Routledge
Taylor & Francis Group

Economic Research-Ekonomska Istraživanja

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/rero20

Investigating the impact of digital influencers on consumer decision-making and content outreach: using dual AISAS model

Sara Javed, Md. Salamun Rashidin & Yun Xiao

To cite this article: Sara Javed, Md. Salamun Rashidin & Yun Xiao (2022) Investigating the impact of digital influencers on consumer decision-making and content outreach: using dual AISAS model, Economic Research-Ekonomska Istraživanja, 35:1, 1183-1210, DOI: 10.1080/1331677X.2021.1960578

To link to this article: https://doi.org/10.1080/1331677X.2021.1960578

Published online: 02 Sep 2021.

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
2022, VOL. 35, NO. 1, 1183–1210
https://doi.org/10.1080/1331677X.2021.1960578

Routledge
Taylor & Francis Group

OPEN ACCESS Check for updates

Investigating the impact of digital influencers on consumer decision-making and content outreach: using dual AISAS model

Sara Javed[a], Md. Salamun Rashidin[a,b] and Yun Xiao[c]

[a]Department of Marketing, University of International Business and Economics (UIBE), Beijing, China; [b]International Trade and Economics, University of International Business and Economics (UIBE), Beijing, China; [c]School of Business, University of International Business and Economics (UIBE), Beijing, China

ABSTRACT
With exponential rise of social media, marketers identify the power and effectiveness of influencer's advertising on social networking site (SNS). Despite comprehensive understanding of the effects of influencers, their outreach to large audience is yet to be addressed. In this article, we have investigated the effects of fashion influencers on consumers' decision-making processes and their content outreach on Instagram by embracing new behavioral consumption model 'dual AISAS model', which is upgraded version of AISAS Model. It is based on theoretical grounding theory of buying behavior and multi-step flow theory. Both offline and online surveys were conducted involving 969 Pakistan Instagram users following digital influencers. Valid data was assessed and analyzed through structural equation modeling. Our findings demonstrate that every path in dual AISAS model is found significant and have profound effect. It reveals that fashion influencers exert powerful influence on consumers' decision-making process. Being so influential, they grab the consumers' attention immediately, engage them, and get wider outreach by upturn in consumer intention in order to spread the fashion content within private networks as well as extended networks. The findings hold robust implications to both theory and practice. Some limitations of the present study offer boulevards to future scholars.

ARTICLE HISTORY
Received 24 November 2020
Accepted 20 July 2021

KEYWORDS
Digital influencers; decision-making; SEM; dual AISAS model; visual centric platform

JEL CODES
M3; M37; M39

1. Introduction

Nowadays, social networking sites such as Instagram, Snapchat, Twitter, Youtube, and Facebook etc. represent valuable 'marketing endeavor' (Dwivedi et al., 2018). The customers' decisions are influenced by these sites (Caslo, 2018). They empower the consumers to search (Chen & Xie, 2008) and exchange the knowledge about products

CONTACT Md. Salamun Rashidin salamun.du@outlook.com

and services with others (Merz et al., 2018). Moreover, social media is playing vital role in digital market as the digital influencer (Mavroudis, 2018). On social networking sites (SNS), online branding of products through business accounts and advertisements has proven to be an efficient marketing strategy (De Vries & Carlson, 2014). On social media, certain users actively create online content (user generated content) and become an opinion leader. Their shared post enriched with reviews, emotions, and personal experience can influence the products, brands, and potential audience (Hsu et al., 2013). Therefore, we have named them as 'digital influencers' (Susarla et al., 2016). Digital influencers have been recognized as more influential (Thakur et al., 2016) thanks to large number of followers (Jin & Phua, 2014). They are ubiquitous in all fields like food (Sony Kusumasondjaja & Tjiptono, 2019), travel (Song et al., 2017), and fashion (Casaló, 2018), but they have seized a mammoth attention specifically in fashion industry (Delisle & Parmentier, 2016). In fashion industry, the opinion of influencers is worthwhile (Wiedmann et al., 2010) because the fashion posts act as a source of inspiration for consumers and have high propensity to influence the consumers' purchase decision (Susarla et al., 2016; Zhu et al., 2015) or shopping behavior. Moreover, it is evident that fashion seekers aid the influencers to spread the content or diffuse the fashion trends within their private network and extended networks (Goldsmith & Clark, 2008) by leveraging the power of social media (Lipsman et al., 2012).

Fashion related products urge the consumers to use visual centric-platform such as Instagram (Mull & Lee, 2014), which reported that its monthly active users were 1 billion in 2018 (Statista—The Statistics Portal, 2018). In this context, Instagram seems reasonable to showcase the products (Locowise, 2017; Štreimikienė et al., 2021). The basic premise behind gaining the popularity of Instagram is that it, unlike other social networking sites, provides an opportunity to brands to post the content in an aesthetic appealing way (image-sharing, photos, videos, stories etc.) (Lyfe Marketing, 2018). The nature of Instagrammer influencer posts encompasses images and videos with textual description. Prior studies have focused primarily on textual platforms such as blogs (Li & Du, 2011), Twitter (Park & Kaye, 2017), and other online communities (Li et al., 2013) with regards to influencers (Zhao et al., 2018). Despite gaining popularity due to its aesthetic visual appeal, which may have a greater impact on users' purchase decision (Mediakix, 2017), studies conducted on visual social networking site i.e. Instagram (Abed, 2018; Li et al., 2018) are limited.

Nevertheless, prior studies have been dedicated to digital influencers and their effects on consumers' decision-making processes need to be explored further. We intended to fulfill the slit by enhancing the understanding about the effects of digital influencers on consumers' decision-making processes. Our study has focused on Instagram bloggers of fashion industry as influencer marketing is intensively used in this industry (Garland & Reed, 2018). Additionally, we employed a novel consumption model 'The Dual AISAS Model' instead of traditional AISAS model because 'traditional AISAS™' only captures the 'purchasing desire' resulting mostly from the posts/photos shared by influencers. Since social influence theory corroborates that consumers' decision-making process is greatly influenced by the reviews, remarks, and suggestions of people connected with them (Zhang et al., 2014), in the prevalent digital network era, consumers can easily seek diverse or detailed information not only in the shape of ads but also in the form of posts or pics from groups and networks etc. in order to get maximum utility from their purchases (Crandall et al., 2008). Dual AISAS model has two flows; first flow is 'traditional AISAS', and the second flow is new 'A + ISAS', which captures the 'sharing desire' spreading of information by consumers within entwined network (Shintara and Yuji, 2018). We have considered this model since it enables the researcher to measure the impact of digital influencers on consumers' decision-making processes (i.e. capturing the offline movement of consumers by assessing their purchasing desire) as well as to identify their content outreach (i.e. capturing the online movement by assessing the reaction of consumers to advertisement or consumer sharing desire). Moreover, it is in line with Chahal (2016) who stated that influencer outreach will get an increasing focus in the future.

The study is designed with following objectives: 1) on the basis of dual AISAS Model, we intend to investigate the impact of digital influencers on consumers' decision-making processes, and 2) on the basis of dual AISAS Model, we intend determine the influencers' published promotional content outreach (coverage). The current study makes the contributions in following ways. This study contributes to the literature of consumers' behavior, digital influencers, and consumers' decision-making processes by examining the effects of digital influencers and determining their content outreach. Furthermore, our study considered 'Dual AISAS Model' as research framework to get better insight on influencer communication and resultant engagement because influencer has the ability to get people engaged on shared image and drive them into action (Freberg et al., 2011) and ultimate outreach of promotional content to larger audience (Nabi et al., 2019). However, we used survey method/technique to complete this research. Finally, the findings of the study assists both brands and digital influencers to identify the right influencers that best resonate with the targeted audience. Additionally, through the lens of this model they can measure the consumer reactions (or consumer behavioral and purchasing data (e.g. monthly basis and quarterly basis etc.)) towards Insta fashionista photos.

The rest of the study is organized as follows. Section 2 presents theoretical grounding, followed by research model development (Section 3). Section 4 describes the employed methodology followed by analysis and findings (Section 5). The last section (Section 6) deals with discussion and concluding remarks about findings and theoretical as well as practical implications of the findings in addition to the limitations and boulevards for future researchers.

2. Theoretical grounding of dual AISAS model

While consumer's behavior is in debate, extant studies have found that consumer's activity processes or purchase decision processes have remained its prime concern (Zhang et al., 2018). To evaluate the processes of consumer decision, a model of consumer decision was initially developed by Howard (Du Plessis et al., 1991). Later on, in 1969, an improvement was made in traditional model by Howard and Sheth (Du Plessis et al., 1991). This model is termed as 'Theory of Buying Behavior'. The theory of buying behavior contained psychological, marketing, and social features. The assimilation of these factors affects the consumers' decision-making processes, and transforms them sequentially into information processing. The five-resultant outcomes of buying behavior model are attention, comprehension, attitude, intention, and purchase (Kavak et al., 2015). In numerous business buying studies (Kavak et al., 2015), especially in retailing sector (De Oliveira & Gosling, 2015), hospitality, tourism (Karl & Reintinger, 2016), and social media (Cheah et al., 2019), theory of buying behavior has been adopted on theoretical grounding.

The present study also utilizes another theory as theoretical foundation titled as the multi-step flow theory. This theory is basically an extension of the *two-step flow* theory (Katz & Lazarsfeld, 1955). As the name implies, this paradigm has multi-dimensional flow; goes through multiple 'channels', i.e. from mass media to online opinion leaders (i.e. digital influencers), and then eventually from opinion leader to wider target audience (Ognyanova, 2017). Successful opinion leaders (i.e. influencers) have an extended network or are connected with more concentrated network (Basille, 2009). Albeit they convey the notion to their followers/subscribers, who in turn spread those notions to other audience (Brosius & Weimann, 1996). Transferring this notion into the context of present study, social networking sites like Instagram, YouTube, Facebook and Twitter provide their audience an option to forward the content to their connections with the click of button. A number of studies have employed multi-step flow theory in media (Brosius & Weimann, 1996) and social media studies (Ognyanova, 2017; Stansberry, 2017).

Therefore, this study embraced two theories as theoretical foundation; theory of buying behavior to investigate the impact of digital influencers on decision-making processes of users (Opinion leaders have the potential to influence the purchasing decision of others across specific product categories (Flynn et al., 1996), and multi-step flow theory to determine their content outreach.

2.1. Digital influencers

The rapid increase in content generated on microblogging platforms compels the network participants to make an attempt to grab the attention, and thus have an influence on peers (Trusov et al., 2010). These opinion leaders have the tendency to influence the members of their social networks by disseminating the information (Chaney, 2001). The studies on information diffusion have particularly concerns about how influential people interact and influence their interpersonal networks. These opinion leaders have now turned into online opinion leaders in the form of bloggers and vloggers (Agarwal et al., 2014), and have gained a power to influence the behavior of others on social media (Ki & Kim, 2019). These influential people on social media are named as social media influencers/digital influencers/digital celebrities. They have accumulated a huge fan base by creating and sharing content on multiple social networking sites. Moreover, brand focuses on identifying these influential people to communicate a brand's message to mass consumers (Talavera, 2017).

They engender a meaning transfer process, wherein they stimulate interest and influence the consumers' attitude towards products or brands and purchases

(Sokolova & Kefi, 2020). Furthermore, extant literature found the influence of promotional content on different e-commerce platforms, such as Facebook (Aswani et al., 2017b), Twitter (Aswani et al., 2017a), Instagram (Ki & Kim, 2019), and other prevalent domains. It revealed that influence is manifested in fashion (Wiedmann et al., 2010), education (Tess, 2013), and healthcare sector (McNeill & Briggs, 2014). Moreover, in virtual communities, it is evident that digital influencers have a momentous effect on consumers' pre-purchase behavior (Sokolova, 2019) and post-purchase behavior (Song et al., 2017). Since they are influential opinion leaders (Agarwal et al., 2014), they have the tendency to persuade their peers (Weeks et al., 2017) to take a specific action (Clow & Baack, 2016) in order to further spread the content to other users (Goldsmith & Clark, 2008). These influential personalities are familiar with their own follower preference, thus they can spread content to more intended consumers with definite consumer psychology that conforms to their admirers (Wei, 2017), and provokes to share it in their own social networks, thus extending the dissemination of content (Kown, 2016). The quicker dissemination or wide outreach of content facilitates in accessing the novel information in network and drives the user engagement (Yu et al., 2015). Moreover, these personalities assist the firms to discern novel consumers' trends and upkeep the new needs of consumers (Aldhaheri & Bach, 2013).

Despite gaining the popularity, a little effort has been made to investigate the effects of digital influencers on consumers' decision-making. Moreover, a little effort has been made to determine the influencers' content outreach (Chahal, 2016). Therefore, we have investigated the effects of digital influencers on consumers' decision-making and have determined their content outreach.

3. Research model development and hypotheses formulation

3.1. New consumption behavior model (dual AISAS), decision processes, & hypotheses development

With the passage of time, consumers ' pattern of buying behavior has changed with the evolution and development of media, and the purchasing behavior model has undergone a change. Various models about consumers' decision-making processes have been used by advertising agencies. The widely used consumer buying behavior model and consumer activity model are AIDA and AIDMA model (Hawaldar & Ullal, 2018; Wei & Lu, 2013). AIDA incorporates four stages: attention, interest, desire, and action. AIDMA incorporates five stages: attention, interest, desire, memory, and action (Hassan et al., 2015). Subsequently, improvement was made in AIDMA model by well-recognized Japanese advertising agency 'Dentsu' (2008). This agency proposed another consumer activity model AISAS (Dentsu Incorporated, 2008). The AISAS model has been created to meet the current needs of digital era, and due to its interactive nature of internet, it will better to elucidate the behavior/activity of consumer on the internet (Wei & Lu, 2013). This model incorporates five processes; attention, search, interest, action, and share. This model has some similarities with AIDMA model. Initially, the advertisement grabs the *attention* of customer, and the customer becomes *interested* in it. The third path of AISAS model is novel, *search,* and gather information from different sources on the internet. The fourth phase is following consumers' *action* to make a purchase and subsequently consumers *share* their experiences on the internet (Cheah et al., 2019). The process after the action has expanded, which illustrates the current consumer behavior. However, this model is not enough to explain the phenomenon which Instagram triggered.

Nowadays, people firmly believe on word-of-mouth communication (WOM) rather than ads. So, the mode we used earlier to get people's attention has become obsolete. On daily basis, we can find information about products or services in the form of photos on Instagram. The photos are not ads, but they are shared by friends or people whom we follow on Instagram. They have a great effect on us because they include their emotions as well (Rashidin et al., 2020a). If they are attractive, they will arise our purchasing-desire or sharing-desire. These two desires are diverse, so they should be detached. The new consumption behavior model, 'The Dual AISAS Model' will help elucidate it further. In October 2015, Dentsu brought a new version of AISAS model named as Dual AISAS model, thanks to the cooperation of digital marketing company Atara LLC, in order to advance the digital communication that further maximizes the sales (Dentsu, 2015). Moreover, it further clarifies the information flowing in the model and the contents of the consumer's interest. Additionally, this model puts the interest into two categories (interest in products and interest in photos/images) by recognizing the worth of activation which leads towards purchases in both categories. It makes the AISAS model as 'Purchasing desire', whereas A + ISAS is 'Sharing desire' or diffusing the information, wherein 'I' stands for 'Interest', 'S' stands for 'Share', 'A' stands for 'Accept' and 'S' stands for 'Spread' as demonstrated in Figure 1 below (i.e. corresponds to the purchasing made through Instagram).

The model begins with an attention phase. It is defined by Venkatraman et al. (2015) as 'a person's 'ability to focus on certain aspects of the environment while ignoring others'. In the era of Web 2.0, the scholars suggested that brands are partnering with digital influencers, wherein they help the brands grab the attention of masses more easily as compared to the celebrities (Ki & Kim, 2019). The attention phase highlights that the influence is instigated from the outwards (influencers), therefore the extent of the influence depends on the user's number of influencers/ digital celebrities following. The vertical flow of Figure 1 demonstrates that user attention is seized though exposure of promotional messages in the form of photos posted by bloggers and vloggers (digital influencers) on Instagram. These influential people attract a lot of attention from internet users and play a key role in word-of-mouth advertising, generating messages and content of use for other people (Meng et al., 2011). For instance, Instagram is one of the digital social media platforms that is being used mostly by opinion leaders to express their opinions about products and services via sharing photos and short videos (Silva et al., 2013). The user rate of influencers following and trust on them (experience) decide the user interest arousal rate. The higher the number of following and trust on influencers, the more the interest will provoke (Javed et al., 2021). The attention and interest that customers have towards the digital influencer's posts create an outcome—searching activities (Hung, 2014; McCartney & Pinto, 2014). According to Korgaonkar et al. (2006), users are

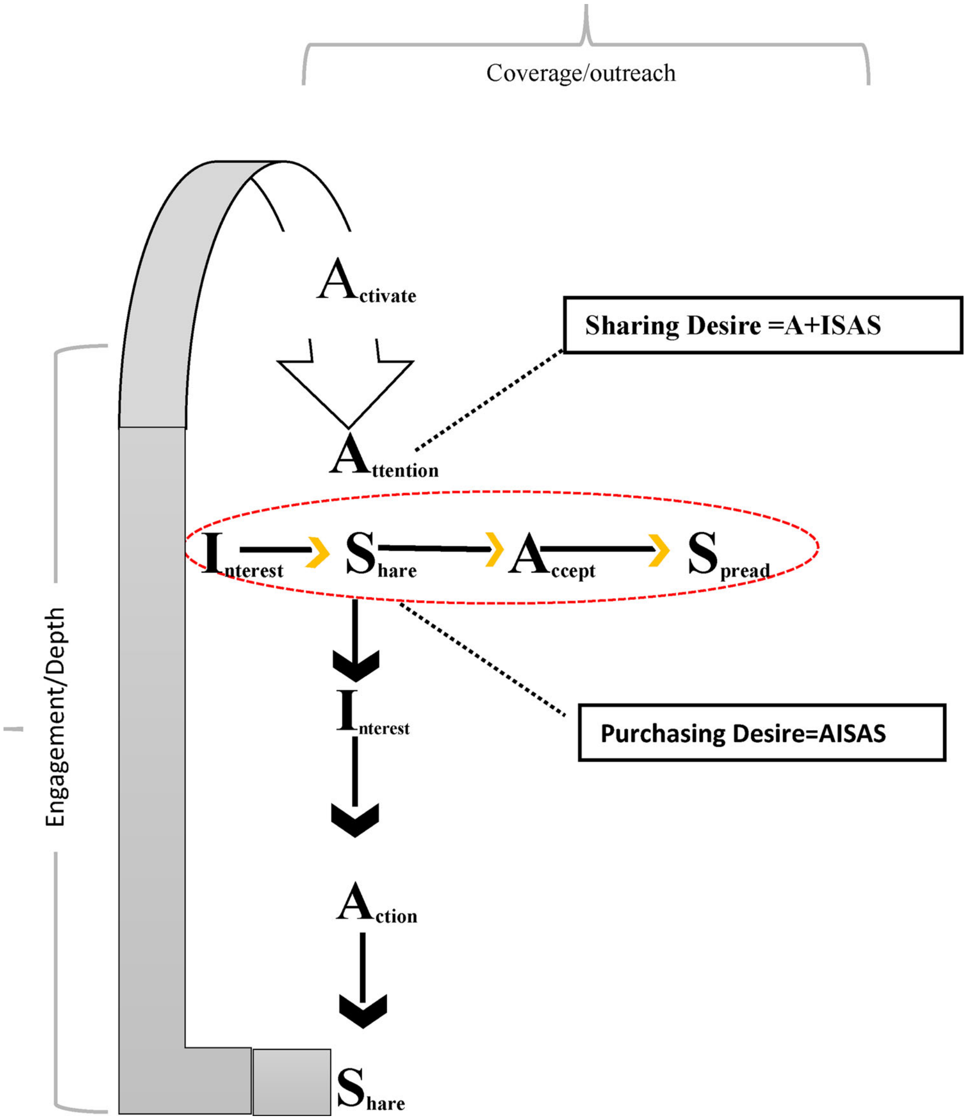

Figure 1. The dual AISAS model. Source: Atara and Dentsu (2015).

more worried about whether only one review is true or manipulated, so while engaged in shopping to experience goods, they will read more reviews in order to verify the quality of the products being considered. This is supported by Park et al. (2009), who found that users tend to search significantly more kinds of information, including both product and customer reviews, when shopping to experience goods than when shopping to search goods. Hence, the use of digital influencers in promotions transforms the user's attention and interest into a high involvement action because influencers have the tendency to deepen the user engagement on shared post (Freberg et al., 2011), and change the attitudes of followers, consequently influencing their intention to buy the recommended products (Renata et al., 2018). These finding are in line with Ki and Kim (2019) study, which revealed that followers who hold positive attitude towards digital influencers are most likely to imitate them, and their mimicry desire drives towards purchase action. Subsequently, the user becomes a transmitter to share his/her experience about product consumption. According to previous studies, the positive attitude towards digital influencer content is linked to content sharing intention at social network (Choi & Lee, 2019). Based on the aforementioned literature, we postulate following hypotheses.

H1: The post of digital influencers has positive impact on user's attention.

H2: The post of digital influencers has positive impact on user's interest rate.

H3: The post of digital influencers has positive impact on user's intention to search more.

H4: The post of digital influencers has positive impact on user's intention to purchase or to act on it.

H5: The post of digital influencers has positive impact on user's intention to share.

On the other hand, last phase 'share' of AISAS begins A + ISAS. Figure 1 depicts that the influence to inwards begins. The influence on followers depends on number of user's followers. Once the user shares the following post, he/she gets reactions in the form of 'Likes', 'Follows', 'Comments', and 'Share'. The post shared here is related to the product itself, service, and brand experience (Amaly & Hudrasyah, 2012; Wei & Lu, 2013). The higher the number of followers, the more received reactions on certain posts. Therefore, it will activate the user to be attention of others. At this point, online searching behavior is not as consistent as before. This could be due to the fact that in instead of searching for information online, other users could just drop a message to their friends or comment on their friends' post to inquire about the product. This may explain why their attention and interest towards friend's posts would likely lead them to communicate with high involvement (Cheah et al., 2019). For instance, though the user's followers get a lot of information on Instagram, they only share the valuable information without making purchase. Additionally, the user's followers get the original information along with emotion, reviews, and comments, so that information is 'unable to ignore = with a strong attention', or in other words, they 'accept' that information. Cheung et al. (2008, 2009) and Cheung and Thadani (2012) defined the acceptance of information as 'a process in which people intentionally engage in the use of information, i.e. it is an intrinsic aspect of individual, in which the individual purposefully judges whether the information received is reliable and can be used in his/her consumption decision-making'. Moreover, it is widely studied and discussed in academia (Cheung et al., 2009; Cheung & Thadani, 2012; Teng et al., 2014). Cheah et al. (2019) conducted a study, in which authors found that information is widely accepted when it is communicated by close friends than celebrities, and the effect of former is greater than latter, because friend's recommendation is based on multi source information fusion (Cheng et al., 2019).

Shintara and Yuji (2018) used 'The Dual AISAS Model' to understand the consumption behavior on SNS and found that consumers tend to trust the information transmitted by other consumers. Moreover, authors found that consumers have ever recommended by sharing and spreading via SNS than before. In addition to this, content spreading plays an important role in motivating followers to express their opinions through the social network, because the goal of sharing information is for others to receive (Lin et al., 2014), and can better leverage the power of social media by paying attention to the content outreach along with private networks (Yu et al., 2015) and extended networks (Lipsman et al., 2012). With a preceding example, this follower becomes the originator and 'spreads' the information within network friends, therefore the information is diffused at an accelerated pace. Particularly, this activity may not affect the purchase of the user, but it affects others', because the spread information can get someone's attention, and in this way, bunch of people make purchases through the platform of Instagram. Therefore, Instagram has an enormous influence to alter the consumer activity/behavior (Sano, 2017). On the basis of above arguments, we develop following hypotheses:

H6: The repost of digital influencers has positive impact on user's follower activation.

H7: The repost of digital influencers has positive impact on user's follower attention.

H8: The repost of digital influencers has positive impact on user's follower interest rate.

H9: The repost of digital influencers has positive impact on user's follower intention to share.

H10: The repost of digital influencers by user's follower has positive impact on other user's acceptance.

H11: The repost of digital influencers by user's follower has positive impact on another user's intention to spread.

In a nutshell, red color looped in our research model around horizontal flow is displaying A + ISAS = Sharing/Dissemination Desire; the interest in product switches from product to communication about goods, services, and spread to outreach (Yajima, 2015). Moreover, it exhibits the flow of diffusion of the brand information, such as advertising and promotion, through the digital network, which assists to determine the influencer content outreach (Chahal, 2016).

4. Methodology

4.1. Instrument and measures

The scale was adapted from 15-item scale of AISAS (a three-item scale of attention, a three-item scale of interest, a three-item scale of search, a three-item scale of action, and a three- item scale of share). Moreover, a scale of active, accept and spread was developed with the help of existent literature (Erz et al., 2018, Teng et al., 2014). Additionally, for more clarity, the study denotes the two types of interest in our model differently, like the post of digital influencers is labeled as 'interest_{pd}', and the interest in posts of friends is labeled as 'interest_{pf}'. The scale used for the measurement of constructs was 5-point Likert scale, ranging from 'strongly disagree = 1' to 'strongly agree = 5'. We validated our scales and measurement model using multiple methods. Firstly, following Ruyter and Bloemer (1999), we executed EFA to confirm the underlying factors using varimax rotation and extracted 11 factors that include attention (Att), interest_{pd} (Int), search (Srch), action (Act), Share (Sha), Active (Actv), Attention (Attnt), Interest_{pf} (Inter), Share (Shre), Accept (Accpt), and Spread (Sprd).

Most of the factor loadings (FLs) were above .80 except Actv3 (FL = .62) and Sprd3 (FL = .51), relevant to active and spread, thus excluded for further proceedings. Moreover, eigen values, 5.921, 3.809, 2.792, 2.546, 2.368, 2.262, 1.688, 1.612, 1.456, 1.202, and 1.025 of factors cumulatively explained 85.605% of the total variance respectively. Secondly, the face and content validity of the scale was ensured by taking the comments from marketing professors. Furthermore, a pilot study was conducted in order to test the content validity of instrument. The survey recorded 62 data points. Among them, 14 data points were ruled out due to disqualification (i.e. screening questions, incomplete questionnaire (i.e. missing values), or extreme uniform values (i.e. all 1 or all 5). As a result, 48 data points remained valid for analysis, representing a response rate of 70.30%. In the pilot study, female respondents had higher representation (52.1%) than male (47.9%). Majority of the participants (50%) lies under the age category of 24-29, followed by 18–23 (39.6%) and above 29–35 (10.4%). With respect to qualification, majority of the respondents (43.8%) have earned a bachelor's degree, followed by masters (37.5%), higher secondary (16.7%), and high school (2.1%). As far as profession is concerned, majority of participants were students (54.2%), followed by job holders (43.8%), and business (2.1%). Majority of the respondents having Instagram accounts were private (79.2%) than having public accounts (20.8%). Half of the participant accounts were linked with SNS (70.8%) than only linked with Twitter (18.8%) and Facebook (10.4%). In addition, reliability analysis was performed to confirm the robustness of measurement. The Cronbach's alpha (α) values were found to be attention = .937, interest_{pd} = .929, search = .906, action = .956, share = .739, active = .903, attention = .896, interest_{pf} = .942, share = .945, accept = .925, and spread = .846. The results indicated that scale is consistent having Cronbach's alpha (α) values greater than .70.

4.2. Contextual research setting

Pakistan has been selected as the setting of this study due to the elevated increase in the usage of social media. According to Ali (2020), 37 million people accessed social media regularly from video sharing platforms like TikTok and YouTube to microblogging sites like Facebook, Twitter, and Instagram. According to NepleonCat (2020), in first half of 2020, Instagram had 6,394,000 active users with a net addition of approximately 4,158,000 users on yearly basis. Among all microblogging platforms, Instagram is becoming the eye-catching platform for fashion industry (Yesmail, 2015; Socialbakers, 2016). It has been rapidly expanding and has gained much popularity in Pakistan (Babar, 2020).

Pakistan fashion industry is boosting rapidly and contributes significantly to the economy (Batool, 2018). It turns to digital media for product reviews and endorsement from common people/influencers instead of celebrities whom they can relate to them (Jamil, 2020). In the context of fashion industry, these influential people create content about skincare, clothing, and makeup and post them on their personal accounts. They have the tendency to attract a great number of followers, and enjoy a massive fanbase (Jamal, 2020). Since the concept of influencer marketing is gaining a significant momentum in Pakistan (Bradri.com, 2019), therefore it has been used as contextual setting for our study to substantiate our study hypotheses.

4.3. Sampling and data collection procedures

Prior to the execution of data collection, Free Statistical Power Calculator version 4.0 was used to determine the minimum required sample size for structural equation modeling (SEM). The findings revealed that in order to achieve statistical power of 80% with number of observed variables $n = 30$, number of latent variables $n = 11$, probability level = .05, and medium effect size = .15, recommended minimum sample size was $n = 900$. Black et al. (2020) suggested a sample of 100, whereas Kline (2005) suggested a sample of 200 to employ structural equation modeling (SEM) method, so our study sample fulfills this threshold for justifying the use of SEM.

Purposive sampling technique was used to select the respondents. It permits the researchers to choose the valid and informative respondents (Sekaran & Bougie, 2016). We conducted both offline and online surveys to collect the data. For offline survey, five doctoral candidates were trained to distribute the English version questionnaire. Moreover, an online questionnaire was designed on Survey Monkey (i.e. host online questionnaire), and the respondents were contacted by posting a web-link of survey on social media pages of different Pakistani public universities. It must be noted that an online survey helps the researcher reach larger numbers of participants besides reaching more relevant respondents by eliminating irrelevant one through filter/screening questions (Denscombe, 2014). Based on survey research, the instrument commenced with an open-ended statement following the critical incident method (Seckler et al.,2015). The open-ended statement asked the participants to read a statement carefully before filling out the rest part of questionnaire: 'Please take you as a viewer of the posts/reposts of fashion influencers you followed on Instagram. Try to explain your perception.' The underlying reason behind this open-ended question was to get a description about the perception of followers. Purposive sampling has been criticized not being able to generalize research outcomes, although a good deal of online research uses this technique because of subjects' accessibility and proximity to the researchers (Roman, 2007). Moreover, purposive sampling is deemed valid and appropriate when the study is exploratory and when the instrument's items are related to the respondents (Elbeltagi & Agag, 2016). In this regard, our study depends on constructs that have not been widely studied in the past, and the targeted respondents were Instagram users who followed fashion influencers, so the instrument was closely related to the respondents. Thus, the research fulfills both requirements for using purposive sampling.

The data was gathered during a period of 6 weeks, from mid of February till March 2020. Moreover, we ensured with the help of screening questions that 'participants had been the user of Instagram for at least 1 year', 'logged in to Instagram at least once in last 30 days', 'made post on Instagram in last 30 days', and had been the 'follower of at least one fashion digital influencer. Participants who met these selection criteria were allowed to further pursue the survey. The questionnaire commenced with cover letter which narrated the broad purpose of study, and ethical statement to keep their personal information confidential (Rashidin et al., 2020b). The operational definition of digital influencers was clearly stated. It had two sections. First section of survey was particularly related to personal traits of the participants, which contained five close ended questions concerning their gender, age, profession, and educational attainment. Before proceeding to second section, we provided a statement '*Please fill out the rest part of questionnaire (Q1–Q15) keeping in mind the digital fashion influencers (bloggers, vloggers, etc.) you followed on Instagram*.' Second section of survey instrument contained 31 close ended questions on five stages of AISAS (to measure purchasing desire) and six stages of A + ISAS (to measure sharing desire). Upon completion of five stages of AISAS, we again provided a statement to participants '*Please fill out the remaining part of questionnaire (from Q 16- Q31) keeping in mind the repost of fashion influencers make by your friends*'. The questionnaire took approximately 10–15 minutes for completion. A total of 525 respondents participated in online survey. In the offline survey, a total of 545 questionnaires were distributed, and 502 questionnaires were returned back, representing a response rate of 92.11%. Fifty-eight questionnaires were discarded due to duplication and incompletion, so 444 questionnaires remained valid for data analysis. Therefore, a total of 969 responses (525 responses from online survey, and 444 responses from offline survey) were valid for data analysis.

5. Analysis and results

5.1. Demographic of respondents

The qualified participants who took part in this study were $n = 969$ as shown in Table 1. The majority of the respondents were females (52.2%) and rest were males (47.8%), which indicates a fair distribution of gender. 59.8% respondents were found to be in 24–29 years of age. Over half of the participants were students (54.9%), followed by job holders (24.8%), and business person (17.2%). Approximately half of the respondents held bachelor's degree (49.6%). The majority of participants had private accounts ($n = 862$, 89.0%), and rest of participants had public accounts ($n = 107$, 11.0%). Additionally, the detail of the participants whose Instagram accounts are synchronized with social media is as follows: Facebook ($n = 412$, 42.5%), Twitter ($n = 256$, 26.4%), and both Facebook and Twitter ($n = 244$, 25.2%). Some participants have not connected their accounts with other SNS ($n = 57$, 5.9%) (see Table 1).

5.2. Measurement model

The statistical analysis was carried out by SPSS AMOS graphics version 21. We checked the reliability and the validity of unobserved constructs through measurement model by performing confirmatory factor analysis. The results of confirmatory factor analysis indicate a good fit of the model (χ^2 (455.588) = 270, $\chi^2/df = 1.687$, SRMR = .035, GFI = .971, AGFI = .949, TLI = .986; CFI = .991; RFI = .966; NFI = .979; IFI = .991; PNFI = .608; PCFI = .615; RMSEA =.027). These model fit indices exhibit that all latent constructs are well measured by their indicators. Through the scores of Cronbach's α and composite reliability (CR), reliability was assessed.

Table 1. Demographic profile of respondents ($N = 969$).

Demographic characteristics	Frequency ($N = 969$)	%
Gender		
Male	463	47.8
Female	506	52.2
Age		
18–23	189	19.5
24–29	579	59.8
29-35	165	17.0
Above 35	36	3.7
Educational attainment		
High School	22	2.3
Higher Secondary School	123	12.7
Bachelor's Degree	481	49.6
Master's Degree	329	34.0
Doctorate	14	1.4
Profession		
Students	532	54.9
Job Holders	240	24.8
Business Person	167	17.2
Others	30	3.1
Instagram account		
Private	862	89.0
Public	107	11.0
Linked with other SNS		
Facebook	412	42.5
Twitter	256	26.4
Both	244	25.2
None	57	5.9
Others	0	

Source: Author own calculation.

Table 2 demonstrates that all constructs are considered reliable by having CR scores above the cut off level .70 (Hair et al., 2011), ranging from 0.837–0.942. Also, α scores surpassed the suggested cut-off level >.70 (Hair et al., 2010), ranging from 0.865–0.943. Convergent validity was tested by employing Fornell and Larcker (1981) approach, which implies that factor loadings of all items should be above .70 and significant. Also, value of average variance extracted from each variable should be greater than .50. Table 2 demonstrates that factor loadings of all construct items are above the threshold level (>.70), with values ranging from 0.778–0.945, and values of AVE are ranging from 0.630–0.844, demonstrating that it is above the recommended cut-off level >.50 (Fornell & Larcker, 1981; Hair et al., 2011), thus the convergent validity is established (Hair et al., 2010). The discriminant validity was ensured by using two tests; first, the square root of average variance extracted (AVE)/diagonal elements should be above the correlations among the variables at the corresponding columns and rows values (Fornell & Larcker, 1981), and second, the correlation among the constructs should not exceed .85 (Kline, 2005) (see Tables 2 and 3).

5.4. Structural model

The results of the measurement model demonstrate a good model fit. The structural model was tested by SPSS Amos graphics version 21.0. The findings of the study are as follows: (χ^2 (88.368) = 35, $\chi^2/df = 2.525$, SRMR = .05; TLI = .951; CFI = .969; RFI = .921; NFI = .950; IFI = .969; PCFI = .617; PNFI = .605; RMSEA = .040).

Table 2. Confirmatory factor analysis.

Constructs	Items	Statements	Scale source	SFL
Attention, CR = .925, α = .924. AVE = .805, √AVE = .897	Att1	The fashion related image posted by digital celebrity attracts me.	Wei & Lu (2013) and Jun-Hwa Cheah et al. (2019)	.909***
	Att2	The fashion related image posted by digital celebrity draws my full attention.		.830***
	Att3	The fashion related image posted by digital celebrity catches my eye.		.950***
Interest, CR = .924, α = .923. AVE = .801, √AVE = .894	Int1	After viewing the fashion related image posted by digital celebrity, I am interested in it.		.876***
	Int2	After viewing the fashion related image posted by digital celebrity, I like the fashion related products.		.911***
	Int3	The image posted by digital celebrity gives me a good impression of the fashion items.		.898***
Search, CR = .922, α = .920. AVE = .798, √AVE = .893	Srch1	After viewing the image posted by digital celebrity, I will search for information about the fashion products		.873***
	Srch2	After viewing the image posted by digital celebrity, I will search for online word-of-mouth about the fashion items.		.910***
	Srch3	After viewing the images posted by digital celebrity, I will compare prices of products within fashion brands.		.897***
Action, CR = .942, α = .942. AVE = .844, √AVE = .918	Act1	After viewing the images posted by digital celebrity, I believe the offered products of fashion brands is worth trying.		.929***
	Act2	After viewing the images posted by digital celebrity, I am willing to buy the fashion related items.		.881***
	Act3	After viewing the image posted by digital celebrity, I think the product will best satisfy my need.		.945***
Share, CR = .890, α = .892. AVE = .729, √AVE = .853	Sha1	After viewing the image posted by digital celebrity, I will forward this advertisement to my friends		.856***
	Sha2	After viewing the image posted by digital celebrity, I will share the information about the fashion products with my friends		.861***
	Sha3	After purchasing and using fashion products, I will share my experiences and do comments about the fashion products.		.845***
Activate, CR = .850, α = .852. AVE = .739, √AVE = .859	Actv1	My friends used to tag me to call upon my attention on repost of fashion influencers.	Awasthi & Choraria, 2015, Erz et al., 2018, Teng et al., 2014, Huhn, 2018).	.811***
	Actv2	The customize #hashtags used by my friends on repost of fashion influencers activates me.		.906***
Attention, CR = .837, α = .837. AVE = .630, √AVE = .793	Attnt1	The repost of fashion influencers by my friends attracts me.	Wei and Lu (2013) and Cheah et al. (2019)	.808***
	Attnt2	The repost of fashion influencers by my friends draws my full attention.		.784***
	Attnt3	The repost of fashion influencers by my friends catches my eye.		.790***
	Inter1	I am interested in what my friends will approve of.		.778***

(*continued*)

Table 2. Continued.

Constructs	Items	Statements	Scale source	SFL
Interest,	Inter2	I will like the repost of fashion influencers by my friends		.892***
CR = .892, α = .862.	Inter3	The repost of fashion influencers by my friends will give me a good impression.		.897***
AVE = .735, $\sqrt{}$AVE = .857				
Share,	Shre1	I will expect to share the information about the repost of fashion influencers		.866***
CR = .894, α = .888.				
AVE = .737, $\sqrt{}$AVE = .858	Shre2	I will intend to forward the repost of fashion influencers to my friends.		.890***
	Shre3	I will do share the repost of fashion influencers by adding my comments.		.818***
Accept,	Accpt1	After viewing the repost of fashion influencers, my friends will more likely to accept (i-e getting likes, comments)	Awasthi & Choraria, 2015, Erz et al., 2018,	.884***
CR = .896, α = .894.				
AVE = .812, $\sqrt{}$AVE = .901	Accpt2	After viewing the repost of fashion influencers, my friends will be greatly influenced.	Teng et al., 2014, Huhn, 2018).	.918***
Spread,	Sprd1	My friends will expect to diffuse the repost of fashion influencers within their network along with reviews/comments/proper captioning.	Awasthi & Choraria, 2015, Erz et al., 2018,	.871***
CR = .895, α = .898.				
AVE = .809, $\sqrt{}$AVE = .899	Sprd2	My friends will expect to diffuse the fashion influencer repost by adding creative #hashtags	Teng et al., 2014, Huhn, 2018).	.928***

Note: SFL = standardized factor loadings, α = Cronbach alpha, CR = composite reliability, AVE = Average variance extracted, $\sqrt{}$AVE = discriminant validity.
$^{***}p < .001$.
Source: Author own calculation.

Table 3. Descriptive statistics and discriminant validity.

Construct	Mean	S.D	VIF	1	2	3	4	5	6	7	8	9	10	11
Attention	3.72	1.23	1.03	**.897**										
$Interest_{pd}$	3.91	1.14	1.19	.075**	**.894**									
Search	4.00	1.12	1.26	.151**	.399**	**.893**								
Action	3.85	1.28	1.07	.139**	.079**	.247**	**.918**							
Share	3.78	.98	1.01	.152**	.440**	.725**	.366**	**.853**						
Activate	4.06	1.01	1.23	.042	.047	.057	-.034	.080*	**.859**					
Attention	4.07	.955	1.27	.053	-.006	.005	-.017	-.004	.282**	**.793**				
$Interest_{pf}$	4.01	.974	1.15	.033	.038	.020	−.19	.052	.355**	.146**	**.857**			
$Share_{d}$	4.08	.953	1.02	.025	.046	.016	−.022	-.020	.034	.106**	.113**	**.858**		
Accept	3.77	1.21	1.16	.037	.050	.074*	.024	.063	.015	.364**	.018	.074**	**.901**	
Spread	3.75	1.22	1.23	.083**	.052	.067*	.073**	.079**	.059	.308**	.019	.118**	.398**	**.899**

The bold digits in the diagonal are square root of AVE.

Note: 1 = attention. 2 = $interest_{pd}$, 3 = search, 4 = action, 5 = share, 6 = activate, 7 = attention 8 = $interest_{pf}$, 9 = share, 10 = accept, 11 = spread.

$^{**}p < .01$.

Source: Author own calculation.

These findings indicate an adequate fit to the model. All fit indices were found to be in acceptable range as recommended by several authors (Hooper et al., 2008; MacCallum & Hong, 1997).

5.4.1. Hypotheses testing

We employed structural equation modeling technique (SEM) to test our research model. In SPSS, we initially checked multicollinearity in our dataset. The score of variance inflation factor (VIF) implies that all the constructs had VIF scores within suggested range <3, therefore multicollinearity is not an issue in our dataset (see Table 3). Moving ahead, the results of path coefficients are exhibited in Table 4. The results suggest that on visual centric platform, consumer attention is seized by fashion influencers and has significant impact on consumer interest$_{pd}$ ($\beta = .054^*$, $t = 2.014$, $p < .05$), therefore H1 was supported. Also, consumer interest$_{pd}$ has powerful influence to search more information ($\beta = .397^{***}$, $t = 13.485$, $p < .001$) by visiting fashion brand websites, acting on it by making purchases ($\beta = .229^{***}$, $t = 7.390$, $p < .001$), and sharing it further on Instagram or other connected SNS ($\beta = .203^{***}$, $t = 9.558$, $p < .001$), therefore H2, H3 and H4 were supported. Moreover, sharing on Instagram leads towards activation of friends to seek latest fashion trends ($\beta = .078^*$, $t = 2.443$, $p < .05$), drawing the attention of friends ($\beta = .301^{***}$, $t = 10.053$, $p < .001$), raising the friends interest$_{pf}$ positively ($\beta = .266^{***}$, $t = 7.389$, $p < .001$) to act on it or share it with their network friends, and taking initiative to activate them ($\beta = .113^{***}$, $t = 3.532$, $p < .001$). The received original information along with friend's emotion gets acceptance from friends in the form of likes, and comments ($\beta = .060^*$, $t = 2.002$, $p < .05$). They spread the information (share) further, and start acting as originator of information for their network friends ($\beta = .396^{***}$, $t = 13.454$, $p < .001$). Therefore, we accepted H5, H6, H7, H8, H9, and H10. Inclusively, all the findings report the first and second inquiry of the present research. Moreover, all the phases involved in AISAS and A + ISAS have profound effect. Figure 2 also exhibits the predictive power (R^2) and the effect size f^2. We followed Hair (1998) approach for assessing R^2 score, which tells us that the variance explained should be >50% in all outcome variables due to predictor variables. The results of current study show that 0.3% interest$_{pd}$ due to attention, 15.8% search due to interest$_{pd}$, 5.4% action due to search, 10.4% share due to action, 0.6% activate due to share, 9.1% attention due to activate, 12.8% interest$_{pf}$ due to attention, 1.3% share due to interest$_{pf}$, 0.4% accept

Table 4. Results of structural model.

Hypotheses	Paths	Standardized estimates	*T*-statistics	Relationship
H1	attention→interest$_{pd}$	.054*	2.014	Supported
H2	interest$_{pd}$→search	.397***	13.485	Supported
H3	search→action	.229***	7.390	Supported
H4	action→share	.203***	9.558	Supported
H5	share→activate	.078*	2.443	Supported
H6	activate→attention	.301***	10.053	Supported
H7	Attention→interest$_{pf}$	.226***	7.389	Supported
H8	interest$_{pf}$→share	.113***	3.532	Supported
H9	share→accept	.060*	2.002	Supported
H10	accept→spread	.396***	13.454	Supported

Source: Author own calculation.

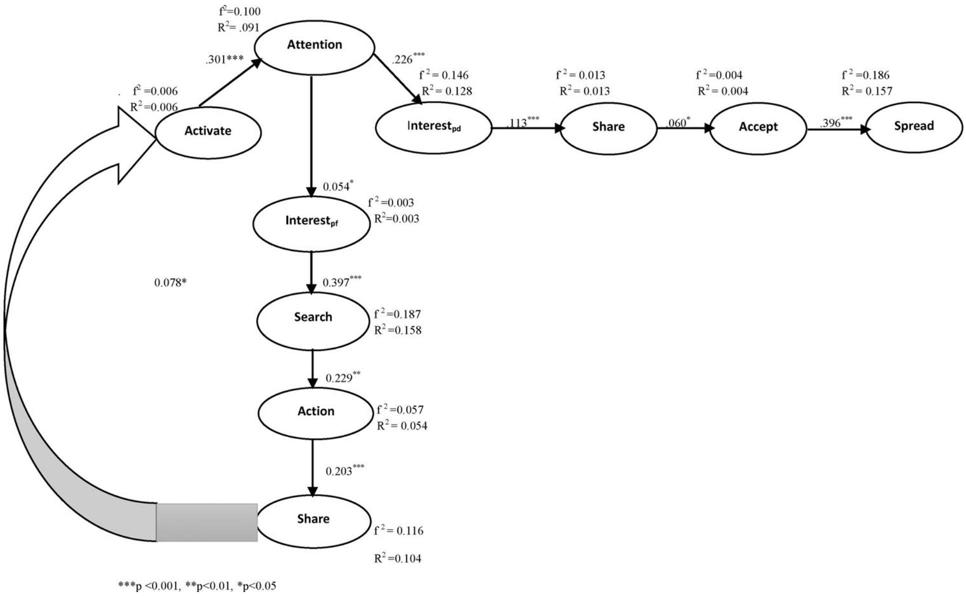

Figure 2. The dual AISAS model.
Source: Author own calculation.

due to share, and 15.7% spread due to accept indicate that R^2 score (71.8%) is above the suggested criteria of 50%.

Moreover, by following Cohen (1988) approach, we also assessed the substantive effect size (f^2) of research model. The suggested threshold for effect sizes by Cohen (1988) is as follow: small effect is .02, medium effect is .15, and large effect is .35. We found that effect size of activate ($f^2 = .006$), accept ($f^2 = .004$), share in A + AISAS($f^2 = .013$), action ($f^2 = .057$) and interest$_{pd}$ ($f^2 = .003$) did not lie under the suggested threshold of Cohen's (1988), but gets support by Sawilowsky (2003) threshold having small and very small effect size. However, attention ($f^2 = .100$), share in AISAS ($f^2 = .116$), and interest$_{pf}$ ($f^2 = .146$) have medium effect size (up to the criteria of Cohen's (1988)), and search ($f^2 = .187$) and spread ($f^2 = .186$) have large effect size (up to the criteria of Cohen's (1988)).

6. Discussion

The exponential growth of social media has entirely revamped the way folks interact, communicate, engage, and spread the information (Hansen et al., 2011) due to transmutation of information platform in order to influence them (Hanna et al., 2011). The present research studied the effects of digital influencers on consumers' decision-making embracing new behavioral consumption model 'dual AISAS Model' has particular value for domestic and international fashion industry of Pakistan. Pakistan fashion industry has seen briskly mounting since the last decade. Our study findings offer valuable contribution to influencers and fashion brands, because consumers are mounting to seek influencers reviews/information. They base their decisions on influencers reviews/information, because consumers mostly go through influencers reviews/opinions before making their buying decision (Casaló et al., 2020).

Our study revealed that presence of digital influencers is influential because they act as a pull factor to fashion brands in Pakistan. Consumers are more likely to seek the information about latest fashion trends from fashion influencers in order to avoid risk in purchase decision (Flynn et al., 1996). Hence, the influencers seized attention of consumers who are seeking fashion news, reviews, and suggestions. The generated content of fashion influencers has significant influence on consumer attention and interest, and prompts them to search more information about fashion brands either by visiting company insta-page or brand website (McCartney & Pinto, 2014). Additionally, digital influencers have the ability to transform attention, interest and drive into action, and get consumer engagement on their shared post (Freberg et al., 2011).

It is evident from our findings that fashion influencers exert a robust influence on consumers' sharing attitude, which is in line with prior literature (Cheah et al., 2019). Additionally, consumers immediately grab the attention of friends by sharing the post/image either through Instagram stories or they go Live on Instagram with their connections (Lipsman et al., 2012) or with online friends (acquaintances, real world friends) (Chu & Kim, 2011; Jin & Phua, 2014). Evidently, according to our findings, sharing begins the activation of network peers and becomes eye-catching for them, because when they see a close friend using fashion products (by wearing those items), they take interest in them and want to buy them (Frosh, 2015). The matter of the fact is that network peers do not get involved in online searching activities because the needed information is asked from friends by dropping personal message and writing comments on their shared post to inquire it further (Cheah et al., 2019), because information conveyed personally can expedite two-way communication (Herr et al., 1991). Evidently, opinion/reviews of consumers are worthwhile for their peers (Paek et al., 2011) although these reviews can be positive or negative (Kwon et al., 2014). Our findings also suggest that consumers provoke their pals to disseminate/share the image/post within their private or extended networks (Chatterjee, 2011) that further leads towards communication about fashion brands by activating your friends (Jin & Phua, 2014, Muntinga et al., 2011), seizes their involvement (to grab a reach, intimacy, and engagement) and gets acceptance at wider level (in the form of 'likes', 'comments', and 'share' on same platform or extended networks such as by linking accounts with Facebook, Twitter, Snapchat, and other SNS). Moreover, an individual is more likely to spread the content/image in his small circle of friends or whole network, after getting a sense of identification from cherished comrade (Yu et al., 2015). Our findings are in line with prior notion that information seekers assist the influencers to spread the content from one consumer to another (Goldsmith & Clark, 2008).

7. Conclusion

A concluding summation is that in contemporary era of digitization, influencers' impact on fashion consumers is an efficient promotional tool to elucidate consumers' decision-making processes. Our findings based on significant association conferred the fact that on visual centric platform/Instagram, digital influencers facilitate the powerful influence on consumers' decision-making processes (Goldsmith & Clark, 2008), particularly in fashion industry (Casaló et al., 2020). Moreover, they offer novel ways to make decisions (Kapitan & Silvera, 2016) and get wider outreach by upturn in consumers intention (awakening their sharing desire) to spread the fashion content within private networks and extended networks (Goldsmith & Clark, 2008). In this regard, consumers (followers) are spreading influencers' promotional content along with their additional knowledge (reviews, comments) to others, thus promoting the influencers, which will eventually escalate their following base (Goldsmith & Clark, 2008).

7.1. Theoretical implication

To the best of our knowledge, this study has made remarkable contributions to theory and practice pertaining to consumers' decision-making processes. Firstly, from the theoretical standpoint, the empirical study embraced multi step flow paradigm and theory of buying behavior to support the research model; to examine the effects of fashion influencers on Pakistani consumers decision-making as well as to determine the content outreach of these influencers. Secondly, the literature has examined the effects of digital influencers on consumers' decision-making processes using AISAS model (Cheah et al., 2019; Wei & Lu, 2013), but in the digital world, this study delved digital influencers and explicated their respective effects on consumers' decision-making processes by using an innovative consumer behavior model 'The Dual AISAS Model', which is an updated version of AISAS (Atara & Denstu, 2015). Thirdly, this study advances our knowledge beyond prior research on effects of digital influencers on consumers' decision-making (Sokolova & Kefi, 2020) by focusing the contexts outside the US and European countries. Earlier research indicates that very few studies have paid attention to influencers marketing particularly in South East Asia region. Therefore, we responded to the call of earlier research, and presented/validated a behavioral consumption model in the contextual setting of Pakistan. Specifically, this model enriches our understanding about effects of digital influencers on consumer attention, interest$_{pd}$, search, action, share, active, attention, interest$_{pf}$, share, accept, and spread. Additionally, it also gives an insight into the extent of this effect on five phases of AISAS and six phases of A + ISAS, which was missing in extant marketing literature, and opens up new avenues for future attempts. It does not only imply how digital influencers affect the individual's buying decision, but also gives an understanding about the fashion influencer content outreach through activating consumer sharing desire to diffuse the fashion trends from one user to another user (i.e. within private network) on the same platform or on different SNS by linking up Instagram accounts (i.e. extended networks) with other SNS (Facebook, Twitter, Snapchat etc.). Therefore, our empirical study particularly contributes to the extant literature of consumer decision-making, consumer behavior, and digital influencers.

7.2. Managerial implications

The findings of this study are critical for both brands and digital influencers because influencer marketing is growing more dynamic in Pakistan (Nasrullah, 2020) with a growing use of Instagram (Eman, 2019). Particularly, Instagram fashionista capitalized on the growth to expand their reach to the audience (Babar, 2020). Moreover, the rapid expansion of fashionista in Pakistan has altered the behavior of consumers (Babar, 2020). The findings revealed that fashion influencers exert a powerful influence on Pakistani consumers' decision-making. Therefore, we suggest fashion influencers to make their posts more influential; original, unique, and attractive content/image by adding creative hashtags and emoji, weave a product in Instagram personal stories, and go Live on Instagram. In this way, the content will grab the attention of existing as well as potential customers, and deepen the consumer engagement (Hashoff, 2017) followed by subsequent positive behavior (Herrando et al., 2018). In addition to this, a positive behavior leads to activation/digital dissemination of information to a greater extent on private networks/closely connected network, and extended network along with an evaluative remark. The reactions/evaluative remarks on a shared post will further influence the friends' purchase decision albeit it is amalgam of influences (Katz & Lazarsfeld, 1955). Moreover, we suggest fashion brands to identify the right influencers that best resonate with the targeted audience. Additionally, we recommend the brands, through the lens of this model, to collect the consumer behavioral and purchasing data (e.g. monthly basis and quarterly basis etc.) or to measure the consumer reactions towards Insta fashionista photos. The effective use of this data helps the brands do right investment in promotions and capitalize their growth.

7.3. Limitations

Like other empirical studies, this empirical research has also some limitations. Firstly, this study used the online promotional method that's why our model corresponds to the purchasing caused by Instagrammers. Additionally, this study is limited to single platform Instagram. Moreover, it is limited to fashion industry solely therefore, findings cannot be completely construed to other industries or products (electronics, food etc.). Our study is limited to a single country Pakistan and collected the data from Pakistanis to validate our model. Finally, our study is limited to cross-sectional data.

7.4. Future research directions

This study is limited in several aspects and gives suggestions to future researchers. Future attempts can be made to test this model on other e-commerce platforms to get better insight into influencer advertising and masses engagement (decision-making) for greater coverage/outreach. The future researchers should test 'The dual AISAS model' in other industries like beauty, food, travel, health, and fitness to increase the robustness of this model. Thirdly, due to the cultural differences and consumer behavior, we recommend future researcher to cross validate the findings of current study by employing this model in other emerging countries as well as developed countries. Future attempt can use longitudinal data to measure eleven phases of dual AISAS model at different point in time or can use experimental design to see how consumers respond to stimuli in diverse scenarios and its effects on consumers' decision-making processes.

These effects are much warranted by taking into consideration customer psychographic (generation, lifestyle, and values) and demographic aspects.

Disclosure statement

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ORCID

Sara Javed http://orcid.org/0000-0002-7234-7690
Md. Salamun Rashidin http://orcid.org/0000-0003-1273-8494

References

Abed, S. (2018). An empirical examination of Instagram as an s-commerce channel. *Journal of Advances in Management Research*, *15* Issue: (2), 146–160. https://doi.org/10.1108/JAMR-05-2017-0057

Agarwal, N., Mahata, D., & Liu, H. (2014). Time and event driven modeling of blogger influence. *Encyclopedia of Social Network Analysis and Mining (ESNAM)*, 2154–2165. Springer, https://doi.org/10.1007/978-1-4614-6170-8_378

Aldhaheri, A., & Bach, C. (2013). How to implement marketing 2.0 successfully. *International Journal of Business and Social Science*, *4*, 36–42. https://doi.org/10.1007/s40429-015-0056-9

Ali, S. A. (2020). The effects of social media and youth in Pakistan. Daily Blochistan Express, January 26. https//www.bexpress.com.pk/2019/12/theeffects-of-social-media-and-youth-in-pakistan/

Amaly, L., & Hudrasyah, H. (2012). Measuring effectiveness of marketing communication using AISAS ARCAS Model. *Journal of Business and Management*, *1* (5), 352–364.

Aswani, R., Ghrera, S. P., Kar, A. K., & Chandra, S. (2017a). Identifying buzz in social media: a hybrid approach using artificial bee colony and k-nearest neighbors for outlier detection. *Social Network Analysis and Mining*, *7* (1), 38.

Aswani, R., Kar, A. K., Aggarwal, S., & Ilavarsan, P. V. (2017b). Exploring content virality in Facebook: A semantic based approach. In *Conference on e-business, e-services and e-society* (pp. 209–220). Springer.

Atara, & Dentsu. (2015). Atara develops 'Dual Aisas Model™', a new consumer behavior models in the network era. https://www.atara.co.jp/news/dual-aisas-2.html

Awasthi, A. K., & Choraria, S. (2015). Effectiveness of celebrity endorsement advertisements: the role of customer imitation behaviour. *Journal of Creative Communications*, *10*(2), 215–234. https://doi.org/10.1177/0973258615597412

Babar, K. (2020). Why are advertisers in Pakistan experimenting with influencer marketing? https://profit.pakistantoday.com.pk/2020/07/26/why-are-advertisers-in-pakistan-experimenting-with-influencer-marketing/

Basille, D. (2009). *Social media influencers are not traditional influencers*. http://www.briansolis.com/2009/11/social-media-influencers-are-not-traditional-influencers/.

Batool, N. (2018). Fashion industry of Pakistan. https://rabah.pk/fashion-industry-in-pakistan/

Black, N., Johnston, M., Michie, S., Hartmann-Boyce, J., West, R., Viechtbauer, W., Eisma, M. C., Scott, C., & de Bruin, M. (2020). Behaviour change techniques associated with smoking cessation in intervention and comparator groups of randomized controlled trials: A systematic review and meta-regression. *Addiction* 115(11), 2008–2020. https://doi.org/10.1111/add.15056.

Bradri.com. (2019). Pakistani influencers who are making the most out of influencer marketing. https://bradri.com/blog/pakistani-influencers-who-are-making-the-most-of-influencer-marketing/.

Brosius, H. B., & Weimann, G. (1996). Who sets the agenda: Agenda-setting as a two-step flow. *Communication Research*, *23*(5), 561–580. https://doi.org/10.1177/009365096023005002

Casaló, L. V., Flavián, C., & Ibáñez-Sánchez, S. (2020). Influencers on Instagram: Antecedents and consequences of opinion leadership. *Journal of Business Research*, *117*, 510–519. https://doi.org/10.1016/j.jbusres.2018.07.005

Chahal, M. (2016). Four trends that will shape media in 2016. Marketing Week. http://www.marketingweek.com/2016/01/08/fourtrends-that-will-shape-media-in-2016

Chaney, I. M. (2001). Opinion leaders as a segment for marketing communications. *Marketing Intelligence & Planning*, *19* (5), 302–308. https://doi.org/10.1108/EUM0000000005647

Chatterjee, P. (2011). Drivers of new product recommending and referral behavior on social network sites. *International Journal of Advertising*, *30*(1), 77–101. https://doi.org/10.2501/IJA-30-1-077-101

Cheah, J.-H., Ting, H., Huei Cham, T., & Ali Memon, M. (2019). The effect of selfie promotion and celebrity endorsed advertisement on decision-making processes: A model comparison. *Internet Research*, *29* (3), 552–577. https://doi.org/10.1108/IntR-12-2017-0530

Chen, Y., & Xie, J. (2008). Online consumer review: Word-of-mouth as a new element of marketing communication mix. *Management Science*, *54* (3), 477–491. https://doi.org/10.1287/mnsc.1070.0810

Cheng, S., Zhang, B., Zou, G., Huang, M., & Zhang, Z. (2019). Friend recommendation in social networks based on multi-source information fusion. *International Journal of Machine Learning and Cybernetics*, https://doi.org/10.1007/s13042-017-0778-1.

Cheung, C., Lee, M., & Rabjohn, N. (2008). The impact of electronic word-of-mouth: The adoption of online opinions in online customer communities. *Internet Research*, *18*(3), 229–247. https://doi.org/10.1108/10662240810883290

Cheung, C., & Thadani, D. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. *Decision Support Systems*, *54*(1), 461–470. https://doi.org/10.1016/j.dss.2012.06.008

Cheung, M., Luo, C., Sia, C., & Chen, H. (2009). Credibility of electronic word-of-mouth: Informational and normative determinants of online consumer recommendations. *International Journal of Electronic Commerce*, *13*(4), 9–38. https://doi.org/10.2753/JEC1086-4415130402

Choi, W., & Lee, Y. (2019). Effects of fashion vlogger attributes on product attitude and content sharing. *Fashion and Textiles*, *6*(1), 1–18. https://doi.org/10.1186/s40691-018-0161-1

Chu, S. C., & Kim, J. (2011). Determinants of consumer engagement in electronic word-of-mouth (eWoM) in social networking sites. *International Journal of Advertising*, *30*(1), 47–75. https://doi.org/10.2501/IJA-30-1-047-075

Clow, K. E., & Baack, D. (2016). Integrated advertising. In *Promotion, and marketing communication* (7th ed.). Pearson Education International.

Cohen, J. (1988). Set Correlation and Multivariate Methods. Chapter 12. In N. J. Hillsdale (Ed.), Statistical power analysis for the behavioral sciences (2nd ed., pp. 467–514). L. Erlbaum Associates. http://www.worldcat.org/title/statistical-power-analysis-for-the-behavioralsciences/oclc/17877467

Crandall, D., Cosley, D., & Huttenlocher, D. (2008). *Feedback effects between similarity and social influence in online communities [Paper presentation]*. In Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 160–168). ACM Press. https://doi.org/10.1145/1401890.1401914

Datareportal. (2020). Digital 2020: Pakistan. https://datareportal.com/reports/digital-2020-pakistan

De Oliveira, S. D., & Gosling, M. (2015). Intent to purchase and consumption of organic food in Minas Gerais, Brazil. *Portuguese Journal of Marketing*, *38*(34), 9–22.

De Vries, N. J., & Carlson, J. (2014). Examining the drivers and brand performance implications of customer engagement with brands in the social media environment. *Journal of Brand Management*, *21*(6), 495–515. https://doi.org/10.1057/bm.2014.18

Delisle, M. P., & Parmentier, M. A. (2016). Navigating person-branding in the fashion blogosphere. *Journal of Global Fashion Marketing*, *7*(3), 211–224. https://doi.org/10.1080/20932685.2016.1167619

Dentsu. (2008). The change of consumer action model: From AIDMA to AISAS. http://www.dentsu.com.tw/
Dentsu. (2015). Buying behavior data, models: Capturing free online and offline movement of consumers. http://www.dentsu.com/business/japan/promotions/buying_behavior.html
Denscombe, M. (2014). *The good research guide: for small-scale social research projects*. McGraw-Hill Education. http://hdl.handle.net/2086/10239
Du Plessis, P., & Rousseau, G., & Blem, N. (1991). *Consumer behaviour. A South African perspective*. Sigma.
Dwivedi, Y. K., Kelly, G., Janssen, M., Rana, N. P., Slade, E. L., & Clement, M. (2018). Social media: The good, the bad, and the ugly. *Information Systems Frontiers*, *20* (3), 419–423. https://doi.org/10.1007/s10796-018-9848-5
Elbeltagi, I., & Agag, G. (2016). E-retailing ethics and its impact on customer satisfaction and repurchase intention. *Internet Research*, *26*(1), 288–310. https://doi.org/10.1108/IntR-10-2014-0244
Erz, A., Marder, B., & Osadchaya, E. (2018). Hashtags: Motivational drivers, their use, and differences between influencers and followers. *Computers in Human Behavior*, *89*, 48–60. https://doi.org/10.1016/j.chb.2018.07.030
Flynn, L. R., Goldsmith, R. E., & Eastman, J. K. (1996). Opinion leaders and opinion seekers: Two new measurement scales. *Journal of the Academy of Marketing Science*, *24*(2), 137–147. https://doi.org/10.1177/0092070396242004
Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312. https://doi.org/10.1177/002224378101800104
Freberg, K., Graham, K., McGaughey, K., & Freberg, L. A. (2011). Who are the social media influencers? A study of public perceptions of personality. *Public Relations Review*, *37* (1), 90–92. https://doi.org/10.1016/j.pubrev.2010.11.001
Frosh, P. (2015). The gestural image: The selfie, photography theory, and kinesthetic sociability. *International Journal of Communication*, *9*, 1607–1628.
Garland, C., & Reed, M. (2018). How to measure the value of influencer marketing. Globus Cosmetic Industry. https://www.gcimagazine.com/business/marketing/How-to-Measure-the-Value-of-Influencer-Marketing-484302621.html
Goldsmith, R. E., & Clark, R. A. (2008). An analysis of factors affecting fashion opinion leadership and fashion opinion seeking. *Journal of Fashion Marketing and Management: An International Journal*, *12*(3), 308–322. https://doi.org/10.1108/13612020810889272
Hair, J. F. (1998). Multivariate data analysis. Prentice Hall. https://www.worldcat.org/title/multivariate-data-analysis/oclc/38014749
Hair, J. F., Black, W. C., Babin, B. J., & Tatham, R. L. (2010). *Multivariate data analysis* (7th ed). Pearson Prentice Hall.
Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202
Hanna A. R., Rohm A, A., & Crittenden, V. L. (2011). We're all connected: The power of the social media ecosystem. *Business Horizons*, *54*(3), 265–273. https://doi.org/10.1016/j.bushor.2011.01.007
Hansen, D., Shneiderman, B., & Smith, M. A. (2011). *Analyzing social media networks with Node XL: Insights from a connected world* (pp. 304). Elsevier.
Hashoff. (2017). Influencer marketer. A hashoff state of the union report (Fall 2017). Hashoff.
Hassan, S., Nadzim, S. Z. A., & Shiratuddin, N. (2015). Strategic use of social media for small business based on the AIDA model. *Procedia - Social and Behavioral Sciences*, *172*, 262–269. https://doi.org/10.1016/j.sbspro.2015.01.363
Hawaldar, I., & Ullal, M. (2018). Influence of advertisement on customers based on AIDA model. *Problems and Perspectives in Management*, *16*, 285–298. https://doi.org/10.21511/ppm.16(4).2018.24

Herr, P. M., Kardes, F. R., & Kim, J. (1991). Effects of word-of-mouth and product attribute information on persuasion: An accessibility-diagnosticity perspective. *Journal of Consumer Research*, *17*(4), 454–462. https://doi.org/10.1086/208570

Herrando, C., Jimenez-Martinez, J., & Martin De Hoyos, M. J. (2018). Surfing or flowing? How to retain e-customers on the internet. *Spanish Journal of Marketing - ESIC*, *22*(1), 2–21. https://doi.org/10.1108/SJME-03-2018-006

Hooper, D., Coughlan, J., & Mullen, M. (2008). Structural equation modelling: guidelines for determining model fit. *Electronic Journal of Business Research Methods*, *4* (1), 53–60.

Hsu, C., Lin, J. C., & Chiang, H. (2013). The effects of blogger recommendations on customers' online shopping intentions. *Internet Research*, *23* (1), 69–88. https://doi.org/10.1108/10662241311295782

Huhn, R., Ferreira, J., Freitas, A., & Leão, F. (2018). The effects of social media opinion leaders' recommendations on followers' intention to buy. *Review of Business Management*, *20*(1), 57–73. https://doi.org/10.7819/rbgn.v20i1.3678

Jamal, A. (2020). Generation Z in Pakistan: Individualistic and collectivist in orientation. In E. Gentina & E. Parry (Eds.), *The new generation Z in Asia: Dynamics, differences, digitalisation (the changing context of managing people)* (pp. 105–117). Emerald Publishing Limited. https://doi.org/10.1108/978-1-80043-220-820201011

Javed, S., Rashidin, M. S., Zhu, M., Xu, Z., Jian, W., & Zuo, S. (January 2021). *Combined effects of drivers and impact of customer satisfaction on brand loyalty: The contingent effect of social trust* (Vol. 1). Sage Open. doi:10.1177/21582440211003566

Jin, S. A., & Phua, J. (2014). Following celebrities' Tweets about brands:' the impact of Twitter-based electronic word-of-mouth (eWoM) on consumers' source credibility perception, buying intention, and social identification with celebrities. *Journal of Advertising*, *43*(2), 181–195. https://doi.org/10.1080/00913367.2013.827606

Kapitan, S., & Silvera, D. H. (2016). From digital media influencers to celebrity endorsers: Attributions drive endorser effectiveness. *Marketing Letters*, *27*(3), 553–567. https://doi.org/10.1007/s11002-015-9363-0

Karl, M., & Reintinger, C. (2016). Mapping destination choice: set theory as a methodological tool. In M. Kozak & N. Kozak (Eds.), *Tourist behaviour: An international perspective* (pp. 74–83). CABI.

Katz, E., & Lazarsfeld, P. (1955). *Personal influence: The part played by people in the flow of mass communications*. The Free Press.

Kavak, B., Tunçel, N., & Özyörük, H. E.; The Business Administration Department of Hacettepe University. (2015). Do small and medium sized enterprises have their unique buying behavior variables? A qualitative approach. *International Journal of Trade, Economics and Finance*, *6* (6), 283–289. https://doi.org/10.18178/ijtef.2015.6.6.483

Ki, C.-W. C., & Kim, Y. -K. (2019). The mechanism by which social media influencers persuade consumers: The role of consumers' desire to mimic. *Psychology & Marketing*, *36*(10), 905–922. https://doi.org/10.1002/mar.21244

Kline, R. B. (2005). *Principles and practice of structural equation modeling* (2nd ed). Guilford Press.

Kline, R. B. (2005). PsycNET record display - PsycNET. http://psycnet.apa.org/record/2005-03476-000

Korgaonkar, P., Silverblatt, R., & Girard, T. (2006). Online retailing, product classifications, and consumer preferences. *Internet Research*, *16*(3), 267–288. https://doi.org/10.1108/10662240610673691

Kusumasondjaja, S., & Tjiptono, F. (2019). Endorsement and visual complexity in food advertising on Instagram. *Internet Research*, *29*(4), 659–687. https://doi.org/10.1108/IntR-11-2017-0459

Kwon, E. S., Kim, E., Sung, Y., & Yoo, C. Y. (2014). Brand followers: Consumer motivation and attitude towards brand communications on Twitter. *International Journal of Advertising*, *33*(4), 657–680. https://doi.org/10.2501/IJA-33-4-657-680

Li, F., & Du, T. C. (2011). Who is talking? An ontology-based opinion leader identification framework for word-of-mouth marketing in online social blogs. *Decision Support Systems*, *51*(1), 190–197. https://doi.org/10.1016/j.dss.2010.12.007

Li, Y., Ma, S., Zhang, Y., & Huang, R. (2013). An improved mix framework for opinion leader identification in online learning communities. *Knowledge-Based Systems*, *43*, 43–51.

Lin, C., Xie, R., Guan, X., Li, L., & Li, T. (2014). Personalized news recommendation via implicit social experts. *Information Sciences*, *254*, 1–18. https://doi.org/10.1016/j.ins.2013.08.034

Lipsman, A., Mudd, G., Rich, M., & Bruich, S. (2012). The power of 'like': How brands reach (and influence) fans through social-media marketing. *Journal of Advertising Research*, *52* (1), 40–52. https://doi.org/10.2501/JAR-52-1-040-052

Locowise. (2017). Instagram follower growth is now lagging behind facebook page likes growth. goo.gl/m0sVm2.

Lyfe Marketing. (2018). The best social media platforms for social media marketing in 2018. https://www.lyfemarketing.com/blog/wp-content/uploads/2018/02/The-Best-Social-Media-Platforms-for-Social-Media-Marketing-in-2018.pdf.

MacCallum, R. C., & Hong, S. (1997). Power analysis in covariance structure modeling using GFI and AGFI. *Multivariate Behavioral Research*, *32* (2), 193–210. https://doi.org/10.1207/s15327906mbr3202_5

Mavroudis, J. (2018). Fame labor. In C. Abidin & M. Brown (Eds.), *Microcelebrity around the globe* (pp. 83–93). Emerald Publishing Limited. https://doi.org/10.1108/978-1-78756-749-820181007

McCartney, G., & Pinto, J. F. (2014). Influencing Chinese travel decisions: The impact of celebrity endorsement advertising on the Chinese traveler to Macao. *Journal of Vacation Marketing*, *20* (3), 253–266. https://doi.org/10.1177/1356766714524203

McNeill, A. R., & Briggs, P. (2014). *Understanding Twitter influence in the health domain: A social-psychological contribution [Paper presentation].* In Proceedings of the 23rd International Conference on World Wide Web (pp. 673–678). ACM.

Mediakix. (2017). Instagram influencer marketing is a 1 billion dollar industry. http://mediakix.com/2017/03/instagram-influencer-marketing-industry-size-how-big/#gs.lttj8Qij.

Meng, F., Wei, J., Zhu, Q. (2011). Study on the impacts of opinion leader in online consuming decision. In *2011 International Joint Conference on Service Sciences* (pp. 140–144). IEEE. https://www.semanticscholar.org/paper/Study-on-the-Impacts-of-Opinion-Leader-in-Online-Meng-Wei/8f736f096d3fdb2a3b1417d8e638787e6bb0a4b5

Merz, M. A., Zarantonello, L., & Grappi, S. (2018). How valuable are your customers in the brand value co-creation process? The development of a customer co-creation value (CCCV) scale. *Journal of Business Research*, *82*, 79–89. September 2017). https://doi.org/10.1016/j.jbusres.2017.08.018

Mull, I. R., & Lee, S. E. (2014). PIN' pointing the motivational dimensions behind Pinterest. *Computers in Human Behavior*, *33*, 192–200. https://doi.org/10.1016/j.chb.2014.01.011

Muntinga, D. G., Moorman, M., & Smit, E. G. (2011). Introducing COBRAs: Exploring motivations for brand-related social media use. *International Journal of Advertising*, *30*(1), 13–46. https://doi.org/10.2501/IJA-30-1-013-046

Nabi, N., O'Cass, A., & Siahtiri, V. (2019). Status consumption in newly emerging countries: The influence of personality traits and the mediating role of motivation to consume conspicuously. *Journal of Retailing and Consumer Services*, *46*, 173–178. https://doi.org/10.1016/j.jretconser.2017.09.009

NapleonCat.c. (2020). https://napoleoncat.com/stats/social-media-users-in-pakistan/2020

Ognyanova, K. (2017). Multistep flow of communication: Network effects. In P. Roessler, C. Hoffner, & L. van Zoonen (Eds.), *he international encyclopedia of media effects* (pp. 1–10). Wiley-Blackwell.

Paek, H., Hove, T., Jeong, H. J., & Kim, M. (2011). Peer or expert? The persuasive impact of YouTube public service announcement producers. *International Journal of Advertising*, *30*(1), 161–188. https://doi.org/10.2501/IJA-30-1-161-188

Park, C. S., & Kaye, B. K. (2017). The tweet goes on: Interconnection of Twitter opinion leadership, network size, and civic engagement. *Computers in Human Behavior*, *69*, 174–180. https://doi.org/10.1016/j.chb.2016.12.021

Park, J., Yoon, Y., & Lee, B. (2009). The effect of gender and product categories on consumer online information search. *Advances in Consumer Research*, *36*, 362–366.

Rashidin, M. S., Javed, S., Chen, L., & Jian, W. (2020a). Assessing the competitiveness of Chinese multinational enterprises development: Evidence from electronics sector. *Sage Open*, *10*(1), 215824401989821. https://doi.org/10.1177/2158244019898214

Rashidin, M. S., Javed, S., Liu, B., & Jian, W. (2020b). *Ramifications of households' nonfarm income on agricultural productivity: Evidence from a rural area of Pakistan*. Sage Open. https://doi.org/10.1177/2158244020902091.

Roman, S. (2007). The ethics of online retailing: A scale development and validation from the consumers' perspective. *Journal of Business Ethics*, *72*(2), 131–148. https://doi.org/10.1007/s10551-006-9161-y

Ruyter, K., & Bloemer, J. (1999). Customer loyalty in extended service settings. *International Journal of Service Industry Management*, *10*(3), 320–336. https://doi.org/10.1108/09564239910276917

Sano, Y. (2017). Instagenic photos' have changed consumer's behavior. https://medium.com/@yuyasano/how-consumer-activity-has-changed-with-instagram-2d544c83fdc9

Sawilowsky, S. S. (2003). A different future for social and behavioral science research (PDF). *Journal of Modern Applied Statistical Methods*, *2* (1), 128–132. https://doi.org/10.22237/jmasm/1051747860

Seckler, M., Heinz, S., Forde, S., Tuch, A. N., & Opwis, K. (2015). Trust and distrust on the web: User experiences and website characteristics. *Computers in Human Behavior*, *45*, 39–50. https://doi.org/10.1016/j.chb.2014.11.064

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach*. John Wiley & Sons.

Shintara, O., & Yuji, K. (2018). Constructing the website to create empathy through interaction between company and customers. *Bulletin of JSSD*, *54*, 502–503.

Silva, T., Melo, P., Almeida, J., Salles, J., Loureiro, A. (2013). A picture of Instagram is worth more than a thousand words: workload characterization and application. In *Proceedings of the International Conference on Distributed Computing in Sensor Systems* (pp.123–132). IEEE.

Socialbakers. (2016). Why fashion brands are thriving on Instagram. https://www.socialbakers.com/blog/2626-why-fashion-brands-are-thriving-on-instagram

Sokolova, K., & Kefi, H. (2020). Instagram and YouTube bloggers promote it, why should I buy? How credibility and parasocial interaction influence purchase intentions. *Journal of Retailing and Consumer Services*, *53*, 1–9. https://doi.org/10.1016/j.jretconser.2019.01.011.

Song, S. Y., Cho, E., & Kim, Y. -K. (2017). Personality factors and flow affecting opinion leadership in social media. *Personality and Individual Differences*, *114*, 16–23. https://doi.org/10.1016/j.paid.2017.03.058

Stansberry, K. (2017). *Multistep flow of communication: online media and social navigation* (pp. 1–9). John Wiley & Sons, Inc. https://doi.org/10.1002/9781118783764.wbieme0058

Statista - The Statistics Portal. (2018). Distribution of Instagram users worldwide as of January 2018, by age and gender. https://www.statista.com/statistics/248769/age-distribution-of-worldwide-instagram-users/

Štreimikienė, D., Mikalauskienė, A., Sturienė, U., & Kyriakopoulos, G. L. (2021). The impact of social media on sales promotion in entertainment companies. *Ekonomie a Management*, *24*(2), 189–207. https://doi.org/10.15240/tul/001/2021-2-012

Susarla, A., Oh, J. H., & Tan, Y. (2016). Influentials, imitables, or susceptibles? Virality and word-of-mouth conversations in online social networks. *Journal of Management Information Systems*, *33* (1), 139–170.

Talavera, M. (2017). Reasons why influencer marketing is the next big thing. Adweek. https://www.adweek.com/performance-marketing/10-reasons-why-influencer-marketing-is-the-next-big-thing/

Teng, S., Khong, K. W., & Goh, W. W. (2014). Persuasive communication: a comparison of major attitude-behaviour theories in a social media context. In *International conference on emerging trends in scientific research* (pp. 82–89). Pak Publishing Group.

Tess, P. A. (2013). The role of social media in higher education classes (real and virtual)–A literature review. *Computers in Human Behavior*, *29* (5), A60–A68. https://doi.org/10.1016/j.chb.2012.12.032

Thakur, R., Angriawan, A., & Summey, J. H. (2016). Technological opinion leadership: The role of personal innovativeness, gadget love, and technological innovativeness. *Journal of Business Research*, *69*(8), 2764–2773. https://doi.org/10.1016/j.jbusres.2015.11.012

Trusov, M., Bodapati, A. V., & Bucklin, R. E. (2010). Determining influential users in internet social networks. *Journal of Marketing Research*, *47* (4), 643–658. https://doi.org/10.1509/jmkr.47.4.643

Venkatraman, V., Dimoka, A., Pavlou, P. A., Vo, K., Hampton, W., Bollinger, B., Hershfield, H. E., Ishihara, M., & Winer, R. S. (2015). Predicting advertising success beyond traditional measures: New insights from neurophysiological methods and market response modeling. *Journal of Marketing Research*, *52*(4), 436–452. https://doi.org/10.1509/jmr.13.0593

Weeks, B. E., Ardèvol-Abreu, A., & Gil de Zúñiga, H. (2017). Online influence? Social media use, opinion leadership, and political persuasion. *International Journal of Public Opinion Research*, *29* (2), 214–239.

Wei, L. R. (2017). The status analysis and prospective development studies of digital celebrity industry in 'Internet+' era. *China Journal of Commerce*, *6*, 20–21.

Wei, P.-S., & Lu, H.-P. (2013). An examination of the celebrity endorsements and online customer reviews influence female consumers' shopping behavior. *Computers in Human Behavior*, *29*, 193–201. https://doi.org/10.1016/S1473-3099(21)00397-2

Wiedmann, K.-P., Hennigs, N., & Langner, S. (2010). Spreading the word of fashion: Identifying social influencers in fashion marketing. *Journal of Global Fashion Marketing*, *1*(3), 142–153. https://doi.org/10.1080/20932685.2010.10593066

Yajima, T. (2015). Think in Dual Aisas, a strategy to sell more. https://dentsu-ho.com/articles/3100.

Yesmail. (2015). Lessons learned: How retailers utilized social media in 2014, trends and takeaways for 2015. Retrieved from goo.gl/p1bgCx, Accessed date: 20 Feb 2019

Yu, Z., Wang, C., Bu, J., Wang, X., Wu, Y., & Chen, C. (2015). Friend recommendation with content spread enhancement in social networks. *Information Sciences*, *309*, 102–118. https://doi.org/10.1016/j.ins.2015.03.012

Zhang, K. Z., Xu, H., Zhao, S., & Yu, Y. (2018). Online reviews and impulse buying behavior: The role of browsing and impulsiveness. *Internet Research*, *28* (3), 522–543. https://doi.org/10.1108/IntR-12-2016-0377

Zhang, X., Li, S., Burke, R. R., & Leykin, A. (2014). An examination of social influence on shopper behavior using video tracking data. *Journal of Marketing*, *78* (5), 24–41. https://doi.org/10.1509/jm.12.0106

Zhao, Y., Kou, G., Peng, Y., & Chen, Y. (2018). Understanding influence power of opinion leaders in e-commerce networks: An opinion dynamics theory perspective. *Information Sciences*, *426*, 131–147. https://doi.org/10.1016/j.ins.2017.10.031

Zhu, Z. B., Su, J., & Kong, L. (2015). Measuring influence in online social network based on the user-content bipartite graph. *Computers in Human Behavior*, *52*, 184–189. https://doi.org/10.1016/j.chb.2015.04.072