DIGITAL HUMANITIES | RESEARCH ARTICLE

Moderating effect of product type on online shopping behaviour and purchase intention: An Indian perspective

Shekhar Singh1* and Sandeep Srivastava1

Abstract: As per the ASSOCHAM-Resurgent survey (2016), around 70 million people in India shopped for something online, and this number is expected to cross 100 million by 2017. This fact clearly reverberates the fact that Indian e-commerce has come a long way. The objective of this paper is to analyse the factors that influence online shopping behaviour of existing online shoppers of India, with a focus on driving continued usage. The study also examines product-specific purchase behaviour of online consumers through a multi-group moderation analysis conducted for electronics and fashion goods. A comprehensive research model was proposed, integrating relevant constructs from existing literature. The model was, then, empirically tested using structural equation modelling on primary data collected through self-administered survey. Data was collected from 344 online shoppers with prior shopping experience. The results showed that perceived usefulness and perceived risk were the top two significant predictors of online purchase intention for Indian consumers. Based on multi-group moderation analysis findings, the study advocated e-commerce companies to build product-specific strategies as different product characteristics require different channel capabilities to enhance the online shopping experience.

ABOUT THE AUTHORS

Mr. Shekhar Singh completed his B.Tech (Information Technology) and MBA (Finance and Marketing) from ABV-IIITM, Gwalior. His MBA thesis was in the area of e-business, titled “Evaluating Online Service Quality Dimensions in E-Businesses using Fuzzy AHP”. After completing his post-graduation, he worked in MNCs like F1F9 India Pvt. Ltd and Ernst & Young Pvt. Ltd. In course of four years in industry, he developed his expertise in the area of financial modelling (project financing in PPP and infrastructure sector). For the last eight years, he is working as Assistant Professor at Jaypee University of Engineering and Technology, Guna, and also pursuing research in the area of online consumer behaviour.

Dr. Sandeep Srivastava has completed his MBA with specialization in marketing in 2001 from Kanpur University. He has completed his Ph.D. in marketing from ABV-IIITM, Gwalior. The title of his research was “Designing customer centric new product development process”.

PUBLIC INTEREST STATEMENT

From selling fashion to grocery through e-commerce portals, the Indian e-commerce market has come a long way. Driven by favourable demographics (young working population), rising middle class, improved Internet penetration, affordable smartphones and Internet connections, India pictures a lucrative and attractive market for global players like Amazon and Alibaba (PWC Report, 2015). But these opportunities do not come without challenges. In a country as diverse as India, where majority of the customers are price-sensitive and majority of sales numbers are only boosted through umpteen discount deals on various occasions, the long-term sustainability of such discount-driven models is questionable for the long-term profitability of these e-commerce firms. Hence, it becomes an interesting area of research to identify determinant factors and growth drivers specific to Indian consumers. The insights drawn from such a study will empower online retailers in engaging consumers by creating an enhanced online experience.

© 2018 The Author(s). This open access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license.
1. Introduction

There has been a tremendous rise in the Indian e-commerce sector, and now the overall market is beginning to take notice of its vast potential. According to Google, an Indian connects to the Internet for the first time every three seconds, and the total number of Internet users in India is expected to reach 730 million by 2020 (Nasscom-Akamai Report, 2016). The overall e-commerce market in India was valued at $17 billion in 2016 and projections for the market size by 2020 differ wildly, ranging from $50 billion to $120 billion. Currently, travel is by far the most popular online service, accounting for 61% of total e-commerce transactions, but retail e-commerce is expected to drive the growth in the future. In the last five years, the competitive landscape has changed. Domestic players like Flipkart and Snapdeal are facing strong competition from global giants like Amazon and Alibaba (funding Paytm), along with niche competitors like Pepperfry.com and Firstcry.com in certain categories. This is an indicator of the market gradually approaching mature competition. First-mover and capital dump advantages are both dying out and financial losses are mounting for these players. Reportedly, Amazon, Flipkart and Snapdeal booked combined losses of Rs 11,754 crore in 2016 (Tyagi & Thomas, 2017). Investors and e-commerce players now have recognized the urgency to come out of this vicious circle of incurring losses to fuel more growth.

E-commerce companies trying to establish footholds in India need to acknowledge that the Indian e-commerce market is different from the US, European or Chinese market. While it is true that the Indian market is poised for exponential growth in the next decade, riding on increased Internet penetration, rising middle class and innovative business models, that will only happen when local challenges are overcome. Amazon’s inventory-led model in the United States was successful as it capitalized on existing logistics and payment infrastructure of United States (Wang, 2017). By contrast, in India, government policies protect offline retailers by restricting online retailers from holding inventory, thus preventing Amazon from replicating its tried and tested model in India. In India, e-commerce retailers are required to operate as marketplaces offering an intermediary platform for buyers and sellers. In case of China, Alibaba’s immense growth in the Chinese market was mainly driven by an increase in the income levels of consumers during the manufacturing boom in the economy (Nair, 2017). In contrast to the United States and China, a large part of the Indian population is poorer and suffers from an ill-equipped infrastructure (both physical and technological, e.g., payment). These factors contribute to making India a tougher market to crack (Sahil, 2016). According to Redseer Consulting, the average annual Indian online spending in 2017 was somewhere between $120 and $140. In case of China, it crossed the $1800 spending mark (Nair, 2017). This dissimilarity partly reflects the wide gap in per capita income of the two countries (India—$1800 vs. China—$8100), India and China. In addition to this, India's vast geography, consisting of 6,000 small cities and 6 lakh villages, accounting for 70% of the population, presents a logistic challenge for e-commerce companies to find profitable ways of delivering goods and expanding beyond the current serviceable 200 main cities of India (Nielson Report, 2017). These discrepancies are validated by the fact that the rise in Internet penetration in India has not converted to increased online shopping numbers. The Internet penetration in India reached 430 million people accessing Internet in 2016, a comparable number compared to 750 million in China (Nair, 2017). Only 14% of the Internet population, however, shopped online in India, compared to 64% in China in 2017 (Sushma, 2017). The stark dissimilarities do not end here.

Other factors that explain the differences in the Indian case are digital maturity of online population and effect of discount retailing. In case of United States, China and Japan, e-commerce began its journey sometime in the early 2000s and it took 12–13 years for e-commerce to gain
acceptance and become really successful. Whereas in India, e-commerce took off around 2011–12, and most of the online consumers have joined the e-commerce bandwagon in the last three to four years (Melville, 2015). According to a Morgan Stanley study (2017), online shopping for an Internet user is related to the digital maturity of the user, which, per se, is a function of how long the user has been online. As more and more users cross the 5-year mark in Internet usage, the study states, they would be more likely to transact online. Consistent with that rationale, a huge surge in online shopping is expected by 2020, with half of the Internet population engaged in online shopping (Sushma, 2017). This expected growth, however, could be affected by the price sensitivity of Indian online shoppers. The price-sensitive behaviour of the shoppers is exacerbated by e-commerce companies, who have made them disloyal and bargain hunters by luring them consistently with incessant discounts. According to Flipkart, more than half of its sales volume comprises of items below $8–10, and most Indian buyers use online shopping for buying low-ticket items (HKTDC Report, 2017). In order to achieve faster market development, it is clear that e-commerce companies need to find innovative and efficient solutions to these challenges. Going forward, e-commerce companies need to focus on changing customer’s buying behaviour through value and differentiation, instead of discounts.

Like the United States and China, electronics and fashion are the top two online retail categories in India (Yadalam, 2015), although the Indian sales figures are nowhere close to those of the United States and China because the Indian middle class is still emerging with access to a smaller disposable income. In the United States and China, online grocery is highly evolved, and in contrast, India is lagging behind in this area (Yadalam, 2015). At the end of 2017, online retail was only 2% of the total Indian retail industry (Forrester Research, 2018). In order to improve this share and to get a meaningful cut of the overall pie, online retailers need to bring in assortments on their platforms to attract more Indian consumer segments that still have not started shopping online. One way this goal can be achieved is by understanding the characteristics of different product categories sold online and by devising product-specific strategies for the targeted consumer segment. An Indian case can serve as an example for other evolving e-commerce markets with similar digital maturity journey.

In summary, the main objectives of this paper are to analyse the factors that influence online shopping behaviour of existing online shoppers of India and also examine the product-specific purchase behaviour of online consumers. With these objectives in mind, we set out to address the following research questions:

(1) What theoretical perspective can help in the formulation of a research model suitable for understanding online consumer behaviour for existing online buyers?

(2) What are the relevant factors and their relationships which influence product purchase behaviour on the online platform?

(3) What insights can be drawn from product-specific behaviour of online buyers for e-commerce vendors and retailers?

A great deal of research effort has been invested in the last few decades for understanding the factors that drive consumer purchase behaviour in traditional and online channels. Researchers have heavily leveraged intention-based frameworks such as theory of reasoned action (TRA) (Fishbein & Ajzen, 1975), theory of planned behaviour (TPB) (Ajzen, 1991) and technology acceptance model (TAM) (Davis, 1989) as the basis for examining purchase behaviour using purchase intention as a proxy. TPB set down the foundation for understanding voluntary individual behaviour in terms of an individual’s attitudes, subjective norms and perceived behavioural control. Adapting this wide-ranging framework to comprehend technology adoption has seen further cross-functional collaboration, resulting in the application of theories like social cognitive theory (Bandura, 1986) and innovation diffusion theory (Rogers, 1962). TAM emerged as a seminal piece that pioneered the idea of perceived usefulness and perceived ease of use as two vital determinants of technology adoption.
Since the turn of the century, research focus on online shopping behaviour has intensified, especially in developed markets. TAM has featured as the basis for many of these studies (Chiu, Chang, Cheng, & Fang, 2009; Dash & Saji, 2008; Hernández, Jiménez, & José Martin, 2011; Limayem, Khalifa, & Frini, 2000). Customer trust, as well as perceived risk, has been recognized as the key piece in explaining long-term customer relationships (Chen & Barnes, 2007; Friedman, Khan, & Howe, 2000; Kim, Ferrin, & Raghav Rao, 2008; Lee & Turban, 2001). In the face of consumer concern over phishing, hacking and fraud, interest in customer trust has only deepened (Alberto & Montoro, 2007). Other studies have further augmented our understanding of online purchase behaviour by exploring the roles of customer’s self-efficacy and website’s characteristics (Belanger, Hiller, & Smith, 2002; Dash & Saji, 2008).

Studies on online shopping behaviour in the Indian context have been few and far between. Existing literature has focussed on deep dives into specific behavioural factors, often demographics (Khare, Khare, & Singh, 2012), in a world of discount-driven retail. With the Indian e-commerce landscape maturing fast, we feel the lack of a model that paints a comprehensive picture of the Indian consumer’s purchase behaviour while accounting for the huge technological and market movements that have taken place in the last few years. In this study, a comprehensive model has been proposed, consisting of essential constructs driving the Indian consumer’s purchase intention and behaviour. To provide specificity to the model, the study focuses on the two biggest categories of online shopping—electronics and fashion—as within the online retail business, fashion and electronics sales heavily outperform sales in other categories (ASSOCHAM-PwC study, 2016; Google & Bain Report, 2016). This allows us to examine the variations in purchase behaviour for electronics and fashion by studying the moderating effects of product type.

This paper begins with a review of the relevant literature. Based on the review, a research model is proposed and corresponding hypotheses related to the factors that affect actual purchase behaviour are developed. Then, hypotheses are empirically tested with primary data collected from the survey. Finally, results are discussed followed by implications for e-commerce vendors.

2. Research model and hypotheses

The current study identifies purchase intention and actual online purchase behaviour as the key outcome variables of the proposed research model (see Figure 1). We aim to validate the antecedents of purchase intention as well as to understand the moderating effect of product type on
the antecedents’ relationship with purchase intention. The inclusion of actual purchase behaviour is intended for studying the often-ignored relationship between intention and actual behaviour.

It is worth clarifying that the model aims to examine continued usage, instead of adoption. Given the current state of e-commerce in India, studying factors that drive continued usage offers more relevant insights to online retailers than studying those that drive adoption. As highlighted by Karahanna, Straub, and Chervany (1999), the antecedents responsible for adoption may differ from those for continued usage. Their study found that perceived usefulness and enhancement in a subject’s social image end up being the only determinants of continued usage over multiple other factors relevant for adoption.

Since the subject under study is a consumer, albeit in a non-traditional online context, the factors influencing consumer behaviour in a traditional setting bear investigation. Fishbein and Ajzen (1975) introduced a subject’s attitude towards behaviour and its perception of the subjective norms as two key determinants of its intention towards behaviour. Ajzen subsequently extended the framework to include subject’s perceived behavioural control, as part of his TPB (1991). Our study is far from being the first one to draw upon TPB’s insights; instead, it is safely buttressed by decades of supporting research for traditional as well as e-commerce channels (Amaro & Duarte, 2015; Khare et al., 2012; Limayem et al., 2000; Pavlou, 2002).

Intention to use online shopping is further confounded by the consumer’s behavioural traits specific to use of e-commerce technology. TAM has been used with much support to unpack the determinants of online user behaviour. Its two key constructs, perceived usefulness and perceived ease of use, have been empirically validated by numerous studies.

In our model, perceived ease of use is replaced by a similar construct—perceived self-efficacy. Davis, one of the authors of TAM, highlighted (Davis, 1989) that Bandura’s concept of self-efficacy is similar to perceived ease of use. He explained that TAM’s perceived usefulness and perceived ease of use are basic determinants of user behaviour in the same way as self-efficacy judgements and outcome judgements, as proposed by Bandura. He proceeded to confirm that perceived ease of use is similar to self-efficacy, the only drawback of using the latter being that it has to be adapted to the situation. We have chosen perceived self-efficacy over perceived ease of use, due to stronger support for the former in empirical studies, compared to the latter (Hernandez et al., 2011; Khalifa & Shen, 2008; Sentosa & Mat, 2012). Perceived self-efficacy in our model also replaces perceived behavioural control from TPB. Perceived behavioural control has self-efficacy and facilitating conditions (Bhattacherjee, 2000) as its antecedents, even though facilitating conditions is an important factor for adoption of online shopping in India. But given our focus on continued usage, we assume that facilitating conditions for online shopping for a user would not change dramatically over continued usage. Therefore, we focus on self-efficacy’s effect on purchase intention instead. We have further augmented the model with trust and perceived risk. Since online shopping goes beyond the common use of a website for non-transactional purposes, the significance of trust in the online platform, the seller and intermediaries becomes paramount, as does the consumer’s perception of risk that is involved during the transaction. The role of trust and perceived risk as outsized determinants of consumer behaviour in the online shopping context has been demonstrated by existing research (Chen & Barnes, 2007; Kim et al., 2008; Lee & Turban, 2001). Counterfeiting, phishing and payment scams have been major problems in the Indian e-commerce market. That is why consumers are still afraid of making prepaid orders and cash on delivery is the most preferred method of placing orders online (Sahil, 2016; Yadalam, 2015).

Similar to the research paradigm followed by Lian and Lin (2008), our study first identifies the relevant determinant factors from extant literature regarding purchase intention and purchase behaviour. Then, in the second step, different product types are zeroed in, based on which the variation in online purchase behaviour of consumers needs to be studied.
Figure 1 shows the proposed research model with antecedents, moderating and outcome variables.

2.1. Purchase intention and actual purchase behaviour

Purchase intention for online shopping is defined as the measurement of willingness of a consumer to make purchase online through an online retailer. As explained in theories like TRA and TPB, this study is interested in understanding the voluntary usage behaviour of online consumers. Introduced by Ajzen (1991), intention has been used in many e-commerce and m-commerce studies either as a direct antecedent to online purchase behaviour or as the outcome variable replacing actual purchase behaviour (Dash & Saji, 2008; Limayem et al., 2000; Venkatesh, Morris, Davis, & Davis, 2003). Taylor and Todd (1995) asserted that behavioural intention is a good predictor of usage behaviour for people with previous experience and familiarity with technology. Sheppard, Hartwick, Warshaw, and Hartwick (1988) conducted a meta-analysis and found strong empirical support for using intention to predict the performance of behaviour. Consequently, in our study, we posit that for existing online buyers with prior experience, their actual usage behaviour will be largely influenced by purchase intention:

H1: Purchase Intention has direct effect on actual purchase behaviour.

2.2. Attitude and subjective norms

Attitude is one of the two key determinants of voluntary behaviour, initially proposed in the TRA (Fishbein & Ajzen, 1975) and further extended in TPB (Ajzen, 1991). In these theories, attitude was defined as the outcome of beliefs held by the subject regarding the consequences of an action in terms of favourableness or unfavourableness. In any decision-making process, these prior cognitive beliefs stored in memory are readily available and they influence the decision (Fazio, Ledbetter, & Towles-Schwen, 2000). The current study defines attitude towards online shopping as a result of an individual’s inherent beliefs about the merits of using online shopping, which implies that if the individual’s attitude towards online shopping is positive, they would find and utilize avenues to use the online medium for shopping. In previous e-commerce studies, attitude towards online shopping has been studied as one of the key determinants of online consumer behaviour (Hernández et al., 2011; Limayem et al., 2000; Lin, 2007; Venkatesh et al., 2003; Zendehdel, Paim, & Osman, 2015). Hence, we hypothesize that attitude plays an important role in users’ intention to use online shopping.

Subjective norms represent the second key determinant of TRA that this study has adopted. Subjective norms are defined as the social pressure that the subject feels from its social connections towards the use of online shopping. In prior researches, subjective norms or social influence have been studied in detail in the context of online consumer behaviour (Khare et al., 2012; Limayem et al., 2000; Lin, 2007; Zendehdel et al., 2015). Thus, we postulate that the subjective norms are instrumental in driving intention to use online shopping.

H2: Attitude has positive and direct effect on purchase intention.
H3: Subjective norms have direct effect on purchase intention.

2.3. Perceived usefulness

Perceived usefulness, introduced under TAM, is a widely understood, accepted and empirically validated factor towards understanding technology adoption and use. Davis (1985) defined perceived usefulness as the degree to which a particular technology can improve the subject’s job performance, in its own view. Dash and Saji (2008) further defined it in the context of online shopping as the “degree to which a consumer believes that using the system from a website would provide access to useful information, comparison and faster online shopping.” The current study adopts this definition for its comprehensiveness in capturing different aspects of online shopping systems.
Multiple studies have validated the significance of perceived usefulness in the context of technology (Chiu et al., 2009; Dash & Saji, 2008; Hernández et al., 2011; Sentosa & Mat, 2012). We hypothesize that its significance holds for online shopping in the Indian context as well.

**H4: Perceived usefulness has positive and direct effect on purchase intention.**

### 2.4. Perceived self-efficacy

Alberta Bandura promoted the role of self-efficacy in human behaviour or “human agency” in cases that require behavioural change (Bandura, 1977, 1986). Self-efficacy was defined as the subject’s perception of its ability to control and exert influence over an action or a behavioural change. As indicated in the definition itself, self-efficacy embodies perceived behavioural control as put forward by TPB. Aside from the range of applications explored by Bandura himself, from understanding anxiety to influencing at-risk behaviour among AIDS patients, other researchers have empirically validated the theory in the e-commerce space (Eastin, 2002; Igbaria & Livari, 1995; Koufaris, 2002).

Igbaria and Livari (1995) explained that the users with low perception of their self-efficacy in controlling computers tend to avoid them. Users in their study (in Finland) displaying higher self-efficacy used computers more and even sought more management support to facilitate their usage. They argued that perceived usefulness alone will not drive an individual’s usage against a low perception of own capabilities, thus making a case for organizational support for new technologies. Eastin (2002) found self-efficacy to be the most important predictor of online shopping, among five other factors, i.e., prior use of telephone, perceived risk, Internet use, perceived convenience and perceived financial benefits. He observed that self-efficacy played a much bigger role in online shopping compared to other e-commerce activities like online banking, online investing and online services.

It stands to reason that perceptions of self-efficacy will affect subject’s attitudes towards technology. Similarly, subjective norms, as well as organizational support, will influence an individual’s perceived self-efficacy. However, our focus, instead of understanding the antecedents of self-efficacy, is on understanding its influence on purchase intention.

**H5: Perceived self-efficacy has direct effect on purchase intention.**

### 2.5. Trust

The role of trust in buyer–seller relationships has been of paramount interest to researchers, even in traditional offline business transactions. The importance of trust is all but amplified by the “spatial and temporal separation” between the buyer and seller in the online world (Chiu et al., 2009). As recapitulated well by Dash and Saji (2008), trust for buyers involves an expectation of competence as well as benevolence from the seller. Competence is often perceived by tangible characteristics of the online system, e.g., firm’s size and reputation (Bramall, Schoefer, & McKechnie, 2004), website’s characteristics like privacy and security (Bart, Shankar, Sultan, & Urban, 2005). Benevolence represents a confident belief from the buyer that the seller will forego opportunities to exploit the buyer’s vulnerabilities.

Lack of trust in online shopping has been found to lead to lower willingness to shop online (Chen & Barnes, 2007; Lee & Turban, 2001; Pavlou, 2002). A positive trust relationship, conversely, would lead to a positive effect on intention to shop online.

**H6: Trust has direct effect on purchase intention.**

### 2.6. Perceived risk

Perceived risk is defined as the potential loss, monetary or non-monetary, perceived by a consumer when contemplating a purchase online compared to the same purchase offline. This definition is
modelled on a similar one used by Amaro and Duarte (2015) for online travel. It also draws from Cox and Rich’s (1964) insights that the loss experienced by the buyer, in addition to being monetary, may be related to loss of time, frustration, etc.

Perceived risks in online transactions have been widely studied. Those leading to financial loss, potential violations of privacy and security and product quality losses are often considered the dominant ones (Bhatnagar, Misra, & Raghav Rao, 2000; Chen & Barnes, 2007; Kim et al., 2008). Examples of financial loss abound, be it in the form of credit card fraud, payment system failures or even user errors that turn contentious. Privacy concerns related to perceived (and often actual) lack of control over Internet’s collection and use of consumer’s private information (Alberto & Montoro, 2007) are quite prevalent. Security risks include threats related to unauthorized access, denial of service, threat to data integrity, etc. (Belanger et al., 2002). Product risk, according to Bhatnagar et al. (2000), varies based on not only the technological complexity of the product, but also whether the product is attached to a consumer’s self-image, e.g., sunglasses. Many of these risks may be overstated and could be countered through information (Friedman et al., 2000).

The current study has decided to focus on perceived risks of the above types. The conjecture is that higher perceived risks would detract consumer interest from online shopping and drive it towards offline alternatives.

H7: Perceived risk has negative and inverse effect on purchase intention.

2.7. Moderating effect of product type

Several product classifications have been discussed in the literature in the context of the online retail domain (Alba et al., 1997; Klein, 1998; Peterson, Balasubramanian, & Bronnenberg, 1997). Nelson (1974) divided the products into two categories: search and experience goods. “Search goods” are those goods that can be evaluated completely based on information available before purchase, whereas “experience goods” require personal experience and involvement with the product. Fashion, in our case, lies towards “experience goods” end of that continuum and electronics products belong to the “search” category. Chiang and Dholakia (2003) used the same classification and determined that the consumer’s intention to shop online was greater for search goods than experience goods. Girard, Silverblatt, and Korgaonkar (2002) studied the influence of product type on consumer preferences for online shopping based on e-tailers’ attributes like convenience, security/privacy, perceived value, customer service, retailer reputation, etc. Lian and Lin (2008) and Keisidou, Sarigiannidis, and Maditinos (2011) tested the relationships of personal innovativeness of information technology (PIIT), self-efficacy, perceived security, privacy and product involvement with consumer attitude and studied how they varied for different product types. Chiu et al. (2009) also termed product type as a potential moderator and recommended it for future studies.

Recently, PwC Total Retail Survey (2017) also gave a glimpse into the variations in online purchase behaviour between different product types. Some differences that are captured include differences in how consumers research, what platform they use for research and purchase and frequency of purchases. How do the aforementioned antecedents behave when moderated by product type? Existing research does not have a clear answer to this question, certainly not in the Indian context. As online shopping is getting segmented by products and market has matured with more players with product niches; the product-based differences in purchase behaviour can be expected to garner vital interest in Indian markets soon as well.

For certain antecedents, i.e., perceived risk, trust and perceived self-efficacy, existing research (e.g., Bhatnagar et al., 2000; Chiang & Dholakia, 2003; Lian & Lin, 2008; PwC Total Retail Survey, 2017) guides us towards a directional hypothesis. For the remaining antecedents, we hypothesize that product type would have a moderating effect but the direction of the effect is to be tested.
H8: Product type has a moderating effect between attitude and purchase intention.
H9: Product type has a moderating effect between subjective norms and purchase intention.
H10: Product type has a moderating effect between perceived usefulness and purchase intention.
H11: Product type moderates the positive effect of perceived self-efficacy on purchase intention such that it is smaller for fashion than for electronics.
H12: Product type moderates the positive effect of trust on purchase intention such that it is smaller for fashion than for electronics.
H13: Product type moderates the negative effect of perceived risk on purchase intention such that it is smaller for fashion than for electronics.

3. Research methodology

3.1. Sampling
The research methodology included primary data collection through a questionnaire survey. As there was no reliable sampling frame available for employing probability sampling methods, a combination of purposive, convenience and snowball sampling was used to collect data for the study. This approach is in line with recommendations from researchers in online domain for such scenarios (Amaro & Duarte, 2015; Chiang & Dholakia, 2003; Goldsmith & Horowitz, 2006). Participants were asked screening questions in section II of questionnaire to ensure they possessed sufficient prior shopping experience, given the study’s focus on purchase behaviour of existing online buyers. Questionnaires were distributed to online buyers during the period of 1 March 2017 to 30 April 2017. Questionnaires were mostly circulated among respondents through email and with the help of social media (Facebook, WhatsApp and Telegram). Most of the respondents (85%) turned out to be from three metropolitan cities of India, i.e., Delhi, Mumbai and Bangalore. According to ASSOCHAM-Resurgent study in 2016, these three cities were also found to be among the top three spenders with respect to online shopping (Banerjee, 2017).

A total of 574 online buyers were contacted through questionnaires, but since the questionnaire used in this study was quite exhaustive, only 483 filled questionnaires were returned. Thus, the response rate of the questionnaire survey was 84.14%. Out of the total, only 344 complete questionnaires with no missing value were found useful for the purpose of study. There are many views regarding suitable sample size in the context of structural equation modelling (SEM). Usually, a sample size of 100-200 is considered adequate for performing SEM (Kline, 2005; Tabachnick & Fidell, 2001; Teo & Noyes, 2014). For multi-group modelling, the thumb rule is 100 cases or observations per group (Kline, 2005). Another widely accepted rule for sample size is that it should be 10 times the number of items that are observed in the research (Nunnally, 1978). As our sample meets these guidelines, we conclude the sample size to be adequate.

The survey was self-administered with instructions provided by the researchers. The participation in the survey was voluntary, and no extra rewards or incentives were provided to respondents. Hence, it can safely be assumed that no response bias occurred in recording data.

3.2. Instrument development
The questionnaire was divided into three sections: the first section was intended to elicit demographic information about the respondent like age, gender, occupation and education; the second section catered to questions regarding the Internet experience and familiarity of the respondents towards Internet and online shopping; and the third section was designed to extract information measuring customer’s perception of the constructs (perceived usefulness, perceived risk, attitude, subjective norms, perceived self-efficacy, trust, intention to use and actual purchasing behaviour (APB)) used in the research model.

All the question items used in the questionnaire were adapted from literature, wherever possible. To increase the validity and precision of the instrument with respect to the Indian environment and to
foresaw any problems that could arise during data collection, a pilot test and pretest were conducted. A pilot questionnaire was formulated and circulated among 22 doctoral students majoring in IT-related courses. The primary objective was to understand how much time respondents took to fill out the questionnaire, the difficulty level of the questions, the consistency and relevance of questions (Chiu et al., 2009). Two questions were dropped from the questionnaire based on the analysis and feedback from pilot test as the participants noted that those questions appeared redundant in the company of other measuring items. Additionally, language and wordings of questions were also simplified and modified to facilitate Indian respondents’ understanding and make the questionnaire easy to comprehend, in general. The final questionnaire (section III) consisted of 33 question items for eight constructs. These constructs are “Perceived usefulness or PUṣe” (6 items), “Perceived risk or PRisk” (6 items), “Perceived self-efficacy or PSE” (3 items), “Trust” (6 items), “Attitude” (4 items), “Subjective norms or SNORM” (3 items), “Purchase intention or PINT” (3 items) and “Actual purchase behaviour or APB” (2 items).

Afterwards, a medium-scale pretest of the questionnaire was conducted with the help of a sample of 75 undergraduate students. Many studies have advocated the fact that student sample is suitable for online behavioural studies (Cassis, 2007; Delafrooz, Paim, & Khatibi, 2011; Lian & Lin, 2008). Exploratory factor analysis was performed to examine whether the items produced the anticipated number of factors and whether the individual items were loaded on their appropriate factor as expected. Principal component analysis with varimax rotation was used to extract the number of factors. For adequacy, KM Bartlett’s test of sphericity and Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy were conducted. A KMO index of 0.5 and above indicates the adequacy of the data for performing factor analysis (Kaiser, 1974). For the pretest data, the KMO value was 0.926 and Bartlett’s test observed a significance level of 0.000 with a chi-square value of 13,794.968, thus meeting the adequacy requirements.

For examining the reliability of each construct, Cronbach’s alpha coefficient was calculated. According to Nunnally (1978), Cronbach’s alpha values are dependent on the number of items in a construct and it should have a minimum value of 0.7. As reported in Table 1, values for all the constructs are greater than 0.7 (all values between 0.815 and 0.922), establishing construct reliability. For evaluating construct validity, both discriminant and convergent validity need to be examined. In Table 1, we see clean factor structure showing factor loadings for each construct and it is also evident that there are no cross-loadings among factors. All the factor loadings are above the minimum cut-off level of 0.5 (Hair, Black, Babin, & Anderson, 2010), establishing convergent validity for the constructs, and the absence of cross-loadings confirms discriminant validity for the constructs. Thus, the above results indicated that no further modifications in the questionnaire were needed and that it was ready for the main study.

The items for measuring perceived usefulness (PUṣe) were adapted from Dash and Saji (2008). Items used for measuring perceived risk (PRisk) were adapted from Khare et al. (2012). Trust questions were taken from Chiu et al. (2009). Attitude questions were based on Limayem et al. (2000) and Hernández et al. (2011). Items for measuring subjective norms (SNorm) were adapted from Limayem et al. (2000). Perceived self-efficacy (PSE) questions were based on Hernández et al. (2011). Items for measuring intention to use (PINT) were taken from Sentosa and Mat (2012). APB questions were adapted from Lin (2007).

A summary of all questionnaire items is presented in Table 2. The questions pertaining to the key constructs have a 5-point Likert scale format (1 being “strongly disagree” to 5 “strongly agree”), and other general questions have tick response format. The construct-related questions have corresponding responses for fashion (apparel and accessories) and electronics (mobiles, computers, etc.) product categories separated out in two columns. While answering the questions, the respondents were advised to imagine how they felt about the questions while doing online shopping for fashion or electronics products in an online environment (i.e., desktop and laptop).
4. Data analysis and results

In this research, SEM has been chosen for data analysis and theoretical model testing. SEM is a multivariate technique where multiple equations can be simultaneously estimated and errors in each variable can be independently assessed (Hair et al., 2010). SEM also has the capability to represent concepts that are not directly observable or measurable, such as latent variables.

Table 1. Factor matrix

| Factor | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    |
|--------|------|------|------|------|------|------|------|------|
| Cronbach's alpha | 0.921 | 0.865 | 0.848 | 0.815 | 0.902 | 0.818 | 0.907 | 0.922 |
| APB1   |      |      |      |      |      |      |      |      |
| APB2   |      |      |      |      |      |      |      |      |
| INT1   |      |      |      |      |      |      |      | 0.585 |
| INT2   |      |      |      |      |      |      | 0.700 |      |
| INT3   |      |      |      |      |      |      | 0.600 |      |
| ATT1   | 0.773 |      |      |      |      |      |      |      |
| ATT2   | 0.762 |      |      |      |      |      |      |      |
| ATT3   | 0.765 |      |      |      |      |      |      |      |
| ATT4   | 0.769 |      |      |      |      |      |      |      |
| SN1    |      |      |      |      |      |      | 0.772 |      |
| SN2    |      |      |      |      |      | 0.752 |      |      |
| SN3    |      |      |      |      | 0.768 |      |      |      |
| TR1    |      |      |      |      |      |      |      | 0.792 |
| TR2    |      |      |      |      |      |      | 0.761 |      |
| TR3    |      |      |      |      |      | 0.751 |      |      |
| TR4    |      |      |      |      | 0.779 |      |      |      |
| TR5    |      |      |      | 0.808 |      |      |      |      |
| TR6    |      |      |      | 0.792 |      |      |      |      |
| PSE1   |      |      |      |      |      |      |      | 0.775 |
| PSE2   |      |      |      |      |      |      | 0.776 |      |
| PSE3   |      |      |      |      |      | 0.771 |      |      |
| PR1    |      |      |      |      |      |      |      | 0.741 |
| PR2    |      |      |      |      |      |      | 0.772 |      |
| PR3    |      |      |      |      |      | 0.769 |      |      |
| PR4    |      |      |      |      | 0.793 |      |      |      |
| PR5    |      |      |      | 0.790 |      |      |      |      |
| PR6    |      |      |      | 0.809 |      |      |      |      |
| PU1    | 0.810 |      |      |      |      |      |      |      |
| PU2    | 0.816 |      |      |      |      |      |      |      |
| PU3    | 0.756 |      |      |      |      |      |      |      |
| PU4    | 0.827 |      |      |      |      |      |      |      |
| PU5    | 0.818 |      |      |      |      |      |      |      |
| PU6    | 0.828 |      |      |      |      |      |      |      |

Extraction Method: Maximum Likelihood.
Rotation Method: Promax with Kaiser normalization.
Rotation converged in six iterations.
This tool also has the ability to verify the consistency of the model with the data and estimate the interrelationships among the constructs. It is also useful for performing path analysis (Turner & Reisinger, 2001).

IBM's Amos v21.0 software package was used for SEM and Statistical Package for Social Sciences (SPSS v21.0), also from IBM, for factor analysis. Maximum likelihood method was used to assess both measurement and structural model (Arbuckle, 2003).

### Table 2. Questionnaire items

| Constructs | Measurement Items |
|------------|-------------------|
| Attitude | Online shopping is a good idea. |
| | Purchasing through the Web is enjoyable. |
| | My general opinion of e-commerce/m-commerce is positive. |
| | Using the Internet to purchase a product seems an intelligent idea to me. |
| Subjective | The members of my family (e.g., parents, spouse, children) think that I should make purchases through the Internet. |
| Norms | My friends think that I should make purchases through Internet. |
| Trust | Based on my experience with the online store in the past, I know it is honest. |
| | Based on my experience with the online store in the past, I know it cares about its customers. |
| | Based on my experience with the online store in the past, I know it is not opportunistic. |
| | Based on my experience with the online store in the past, I know it keeps its promises to its customers. |
| | Based on my experience with the online store in the past, I know that the transactions will be successful. |
| | Based on my experience with the online store in the past, I know it is trustworthy. |
| Perceived Self-Efficacy | I feel capable of buying a product on the Internet. |
| | I feel capable of finding shopping sites on the Internet. |
| | I feel comfortable looking for information about a product on the Internet. |
| Perceived Risk | I think online websites are risky for financial transactions. |
| | I worry about the safety in using the credit card. |
| | I worry that my personal information may be misused if I shop online. |
| | I worry if the products ordered through online websites would be delivered. |
| | I am not comfortable with the security aspects of online transactions. |
| | I worry about the quality of the product that may be delivered if I order through online websites. |
| Perceived Usefulness | Online store offers more useful information about the choices available. |
| | Online store improves my ability in assessing products online. |
| | Online store enhances my effectiveness to purchase products/services online. |
| | Using the Internet for shopping saves me money. |
| | Online store eliminates time constraint, so I can purchase products at any time I like. |
| | Online store is more user-friendly than an existing physical store. |
| Purchase Intention | Given that I had access to Internet purchasing, I predict that I would use it. |
| | I intend to use Internet purchasing in the future. |
| | I intend to use Internet purchasing as much as possible. |
| Actual Purchase Behaviour | I prefer online shopping for buying fashion/electronics products. |
| | I frequently use online shopping. |
4.1. Profile of respondents

The details of these respondents are reported in Table 3. Out of the total of 344 respondents, 65% were male and the remaining 35% were female, which has been highlighted in many national surveys in India (ASSOCHAM Study, 2017; eShopworld Report, 2017). Regarding occupational background, the sample consisted of around 20% students, 53.8% office workers, 8% self-employed and 18.3% homemakers. Similarly, around 10% of the respondents were in the under-18 age group; 32% were in the age bracket of 18–25; 43% belonged to the age group of 25–35, 11% were in the age group of 35–45 and the rest 4% were in the above-45 age group. According to ASSOCHAM survey (2016), the distribution of regular online shoppers in India based on age group is as follows: 18–25 (38%), 26–35 (52%), 36–45 (8%) and 46–60 (2%) (Narasimhan, 2016). The same fact is reiterated by the eShopworld Report (2017), which provides the age- and gender-wise demographic profile of Indian shoppers for 2016 based on insights derived from eShopWorld data, Statista, WorldBank, OECD and other industry sources. Thus, it can safely be assumed that the respondents’ profile in our survey is similar to the national demographics of online buyers.

4.2. Descriptive statistics

For both fashion and electronics groups, the sample size was 344 for each group as the respondents provided separate data points for each group by responding to the same question twice for each group. After screening data for missing values, normality tests were performed on the data as normality is an important consideration before carrying out SEM. To test univariate normality, the acceptable values for skewness and kurtosis are between $-2$ and $+2$ (Field, 2009; Gravetter & Wallnau, 2014; Trochim & Donnelly, 2006). As shown in Table 4, in our data, the skewness values range from $-1.06$ to $0.062$ and values of kurtosis vary between $-0.56$ and $0.59$. Additionally, standard deviation values are between 0.68 and 0.84 on a 5-point scale, indicating that the data is suitable for SEM analysis (Teo & Noyes, 2014).

4.3. Confirmatory factor analysis

The results of confirmatory factor analysis (CFA) are divided into two components: one for measurement model and the other for structural model (Anderson & Gerbing, 1988). The measurement model examines the relationship between latent variables and observed variables, whereas the structural model performs the path analysis among the latent variables. Measurement model assessment was conducted for construct validity, invariance test and goodness of fit. Once a satisfactory measurement model is achieved, the structural model is developed for studying the structural relationship between the constructs through path estimates.

### Table 3. Demographic characteristics of the sample

| Measure       | Item          | Frequency | %   |
|---------------|---------------|-----------|-----|
| Gender        | Male          | 225       | 65.4% |
|               | Female        | 119       | 34.6% |
| Age           | Under-18      | 35        | 10%  |
|               | 18-25         | 110       | 32%  |
|               | 25-35         | 148       | 43%  |
|               | 35-45         | 38        | 11%  |
|               | >45           | 13        | 4%   |
| Education     | Undergraduate | 69        | 20%  |
|               | Graduate      | 161       | 47%  |
|               | Postgraduate  | 114       | 33%  |
| Occupation    | Student       | 69        | 20%  |
|               | Office worker | 185       | 53.8%|
|               | Self-employed | 27        | 7.8% |
|               | Homemakers    | 63        | 18.3%|
4.3.1. Model fit—measurement model

The first step in CFA is to analyse the model fit values of the measurement model. In Figure 2, measurement model of the constructs used in the model is displayed. All the items in the constructs have loadings greater than the minimum cut-off of 0.7, as shown in Figure 2. The chi-square to degrees of freedom ratio (CMIN/df), root mean square error of approximation (RMSEA), comparative fit index (CFI), standardized root mean residual (SRMR) are used to measure the fit of the model. Model fit values with their cut-off criteria (Li-Tze & Bentler, 1999) are shown below in Table 5 (Gaskin & Lim, 2016), indicating that the goodness of fit for our measurement model is adequate. The second step of the measurement model is to assess the construct reliability and validity of the instrument by examining both convergent and discriminant validity.

| Decision Variables | Skewness | Kurtosis | Standard Deviation |
|--------------------|----------|----------|--------------------|
| APB1               | 0.035    | -0.130   | 0.842              |
| APB2               | 0.063    | -0.020   | 0.795              |
| INT1               | -0.499   | -0.382   | 0.780              |
| INT2               | -0.493   | -0.492   | 0.770              |
| INT3               | -0.520   | -0.372   | 0.771              |
| ATT1               | -0.763   | 0.326    | 0.739              |
| ATT2               | -0.587   | -0.363   | 0.745              |
| ATT3               | -0.605   | -0.177   | 0.733              |
| ATT4               | -0.605   | -0.262   | 0.742              |
| SN1                | -0.609   | -0.227   | 0.764              |
| SN2                | -0.661   | 0.150    | 0.747              |
| SN3                | -0.643   | -0.107   | 0.755              |
| TR1                | -0.656   | -0.395   | 0.747              |
| TR2                | -0.648   | -0.258   | 0.740              |
| TR3                | -0.611   | -0.215   | 0.738              |
| TR4                | -0.714   | -0.240   | 0.738              |
| TR5                | -0.606   | -0.409   | 0.736              |
| TR6                | -0.744   | 0.240    | 0.733              |
| PSE1               | -0.959   | 0.536    | 0.692              |
| PSE2               | -0.652   | -0.569   | 0.681              |
| PSE3               | -0.825   | -0.002   | 0.676              |
| PR1                | -0.989   | 0.514    | 0.721              |
| PR2                | -0.866   | -0.023   | 0.735              |
| PR3                | -0.927   | 0.198    | 0.728              |
| PR4                | -0.887   | 0.012    | 0.724              |
| PR5                | -0.812   | 0.000    | 0.723              |
| PR6                | -0.946   | 0.186    | 0.741              |
| PU1                | -0.965   | 0.265    | 0.717              |
| PU2                | -1.031   | 0.439    | 0.719              |
| PU3                | -0.892   | -0.002   | 0.716              |
| PU4                | -1.015   | 0.453    | 0.724              |
| PU5                | -1.063   | 0.593    | 0.708              |
| PU6                | -1.026   | 0.575    | 0.694              |
4.3.2. Reliability and validity

Convergent validity shows the degree of confidence that the questionnaire items are adequately measuring the construct or they converge to a specific construct. To test convergent validity, average variance extracted (AVE) is calculated, which measures the level of variance captured by a construct versus the level due to measurement error (Fornell & Larcker, 1981; Hair et al., 2010). The minimum accepted value for AVE is 0.5 (Li-Tze & Bentler, 1999). As shown in Table 6 (Gaskin & Lim, 2016), the AVE values for all constructs in our study are greater than 0.5, ranging from 0.582 to 0.855. Thus, the results conform to convergent construct validity test.

Table 5. Model fit—Measurement model

| Measure     | Estimate | Threshold | Interpretation |
|-------------|----------|-----------|----------------|
| CMIN        | 764.484  | —         | —              |
| df          | 467      | —         | —              |
| CMIN/df     | 1.637    | Between 1 and 3 | Excellent |
| CFI         | 0.978    | >0.95     | Excellent      |
| SRMR        | 0.032    | <0.08     | Excellent      |
| RMSEA       | 0.030    | <0.06     | Excellent      |
| P-close     | 1        | >0.05     | Excellent      |

Notes: Li-Tze and Bentler (1999); Gaskin and Lim (2016)
|       | CR   | AVE | PRisk | PUse | Trust | Attitude | PSE  | SNorm | APB  | PINT |
|-------|------|-----|-------|------|-------|----------|------|-------|------|------|
| PRisk | 0.907| 0.619| 0.787 |      |       |          |      |       |      |      |
| PUse  | 0.922| 0.662| -0.312*** | 0.814|       |          |      |       |      |      |
| Trust | 0.902| 0.604| -0.268*** | 0.423*** | 0.777 |          |      |       |      |      |
| Attitude | 0.848| 0.582| -0.174*** | 0.246*** | 0.319*** | 0.763 |      |       |      |      |
| PSE   | 0.818| 0.599| -0.253*** | 0.392*** | 0.285*** | 0.181*** | 0.774|       |      |      |
| SNorm | 0.815| 0.595| -0.245*** | 0.230*** | 0.157*** | 0.06 | 0.207*** | 0.771|      |      |
| APB   | 0.922| 0.855| -0.360*** | 0.499*** | 0.354*** | 0.228*** | 0.363*** | 0.271*** | 0.925|      |
| PINT  | 0.865| 0.681| -0.562*** | 0.675*** | 0.579*** | 0.394*** | 0.545*** | 0.366*** | 0.799*** | 0.825|

Singh & Srivastava, Cogent Arts & Humanities (2018), 5: 1495043
https://doi.org/10.1080/23311983.2018.1495043
For discriminant validity check, the square root values of AVE (shown on the diagonal) are compared with all other inter-factor correlations, and the square root AVE values should be greater than the values of correlations with other factors (Lee, Choi, & Kang, 2009). In the correlation matrix shown in Table 6, all such values are greater than the correlations and all correlations are lower than 0.80, which confirms discriminant validity for our data. We also calculate composite reliability (CR) to measure the reliability of constructs used in the model. CR is considered a less biased estimate of reliability than Cronbach’s alpha. The minimum accepted value of CR is considered to be 0.7 (Hair et al., 2010), and all latent variables in our model demonstrate good reliability with CR values greater than 0.7 for all the constructs.

4.3.3. Invariance test
In the final stage of the analysis, we plan to conduct a multi-group moderation test on the structural model with a categorical moderator variable called product type. Hence, it becomes imperative to conduct configural, metric and scalar invariance tests on the measurement model. The invariance tests are considered necessary to confirm the equivalence of constructs so that any difference detected after that could be related to the moderating effect (Byrne, 2010; Hair et al., 2010).

Configural invariance indicates that the specified model fits the data well in all groups. For testing configural invariance, two groups were created in the measurement model, Fashion and Electronics, and then the model was run freely (without constraint). As shown in Table 7 (Gaskin & Lim, 2016), all the model fit values are above the cut-off criteria, indicating that the data fits both the groups and the factor structure across is same. Metric invariance test is considered a stronger test of invariance. For metric invariance test, first, the measurement model with two groups is run freely and then the model is constrained to be equal across groups. After that, chi-square difference test is performed on the values obtained from the two model runs. The results are shown in Table 8; the p-value (0.934 > 0.05) indicates that the chi-square difference is not significant and groups are not different at the model level in our case.

The third step of measurement invariance involves testing the equality of intercepts across groups (Campbell, Barry, Joe, & Finney, 2008), also known as scalar invariance. In other terms, it is validated that both the groups use the response scale in a similar way (Steenkamp & Baumgartner, 1998). Therefore, if scalar invariance is not achieved, then measurement invariance is not fully supported. For scalar invariance test, the model is constrained across groups for intercepts and then the chi-square difference test is performed for assessing the significance. As shown in Table 8, the p-value (0.103 > 0.5) indicates that full scalar invariance is achieved for our measurement model.

4.4. Structural model analysis
To test the hypothesized framework, a structural model displaying structural relationships between the studied constructs is shown in Figure 3. For assessing the model, model fit indices

| Measure | Estimate | Threshold | Interpretation |
|---------|----------|-----------|----------------|
| CMIN   | 1245.762 | —         | —              |
| df     | 934      | —         | —              |
| CMIN/df| 1.334    | Between 1 and 3 | Excellent  |
| CFI    | 0.977    | >0.95     | Excellent      |
| SRMR   | 0.038    | <0.08     | Excellent      |
| RMSEA  | 0.022    | <0.06     | Excellent      |
| PClose | 1        | >0.05     | Excellent      |
were calculated as shown in Table 9 (Gaskin & Lim, 2016). The values for chi-square with degrees of freedom (CMIN/df) = 1.7, CFI = 0.975, SRMR = 0.034 and RMSEA = 0.032 provide enough evidence for standard model fit. As evident in Table 9, all the model fit values are well above the commonly acceptable levels. Hence, the model was deemed suitable for further path analysis and hypothesis testing.

4.4.1. Path analysis
In Figure 3, standardized path coefficients are shown. As R-squared ($R^2$) value for the model at APB construct is 0.59, it indicates that model accounted for 59% variance in APB. As per Henseler, Ringle, and Sinkovics (2009), if the $R^2$ value is greater than 0.5, then the model has moderate predicting power. Hence, it can be safely stated that our model has good explanatory power for the dependent variable, APB.

### Table 8. Metric and Scalar invariance test

|          | $\chi^2$ | df | $P$-value |
|----------|----------|----|-----------|
| Unconstrained base model$^a$ | 1245.762 | 934 |           |
| Fully constrained model (factor loadings constrained)$^b$ | 1267.486 | 967 |           |
| Fully constrained model (intercepts constrained)$^c$ | 1326.646 | 1000 |           |
| Number of groups | 2 | | |

| Difference (a-b) | 21.724 | 33 | 0.934$^{ns}$ |
| Difference (a-c) | 80.884 | 66 | 0.103$^{ns}$ |

$^{ns}$ represents not significant.

Figure 3. Structural model.
Results for path analysis and hypothesis testing are reported in Table 10. Standardized path coefficients and their statistical significance for each relationship are shown along with the \( p \)-value. All the relationships in this model are found to be statistically highly significant at 99% confidence level (i.e., \( p \)-value < 0.001). All the hypotheses (H1 to H7) are accepted, with perceived usefulness (\( \beta = 0.349 \)) found to be the most important factor in predicting purchase intention and eventually, actual purchase behaviour. Perceived risk (\( \beta = -0.27 \)) was also found to be a significant contributor in impacting purchase intention and actual purchase behaviour.

### 4.4.2. Multi-group moderation analysis

To examine the moderating impact of product type on the relationships between the predictor variables and observed variables, multi-group analysis was performed as product type is a categorical moderator. Two groups were created according to the product type, i.e., Fashion and Electronics. For both groups, the data set contained 344 items, equivalent to the sample size of the study. For the first time, the model was run unconstrained to freely estimate all the path coefficients. The model results of both groups are shown in Figure 4. Then, the model was run after constraining one path at a time and for each path, chi-square (\( \chi^2 \)) difference test was performed at each path level (Jöreskog & Sörbom, 1993). In chi-square (\( \chi^2 \)) difference test, the differences between the chi-square values from both groups are analysed at each path level and if the differences are found significant, then the path exhibits moderating effect caused due to the moderator. The results of multi-group moderation analysis are shown in Table 11.

From Table 11, it is clear that other than the relationship between perceived usefulness and purchase intention, all other relationships do not display significant difference among the two groups. PUse–PINT relationship has a significant difference (\( \Delta \chi^2 = 4.029 \)) at 95% confidence level (\( p < 0.05 \)), and this relationship exhibits moderation effect due to product type. The product type moderation on this path implies that online consumers find more perceived usefulness while buying electronics than buying fashion online. The finding also indicates that in the online environment of desktop and laptop, online consumers recognize more benefits and sense more

**Table 9. Structural model fit values**

| Measure   | Estimate | Threshold | Interpretation |
|-----------|----------|-----------|----------------|
| CMIN      | 804.318  | —         | —              |
| df        | 473      | —         | —              |
| CMIN/df   | 1.700    | Between 1 and 3 | Excellent |
| CFI       | 0.975    | >0.95     | Excellent      |
| SRMR      | 0.034    | <0.08     | Excellent      |
| RMSEA     | 0.032    | <0.06     | Excellent      |
| PClose    | 1        | >0.05     | Excellent      |

**Table 10. Standardized path coefficients**

| Hypothesis | Path Direction | Path Coefficient | Rejected/Accepted |
|------------|----------------|------------------|-------------------|
| H1         | PINT → APB     | 0.769***         | Accepted          |
| H2         | Attitude → PINT| 0.126***         | Accepted          |
| H3         | SNorm → PINT   | 0.130***         | Accepted          |
| H4         | PUse → PINT    | 0.349***         | Accepted          |
| H5         | PSE → PINT     | 0.216***         | Accepted          |
| H6         | Trust → PINT   | 0.213***         | Accepted          |
| H7         | PRisk → PINT   | -0.270***        | Accepted          |

Notes: ***\( p < 0.001 \).
satisfaction in online shopping in case of buying electronics rather than fashion. Thus, only hypothesis H10 is accepted and rest all six hypotheses (H8 to H13) are not supported.

The $R^2$ values at actual purchase behaviour in both groups (Fashion and Electronics) are above 0.5 ($R^2 = 0.61$ for Fashion, $R^2 = 0.55$ for Electronics; Figure 4) level, indicating that both models have good predicting power and they explain the observed variable moderately well. The results show that the structural model as a whole explained 61% of the variance in the actual purchase behaviour of online consumers for fashion products and 55% for electronics products.

5. Discussion and conclusion

Most of the existing literature on online purchasing behaviour has focussed mostly on developed markets such as the United States, Europe, China and Malaysia. Hence, from the outset, the main goals of the present study were threefold: (1) to propose a research model based on existing literature and test it in the Indian context as there are not many such studies done in the past; (2) to identify factors that are most relevant for online vendors in retaining customers as this study
highlights the online consumer behaviour of consumers who already have experience with the online channel; and (iii) to study the moderating effect of product type on the medium (i.e., desktop and laptop) of online shopping. As discussed above, in the “Results” section, the results provide strong support for the theoretical proposed model. The overall results indicate that perceived usefulness, perceived risk, trust, perceived self-efficacy, attitude and subjective norm were all significant determinants of purchase intention and ultimately, actual purchase behaviour.

The present research establishes the fact that perceived usefulness of a website encourages the customer to buy online and is the most important driver of online purchases. This result is consistent with extant literature which suggests that online shopping behaviour is influenced by the consumer’s perceived usefulness (Chiu et al., 2009; Dash & Saji, 2008; Venkatesh & Davis, 2000). Some of the past studies have used convenience-related constructs like perceived benefit, innovativeness, etc., to study purchase intention in place of perceived usefulness and found similar results (Amaro & Duarte, 2015; Escobar-Rodríguez & Bonsón-Fernández, 2016; Forsythe, Liu, Shannon, & Gardner, 2006).

In earlier studies, it was found that perceived risk is an important antecedent of online shopping (Biswas & Biswas, 2004; Forsythe et al., 2006; Zendehdel et al., 2015; Zimmer, Arsal, Al-Marzouq, & Grover, 2010). In many other studies, it was found that perceived risk is one of the common barriers in the context of online shopping transactions. These findings are reaffirmed in our study, which empirically demonstrated that perceived risk has negative and direct impact on purchase intention, which in turn impacts actual purchase behaviour. One of the reasons due to which many consumers in India still prefer cash on delivery mechanism above online payments (CII Report, 2016). Our findings are in sync with those of Amaro and Duarte (2015), who commented that despite increasing trust of consumers in computer systems and online shopping, perceived risk continues to negatively affect online travel purchase intention.

Trust has been a salient factor in purchase intention, customer relationship building and website loyalty (Amaro & Duarte, 2015; Chiu et al., 2009; Kim et al., 2008; Zimmer et al., 2010). Our results also emphasize on the importance of trust for purchase intention, though in our study trust is not the most important factor. A possible explanation for this can be that our study is focussed on understanding shopping behaviour of existing consumers rather than acquiring potential new consumers. When consumers are already familiar with a system and having already resolved any trust issues concerning online shopping, factors like perceived usefulness and perceived risk may become more prominent. This finding is consonant with Zimmer et al. (2010), who pointed out that prior experience with a website can build trust between the website and the user.

The effect of perceived self-efficacy on individual perceptions and behaviour has been studied in many past studies (Dash & Saji, 2008; Hernández et al., 2011; Lian & Lin, 2008; Lin, 2007). Online shopping can only evolve and succeed if consumer’s acceptance, satisfaction and frequency of use of online shopping are high. In our study, the results clearly demonstrated that perceived self-efficacy had a positive influence on purchase intention, demonstrating that it is a significant contributor even for existing online shoppers. This means that online users’ purchase intention is fostered by their perception of how easy and convenient it is to use desktops and laptops for the purpose of online shopping. Hence, online vendors should place particular emphasis on ensuring that online websites have easy-to-use interfaces, fast search options, easy navigation through webpages and easy-to-find shopping assistance, in order to have satisfied consumers and increase their lifetime value through long-term purchase behaviour.

In our study, attitude and subjective norm are relegated to the least significant contributors. In previous studies, attitude and subjective norms have been found to be important determinants of online shopping behaviour and these factors directly affect intention (Amaro & Duarte, 2015; Forsythe et al., 2006; Hernández et al., 2011; Taylor & Todd, 1995; Zimmer et al., 2010). In sync
with previous studies, this research also establishes the causal relationship between intention and usage behaviour (Lin, 2007; Taylor & Todd, 1995; Venkatesh & Davis, 2000; Zimmer et al., 2010).

The study’s major original contribution was the analysis of the moderating effect of product type on the online medium. The moderation role of product type was confirmed in the analysis of relationship between perceived usefulness and purchase intention. The results indicate that consumers perceive more usefulness and benefit while shopping for electronics items online than shopping for fashion items. It is possible, however, that this moderating behaviour is more prominent for online consumers shopping through desktops and laptops and that it differs for buyers using smartphones. Online buyers shopping through the online medium (desktops and laptops) may find online shopping for electronics more worthwhile than fashion for two reasons: first, due to high average expenditure on electronics than fashion products, and second, due to the higher importance of touch-and-feel aspect for fashion products compared to electronics. The observation is consistent with Chiang and Dholakia’s findings (2003) that online purchase intention is higher for “search goods” than for “experience goods”. Our moderation finding is also consistent with the findings of other studies (Girard et al., 2002; Klein, 1998; Moon, Chadee, & Tikoo, 2008) stating that online shopping is more appropriate for search goods compared to experience goods, which implies that e-commerce vendors need to explore new multitude of innovations offering personalization and innovativeness for improving the purchase experience of experience goods like fashion (Escobar-Rodríguez & Bonsón-Fernández, 2016).

5.1. Implications for practice

The present study provides a lot of practical insights for online vendors and their managers in the Indian context. As consumers overcome the stage of initial adoption and start to recognize the advantages of online shopping, it becomes imperative for the e-commerce players like Amazon and Flipkart to engage these consumers with outstanding online user experience. As suggested by the results of this study, online retail companies should focus on increasing the perceived usefulness of online shopping experience for the e-shoppers. According to the latest Akamai Report (2017) on online Web performance, a 100 ms delay in website load time lowers the conversion rate by 7%. Hence, it is important for the online retail companies to provide seamless and reliable Web experience to its consumers. There have been episodes of server failures and other technical issues with Flipkart and Amazon on many flash sale days. These kinds of service failures need to be minimized for e-commerce to be accepted in the long term. In addition, e-commerce players should increase their investments in artificial intelligence (AI) technologies to provide more customized and personalized online experience to the consumers using smart and predictive analytics. AI technologies can help in simplifying image search, automated meta-tag generation and real-time recommendation about products that will grab consumer attention and engage them for longer. With the vast repository of shopping and other data, AI technologies can solve a host of problems for e-retailers through language translation, automated answering of consumer queries, product recommendations, product search and future purchase predictions. With digital devices, cloud computing and social media, online sellers have an unprecedented opportunity for growth, which can be achieved by engineering enhanced customer experiences.

Online retailers, especially mass online retailers like Flipkart and Amazon, stand to benefit from boosting their platform’s perceived usefulness for fashion products. New technologies such as virtual walls and virtual mirrors can play a big role in improving the retail customer experience, thereby encouraging boosting perceptions. Virtual mirrors let shoppers “try on” clothes and accessories virtually before making buying decisions. In addition to adopting the right technologies, these retailers need to adapt their business models to provide an omni-channel experience to the consumers. This will entail integrating the strong aspects of in-store experience (measurements, touch-and-feel, guided shopping, etc.) with those of online channel (comparison shopping, ordering, delivery, etc.) (Sopadjieva, Dholakia, & Benjamin, 2017).
In respect of perceived risk, online vendors should implement strategies that guarantee riskless online payment processing and risk-free online shopping experience. As suggested by Collier and Bienstock (2006), online vendors should give paramount importance to three aspects of order delivery: timeliness of the order, accuracy of the order and condition of the order. In addition to order fulfillment, e-commerce retailers should also devise a mechanism for secure transactions by employing safe and reliable security systems and educate consumers about different evolving payment technologies like mobile wallets, unified payment interface (UPI), SSL protocols in payment systems, multi-tier authentication, real-time PIN generation and security approval symbols on websites so that consumers are encouraged to shop again in future (Zendehdel et al., 2015). In addition, safety and privacy of the consumer’s personal and financial information have to be ensured so that these issues are the least of consumers’ worries.

Finally, to ensure continued success of the yet-evolving e-commerce ecosystem, it is essential to involve all stakeholders—consumers, marketers, sellers, website managers as well as developers—in the service or product development. A customized and personalized online shopping experience will be the face of future e-commerce services, and online vendors need to build innovative service offerings using advanced technologies. Other than the metropolitan cities, new consumer base is spreading across tier 2 and tier 3 cities in India and e-commerce companies should target this untapped market by executing effective and near-real-time marketing campaigns. According to the 2011 Indian census, cities having a population of more than 4 million are classified as metropolitan cities; cities with a population of above 1 million are known as tier 2 cities; and cities with a population of at least 1 lakh are categorized as tier 3 cities (India Census report, 2011).

6. Limitations and directions for future research
Despite following rigorous research methods and statistics in this study, there are several limitations to this study, and they should be addressed in future studies. The first obvious limitation is its small sample size. Though the sample size is adequate for applying SEM as per existing literature, there is a possibility that it might not completely represent the vast Indian online population. Therefore, there can be a potential bias in the results and that may affect the extent to which these findings are generalizable. Future researchers are recommended to conduct data collection using random sampling from a large diverse population.

Since this research is a cross-sectional study that analyses data collected from a representative subset of population at a specific point in time, it could at best provide a snapshot of online consumer intention and behaviour at a single point in time. This study cannot comment on the understanding of changing intention and behaviour of online consumers over time. Therefore, future researchers may undertake longitudinal studies gathering data from the same respondents repeatedly over a time period. The findings from such studies would not only help in formulating an effective model capable of predicting beliefs and behaviour over time, but also enhance our understanding of the causality and the interrelationships between variables. In this research, moderating effects of the product type are examined on the proposed model in the online environment of desktops and laptops. More research can be conducted to examine the moderating effect of product type in the mobile environment, or moderating effect of demographic variables like education level, gender or age. These studies will help in unravelling India-specific challenges and directions for future growth of e-commerce players.

Funding
The authors received no direct funding for this research.

Author details
Shekhar Singh1
E-mail: shekhar.iiitm@gmail.com
ORCID ID: http://orcid.org/0000-0002-4244-4297
Sandeep Srivastava1
E-mail: sandy.iiitm@gmail.com
1 Department of Humanities & Social Sciences, Jaypee University of Engineering and Technology, Guna, India.

Citation information
Cite this article as: Moderating effect of product type on online shopping behaviour and purchase intention: An Indian perspective, Shekhar Singh & Sandeep Srivastava, Cogent Arts & Humanities (2018), 5: 1495043.

References
Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. doi:10.1016/0749-5978(91)90020-T
Biswa, D., & Biswas, A. (2004). The diagnostic role of signals in the context of perceived risks in online shopping: Do signals matter more on the Web? *Journal of Interactive Marketing*, 18, 30–45. doi:10.1002/dir.20010

Bramhall, S., Schoefer, K., & McKeechnie, S. (2004). The determinants and consequences of consumer trust in e-retailing: A conceptual framework. *Irish Marketing Review*, 17(1/2), 13–22.

Byrne, B. M. (2010). *Structural Equation Modelling with AMOS: Basic concepts, application, and programming* (2nd ed.). New York, NY: Routledge Taylor & Francis Group.

Campbell, H. L., Barry, C. L., Joe, J. N., & Finney, S. J. (2008). Configural, metric, and scalar invariance of the modified achievement goal questionnaire across African American and white university students. *Educational and Psychological Measurement*, 68(6), 988–1007. doi:10.1177/0013164408318766

Cassis, C. (2007). *College students help fuel ever—Growing Internet sales*. Retrieved from http://media.www.dailypreps.com/media/storage/paper87/news/Chen,Y.-H.,&Barnes,S.(2007).Initialtrustandonlinetraderetailerbehaviour.*IndustrialManagement&DataSystems*,101(3),21–36.doi:10.11108/0263557010719034

Chiang, K. P., & Dholakia, R. R. (2003). Factors driving consumer intention to shop online: An empirical investigation. *Journal of Consumer Psychology*, 13(1–2), 177–183.

Chiou, C. M., Chang, C. C., Cheng, H. L., & Fang, Y. H. (2009). Determinants of consumer repurchase intention in online shopping. *Online Information Review*, 33(4), 761–784. doi:10.1108/14685420910985710

CII Report. (2016). *e-Commerce in India – A game changer for the economy* [Online]. Retrieved November 8, 2016, from http://www.assocham.org/newsdetail.php?id=6527

Collier, J. E., & Bienstock, C. C. (2006). Measuring service quality in e-retailing. *Journal of Service Research*, 8, 260–275. doi:10.1177/1094670505278867

Cox, D. F., & Rich, S. U. (1964). Perceived risk and consumer decision-making: The case of telephone shopping. *Journal of Marketing Research*, 32–39. doi:10.2307/3150375

Dash, S., & Saji, K. B. (2008). The role of consumer self-efficacy and website social-presence in consumers’ Adoption of B2C online shopping: An empirical study in the indian context. *Journal of International Consumer Marketing*, 20(2), 33–48. doi:10.1300/J046v20n02_04

Davis, F. D. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results (Diss. Massachusetts Institute of Technology).

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319–340. doi:10.2307/249008

Delafroz, N., Pain, L. H. J., & Khatibi, A. (2011). A research modeling to understand online shopping intention. *Australian Journal of Basic and Applied Sciences*, 5, 70–77.

Eastin, M. S. (2002). Diffusion of e-commerce: An analysis of the adoption of four e-commerce activities. *Telematics and Informatics*, 19, 251–267. doi:10.1016/S0736-5853(01)00005-3

Escobar-Rodriguez, T., & Bonsón-Ferrández, R. (2017). Analysing online purchase intention in Spain: Fashion e-commerce. *Information Systems and e-Business Management*, 15(3), 599–622.

eShopWorld Report. (2017). *Indian eCommerce insights* (358 Million people in India will shop online by 2020).
Fazio, R. H., Ledbetter, J. E., & Towles-Schwen, T. (2000). On the costs of accessible attitudes: Detecting that the attitude object has changed. Journal of Personality and Social Psychology, 78(2), 197. doi:10.1037//0022-3514.78.2.197

Field, A. (2009). Discovering statistics using SPSS. London: SAGE.

Fishbein, M., & Ajzen, I. (1975). Beliefs, attitudes, intention, and behavior: An Introduction of theory and research. Reading, MA: Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. doi:10.2307/3151312

Forrester Research. (2018). Ecommerce growth fell 26% in 2017: Forrester Research - The Economic Times [Online]. Retrieved June 20, 2018, from https://economictimes.indiatimes.com/small-biz/startups/news-buzz/ecommerce-growth-fell-26-in-2017-forrester-research/articleshow/62733708.cms

Forsythe, S., Liu, C., Shannon, D., & Gardner, L. C. (2006). Development of a scale to measure the perceived benefits and risks of online shopping. Journal of Interactive Marketing, 20, 55–75. doi:10.1002/dir.20061

Friedman, B., Khan, P. H., Jr, & Howe, D. C. (2000). Trust online. Communications of the ACM, 43(12), 34–40. doi:10.1145/355112.355120

Gaskin, J., & Lim, J. (2016). Model fit measures. AMOS Plugin. Gaskin'station's StatWiki.

Girard, T., Silverblatt, R., & Korgaonkar, P. (2002). Influence of product class on preference for shopping on the internet. Journal of Computer-Mediated Communication, 8(1).

Goldsmith, R. E., & Horowitz, D. (2006). Measuring motivations for online opinion seeking. Journal of Interactive Advertising, 6(2), 1–14. doi:10.1080/15252019.2006.10722114

Google & Bain Report. (2016). Impact of digital on beauty and hygiene [Online]. Retrieved March 3, 2017, from http://www.ibhaindia.com/wp-content/uploads/2016/02/Bain-Google-Insight-Knowledge-PPT.pdf

Gravetter, F., & Wallnau, L. (2014). Essentials of statistics for the behavioral sciences (8th ed.). Belmont, CA: Wadsworth.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Englewood Cliffs: Prentice Hall.

Henseler, J., Ringle, C., & Sinkovics, R. (2009). The use of partial least squares path modeling in international marketing. Advances in International Marketing (AIM), 20, 277–320.

Hernández, B., Jiménez, J., & José Martin, M. (2011). Age, gender and income: Do they really moderate online shopping behaviour? Online Information Review, 35 (1), 113–133. doi:10.1108/14684521111113814

HKTDC Report. (2017). E-commerce market developments in India and the opportunities for Hong Kong (2) [HKTDC Online]. Retrieved June 20, 2018, from https://economists-pick-research.hktdc.com/business-news/article/Research-Articles/E-commerce-Market-Developments-in-India-and-the-Opportunities-for-Hong-Kong-21/preview/1X1X0000001X0AO8TOX.htm

Igbaria, M., & Iwan, J. (1995). The effects of self-efficacy on computer usage. Omega, 23(6), 587–605. doi:10.1016/0305-0483(95)90035-6

India Census. (2011). Census of India 2011 provisional population totals urban agglomerations and cities [Online]. Retrieved June 20, 2018, from http://censusindia.gov.in/2011-prov-results/paper2_data_files/India21/DataHighlight.pdf

Jöreskog, K. G., & Sörbom, D. (1993). LISREL 8: Structural equation modeling with the SIMPLIS command language. Chicago, IL: Scientific Software International.

Kaiser, H. F. (1974). An index of factorial simplicity. Psychometrika, 39(1), 31–36. doi:10.1007/BF02291575

Karahanna, E., Straub, D. W., & Chevray, N. L. (1999). Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. MIS Quarterly, 183–213. doi:10.2307/249751

Kesisidou, E., Sarigiannidis, L., & Maditinos, D. (2011). Consumer characteristics and their effect on accepting online shopping, in the context of different product types. International Journal of Business Science & Applied Management, 6(2).

Khalifa, M., & Ning Shen, K. (2008). Explaining the adoption of transactional B2C mobile commerce. Journal of Enterprise Information Management, 21(2), 110–124. doi:10.1108/17413090810851372

Khare, A., Khare, A., & Singh, S. (2013). Attracting shoppers on-line—Challenges and opportunities for the Indian retail sector. Journal of Internet Commerce, 11(2), 161–185. doi:10.1080/15332861.2012.689570

Kim, D. J., Ferrin, D. L., & Raghav Rao, H. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. Decision Support Systems, 44(2), 544–564. doi:10.1016/j.dss.2007.07.001

Klein, L. R. (1998). Evaluating the potential of interactive media through a new lens: Search versus experience goods. Journal of Business Research, 41, 195–203. doi:10.1016/S0148-2963(97)00062-3

Kline, R. B. (2005). Principles and practice of structural equation modeling (2nd ed.). New York, NY: Guilford.

Koufaris, M., Labarbera, P. A., & Kambil, A. (2001). Consumer behavior in web-based commerce: An empirical study. International Journal of Electronic Commerce, 6(2), 115–138. doi:10.1080/10864415.2001.11044233

Koufaris, M. (2002). Applying the Technology Acceptance Model and Flow Theory to Online Consumer Behavior. Information Systems Research, 13(2), 205–23.

Lee, H., Choi, S.-Y. A., & Kang, Y. S. (2009). Formation of e-satisfaction and repurchase intention: Moderating roles of computer self-efficacy and computer anxiety. Expert Systems with Applications: an International Journal, 36(4), 7848–7859. doi:10.1016/j.eswa.2008.11.005

Lee, M. K. O., & Turban, E. (2001). A trust model for consumer internet shopping. International Journal of Electronic Commerce, 6(1), 75–91. doi:10.1080/10864415.2001.11044227

Lian, J. W., & Lin, T. M. (2008). Effects of consumer characteristics on their acceptance of online shopping: Comparisons among different product types. Computers in Human Behavior, 24(1), 68–65. doi:10.1016/j.chb.2007.01.002

Limayem, M., Khalifa, M., & Frini, A. (2000). What makes consumers buy from Internet? A longitudinal study of online shopping. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 30(4), 421–432. doi:10.1109/3468.852436

Lin, H.-F. (2007). Predicting consumer intentions to shop online: An empirical test of competing theories. Electronic Commerce Research and Applications, 6(2007), 433–442. doi:10.1016/j.elerap.2007.02.002
Li-Tze, H., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal, 6(1), 1–55. doi:10.1080/10705519908540118

Melville, L. J. (2015). eMarketer says E-commerce in China beats out India’s Market by 80 Times | Wholesale News [Online]. Retrieved June 20, 2018, from https://www.toppenwholesale.com/news/emarketer-e-commerce-china-beats-indias-market-80-times-20505.html

Moon, J., Chadee, D., & Tikoo, S. (2009). Culture, product type, and price influences on consumer purchase intention to buy personalized products online. Journal of Business Research, 61(1), 31–39. doi:10.1016/j.jbusres.2006.05.012

Nair, R. P. (2011). Will Indian e-commerce ever match up to the Chinese dragon? [Online]. Retrieved June 20, 2018, from https://yourstory.com/2017/10/india-china-ecommerce/

Narasimhan, P. (2016). E-commerce industry to cross $38 billion this year: Assocham [Online]. Retrieved October 07, 2016, from http://www.thehindu.com/business/E-commerce-industry-to-cross-38-billion-this-year-Assocham/article13977121.ece

Nasscom-Akamai Report. (2016). The future of internet in India [Online]. Retrieved Jun 08, 2017, from http://www.nasscom.in/sites/default/files/media_pdf/nasscom_akamai_technologies_report_showcase_how_internet_changing_india.pdf

Nunnally, J. C. (1978). Psychometric theory (2nd ed.). New York, NY: McGraw-Hill.

Pavlou, P. A. (2002). What drives electronic commerce? A Theory of planned behavior perspective. Academy of Management Proceedings 2002(1), Academy of Management. doi:10.5465/0pp.2002.7517579

Peterson, R. A., Balasubramanian, S., & Bronnenberg, B. J. (1999). Exploring the implications of the Internet for consumer marketing. Journal of the Academy of Marketing Science, 25, 329–346. doi:10.1177/0921005899025005

PWC Report. (2015). Ecommerce in India accelerating growth [Online]. Retrieved May 9, 2017, from https://www.pwc.in/assets/pdfs/publications/2015/ecommerce-in-india-accelerating-growth.pdf

PwC Total Retail Survey. (2017). 10 retailer investments for an uncertain future [Online]. Retrieved July 19, 2017, from https://www.pwc.com/gx/en/industries/consumer-services/assets/total-retail-2017.pdf

Rogers, E. M. (1962). Diffusion of innovations (1st ed.). New York, NY: Free Press of Glencoe.

Sahil. (2016). Why eCommerce in India is diminutive when compared to countries like China & Brazil [Online]. Retrieved June 20, 2018, from https://www.indiantelecom.teller.com/article/multi-channel/eretail/why-e-commerce-in-india-is-diminutive-when-compared-to-countries-like-China-Brazil-05323/

Sentoza, I., & Mat, N. (2012). Examining A Theory Of Planned Behavior (TPB) and Technology Acceptance Model (TAM) in internet purchasing using structural equation modeling. Journal of Arts, Science & Commerce, III(2), 2.

Sheppard, B. H., Hartwick, J., Warshaw, P. R., & Hartwick, J. O. N. (1988). The theory of reasoned action: Meta-analysis of with modifications for recommendations and. Journal of Consumer Research, 15(3), 325–343. doi:10.1086/209170

Sopadijeva, E., Dholakia, U., & Benjamin, B. (2017). A study of 46,000 shoppers shows that omnichannel retailing works. Harvard Business Review, 3.

Steenkamp, J. B. E., & Baumgartner, H. (1998). Assessing measurement invariance in cross-national consumer research. Journal of Consumer Research, 25(1), 78–90. doi:10.1086/209528

Sushma, U. N. (2017). Morgan Stanley explains why India’s e-commerce market is a hot investment opportunity [Online]. Retrieved March 18, 2018, from https://qa.com/1089559/morgan-stanley-explains-why-indias-e-commerce-market-is-a-hot-investment-opportunity/

Tabachnick, B. G., & Fidell, L. S. (2001). Using multivariate statistics (4th ed.). Boston, MA: Allyn & Bacon.

Taylor, S., & Todd, P. A. (1995). Assessing IT usage: The role of prior experience. MIS Quarterly, 19(4), 561–570. doi:10.2307/249633

Teo, T., & Noyes, J. (2014). Explaining the intention to use technology among pre-service teachers: A multi-group analysis of the unified theory of acceptance and use of technology. Interactive Learning Environments, 22(1), 51–66. doi:10.1080/10494820.2011.641674

Trochim, W. M., & Donnelly, J. P. (2006). The research methods knowledge base (3rd ed.). Cincinnati, OH: Atomic Dog.

Turner, L. W., & Reisinger, Y. (2003). Shopping satisfaction for domestic tourists. Journal of Retailing and Consumer Services, 8, 15–27. doi:10.1016/S0167-4717(01)00033-7

Tyagi, C., & Thomas, A. (2017). Losses of Flipkart, Amazon & Snapdeal would have allowed ISRO to go to Mars 24 times [Online]. Retrieved May 17, 2017, from http://economictimes.indiatimes.com/small-biz/startups/losses-of-flipkart-amazon-snapdeal-would-have-allowed-isro-to-go-to-mars-24-crore-times/articleshow/56679850.cms

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46 (2), 186–204. doi:10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27, 425–448. doi:10.2307/30036540

Wang, B. (2017). Alibaba insider explains why Amazon lost in China and how it applies to India’s current ecommerce rise | NextBigFuture [Online]. Retrieved June 20, 2018, from https://www.nextbigfuture.com/2017/11/alibaba-insider-explains-why-amazon-lost-in-china-and-how-it-applies-to-indias-current-ecommerce-rise.html doi:10.3168/jds.2017-14085

Yadalam, R. (2015). E-commerce in US vs Indian E-Commerce: Identifying the missing pieces [Online]. Retrieved June 20, 2018, from http://www.iamwire.com/2015/01/e-commerce-vs-indian-e-commerce-identifying-missing-pieces/108066

Zendehdel, M., Paim, L. H., & Osman, S. B. (2015). Students’ online purchasing behavior in Malaysia: Understanding online shopping attitude. Cogent Business & Management, 2(1), 1078428. doi:10.1080/23311975.2015.1078428

Zimmer, J. C., Arsal, R. E., Al-Marzouq, M., & Grover, V. (2010). Investigating online information disclosure: Effects of information relevance, trust and risk. Information & Management, 47, 115–123. doi:10.1016/j.im.2009.12.003
