively looking for information. Related to that matter, we found that serendipity benefited from more active information search (in the form of BRS and BPS). Although this finding could seem counterintuitive to those associating serendipity with luck or randomness, it is in line with research in the domain of creativity, which suggests that people who are highly focused and immersed in a task can be more creative (Mainemelis 2001). Creativity has two defining aspects (novelty and usefulness) that relate closely to serendipity, which involves encountering unexpected and valuable product-related information. Thus, future work could explore how this literature may be used to investigate the role of the search task and the intensity of the search in inducing serendipity.

Efficiency may be another related benefit of a social circle design, but our study did not examine it. We observed that the extent of information processing in the social circle experimental group (i.e., the BRS for each product that users considered) was low compared to that in the CGC or hybrid design groups. Indeed, the participants in the social circle condition accessed three to four times *fewer* reviews per product than participants in the two other conditions (Table 7), and this was not due to a ceiling effect (i.e., it had nothing to do with the volume of content available to them being too low). In other words, future research could examine whether the content acquisition strategy induced by social circle designs improves the return on search by yielding more useful information per unit cost (Pirulli and Card 1999). This is a particularly interesting issue because frugality, that is, the ability to reach equivalent outcomes with fewer resources, may not always be desirable from a

platform owner perspective. Indeed, it may depend on the type of strategy adopted by platform owners. Although stickiness (i.e., the capacity of a website to incite users to stay and consume more information) is usually an asset in the context of an advertising-based monetization strategy, it may be detrimental if the key objective is to provide efficient search experiences and to create repeated transactions. It has been a long time since Simon first highlighted that “a wealth of information creates a poverty of attention, and a need to allocate that attention efficiently among the overabundance of information sources that might consume it.” (Simon 1971 pp. 40–41). This is even more relevant in a digital era, where the time and attention of users are precious resources that online companies compete to capture. These observations call for more research on the other benefits of social designs in e-commerce as well as on the value and means to create serendipitous online shopping experiences that remain frugal (Bura 2016).

There are two additional research avenues that seem especially interesting to pursue in the future. First, although we have focused on the drivers of serendipity, especially on the role of social designs, it would be worthwhile to investigate questions associated with the subsequent effects of serendipity. For example, do serendipitous online product search experiences lead to better or more satisfying product choices? Do they influence impulsive purchases? Second, online social networks are considered to be an important threat by privacy conscious Internet users. Therefore, it is possible that social circle and hybrid designs, which both incorporate features exploiting users’ personal relationships information, may be highly unappealing to some users. Sharing personal (e.g., social) information with platform owners and with other users often involves tradeoffs between costs (e.g., giving away information) and benefits (e.g., obtaining personalized recommendations) (Awad and Krishnan 2006), and future research could examine how and to which extent such tradeoffs become salient in a social commerce context.

## **CONCLUSION**

Online environments that afford serendipitous product search experiences are in a better position to engage and satisfy shoppers, but it is notoriously difficult to design them with the goal of obtaining an outcome that, by definition, requires a degree of chance or surprise. The present study reveals, and explains why, social commerce designs that incorporate shoppers’

social circles are instrumental in creating the conditions for unexpectedness and informational relevance to manifest themselves and help cultivate serendipity. In a word, the findings improve the understanding of the concept of serendipity and identify a key differentiating value of social commerce environments.

### Acknowledgment

This research has been funded by the Canada's Social Sciences and Humanities Research Council (SSHRC).

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