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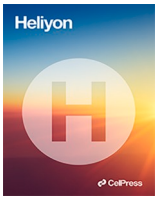

Research article

How information and communication overload affect consumers' platform switching behavior in social commerce

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ABSTRACT

In social commerce, users are increasingly resorting to social media platforms to search for information, purchase goods, and share shopping experiences. However, social media use may also affect users' emotions negatively, causing them to switch platforms. Therefore, this study aims to investigate how negative factors (i.e., information and communication overload) affect consumers' platform-switching behavior in social commerce. Drawing on the stimulus-organism-response (SOR) model, this study established a research framework and conducted an online survey in China. A purposive sampling technique was used to collect the data, generating 477 valid responses. Data analysis, based on structural equation modeling, indicates that information and communication overload, and online fatigue positively affect platform-switching intention. The effect of the intention to switch on behavior is moderated by switching costs. Mediation analysis shows that information and communication overload can indirectly influence switching behavior through online fatigue and switching intention. This study incorporates the novel aspects of switching costs in examining the driving forces behind platform-switching in social commerce, thereby theoretically adding value to the existing body of knowledge. Apart from this, our findings also bear significant practical implications and are valuable for social commerce platforms and sellers to improve their user experience and retain existing customers.

1. Introduction

In recent years, the fusion of e-commerce and social media platforms, also known as social commerce, has garnered increasing attention. Social commerce is a business mediated by social media that integrates both, online and offline environments [1]. The global social commerce revenue reached $724 billion in 2022, and is projected to surpass $60 trillion by 2030. Asian countries are particularly enthusiastic about social commerce, with over 80 % of the Internet users engaged as social buyers in Thailand, India, and China [2]. Concurrently, research on social media platforms, serving as conduits for social commerce, has witnessed a sharp increase. These platforms allow users to share information with friends and consumers, shaping their shopping environments through social interactions [3]. Social media, the primary channel for communication and promotion between businesses and consumers, actively reshapes people's daily lives.

Nevertheless, while social media provides tremendous convenience to users, its negative aspects are becoming increasingly apparent. User satisfaction with platforms is declining, causing declining loyalty towards a specific platform and choosing from

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multiple platforms [4]. This trend has led to platform-switching behavior. Previous studies have extensively investigated consumer switching behaviors. Most have focused on interchannel switching, such as offline-online switching [5], web-app switching [6], and cross-channel switching [7]. A few studies have investigated inter-platform switching in traditional [8,9] and live-streaming e-commerce [10]. Most platform-switching studies consider dissatisfaction to be the most common cause for consumers to switch platforms [11,12]. However, the understanding of consumers platform-switching behavior remains inadequate, especially in the context of social commerce.

Among the discussions on the antecedents of switching behavior on social media platforms, the issue of overload has received widespread scholarly attention, particularly regarding its impact on negative usage intentions. Numerous studies suggest that information overload positively influences negative usage behavior [13,14]. Some studies have also focused on the effects of communication and feature overload, apart from those of excess information, on usage behaviors. Maintaining connections with others on social media platforms implies the possibility of receiving various types of interconnected information, and excessive interference may surpass an individual's communicative capacity, leading to communication overload and subsequent to usage-discontinuing behavior [15]. While most studies concentrate on negative or usage discontinuation behaviors, research on switching behaviors is relatively limited. How information and communication overload promotes user-switching behavior, therefore, requires further investigation.

Researchers have also explored the negative impacts of social media from the perspective of emotional influence on consumers. One such adverse effect is social fatigue. For instance, with the emergence of factors like overload, the number of dynamic members on various mobile social network service (SNS) platforms, including Facebook, TikTok, YouTube, and Instagram, has significantly decreased [15]. Users start getting overwhelmed by the plethora of information and crowded relationships, as the influx of information and demand for communication surpasses their cognitive load [16]. This results in users experiencing negative emotions, such as fatigue, preventing them from making informed decisions [17]. However, the role of online (social) fatigue in consumers' platform switching in social commerce remains unexplored.

Furthermore, according to classical behavior theory, behavioral intention is a direct determinant of behavior [18]. Research has indicated that switching intention directly influences switching behavior [19]. In switching behavior research, many studies have focused only on behavioral and viewing intentions as valid proxies for behavior. However, even when users are dissatisfied with their performance and services, they may not necessarily adopt switching-behavior. This is because, influenced by various contextual factors, a gap may exist between intention and behavior [20,21]. One of the noteworthy factors is the cost of switching. Previous studies have identified various forms of switching costs in specific contexts, such as psychological and functional costs in the context of AI voice assistants [22] or those pertaining to process and relationship in the transition from physical to mobile stores [23]. In social commerce, the effect of specific switching costs on the relationship between platform-switching intentions and behavior remains to be investigated.

The research gaps discussed above generate three specific research objectives. The first is to investigate how platform overload, including information and communication overload, affects consumer platform-switching behavior in the context of social commerce. The second is to explore the role of online (social) fatigue in platform-switching by consumers. The final research objective of this study is to explore the effect of switching costs on the relationship between switching intention and behavior.

2. Literature review and research hypotheses

2.1. Theoretical foundations

Many previous platform-switching studies have employed the push-pull-mooring (PPM) framework as a theoretical lens to explain user behavior [5,24,25]. Such research primarily investigates the extrinsic (push) and intrinsic (pull) factors affecting consumers' switching behavior, but rarely focuses on consumers' emotional response processes. Other research has included emotional variables in theoretical frameworks, such as stimulus-organism-response (SOR), cognition-affect-conation (CAC), stressor-strain-outcome (SSO), and uses and gratifications (U&G) [8,15,16,26], to understand consumer behavior for platform usage. However, transfer behavior has not been discussed in these studies.

This study employs the stimulus-organism-response (SOR) model as a research framework to understand consumers' platform-switching behavior in social commerce. This is because SOR allows researchers to incorporate new stimuli and associated emotional reaction factors, as required. In the SOR model, "S" represents external environmental stimulation, "O" signifies the internal state of mind, and "R" denotes the behavioral response. The SOR model is a pivotal theory in psychological research that posits that external environmental stimuli influence individuals' internal states, subsequently shaping their behavioral responses [27]. This model is derived from the S–R paradigm, wherein stimuli are posited to directly generate a behavioral response. Eroglu et al. [28] introduced this model into the realm of online shopping. Since then, it has been widely utilized in online shopping environments to elucidate the relationship between external stimuli, psychological perceptions, and behavioral responses. Furthermore, the SOR model has been applied successfully in information systems research to explain the impact of external environmental factors on user behavioral tendencies [29]. The SOR model has proven valuable in social commerce literature [30–32].

Previous studies investigated different S, O, and R variables. This study introduces information and communication overload as stimuli, online fatigue as an organism's emotional reaction, and platform-switching intention as a response. Additionally, prior research has typically viewed behavioral intention as the endpoint of response (R) in the SOR. This is because classical behavioral theories, such as the theory of planned behavior (TPB) [18], have proven that intention is the primary determinant of behavior, leading many researchers to view it as a valid proxy for behavior. However, as discussed in Section 1, the relationship between intention and behavior may be influenced by many contextual factors. Therefore, this study introduces switching costs to understand the gap

between platform switching intentions and behavior. Based on the above discussion, a research model is proposed, as shown in Fig. 1.

2.2. Information overload

In the context of social media, Hattingh et al. [33] propose two forms of overload related to social media platforms: information overload and communication overload. The former occurs when, with the widespread use of social media, individuals encounter a substantial volume of information, exceeding their information-processing capabilities [15]. A significant increase in the volume of information reaches the limit of users' information processing capabilities, thereby influencing decision outcomes [34]. Several studies have noted the negative impact of information overload on mental health. Given the limited capacity of individuals to process information, facing an excessive amount of information generates negative emotions, such as anxiety, fatigue, and dissatisfaction [10]. Wang and Li [35] indicated that information overload exacerbates social media fatigue, thereby increasing user dissatisfaction. Liu et al. [36] conducted a survey of Generation Z users in the United Kingdom and arrived at similar results, revealing that perceived information overload exacerbated social media fatigue as well as the fear of COVID-19, thereby inducing users to withdraw from social media. Additionally, information overload can directly or indirectly lead to negative behavioral consequences, such as information avoidance and discontinuation behaviors. Based on the SOR model, we propose the following hypotheses:

H1. Information overload positively influences online fatigue.

H2. Information overload positively influences switching intention.

2.3. Communication overload

Communication overload refers to a state wherein users' attention is disrupted, and their ongoing tasks are excessively disturbed when facing communication and dialogue requests from other users, exceeding their communication capacity [37]. As social networks expand, frequent interactions may lead to an imbalance between communication demands and human cognition. Excessive communication requests, which surpass users' limits, may bewilder them. Communication initiated by unexpected parties partially diverts user attention, increasing investment of time and energy [29]. Excessive necessary or unnecessary communication requests cause communication overload, leading to psychological fatigue [33] and result in usage discontinuation behaviors. Studies have confirmed the crucial role of communication overload as a precursor to online fatigue. Pang et al. [16] surveyed 442 smartphone users and revealed that communication overload significantly influenced psychological fatigue. Lin et al. [37] investigated 502 WeChat users, reaching the same conclusion that communication overload increases user fatigue. Based on the SOR model, we propose the following hypotheses:

H3. Communication overload enhances online fatigue.

H4. Communication overload enhances switching intention.

2.4. Online fatigue

Previous studies define social media fatigue as the mental exhaustion experienced by the users who participate in, and interact on various online social media platforms, thereby experiencing an overload of technology, information, and communication [38]. Fatigue is a negative emotional manifestation and scholars have explored and demonstrated the various consequences of online fatigue. Research has identified outcomes, such as information avoidance intention [34], discontinued usage intention [39], interruption intention [36], and disappointment and anxiety [38]. The resulting behaviors include discontinued usage [40], social media fatigue [41], etc. Hwang et al. [42] surveyed 180 Korean SNS users and demonstrated that fatigue significantly influences switching behavior among users. Based on the SOR paradigm, this study proposes the following hypotheses:

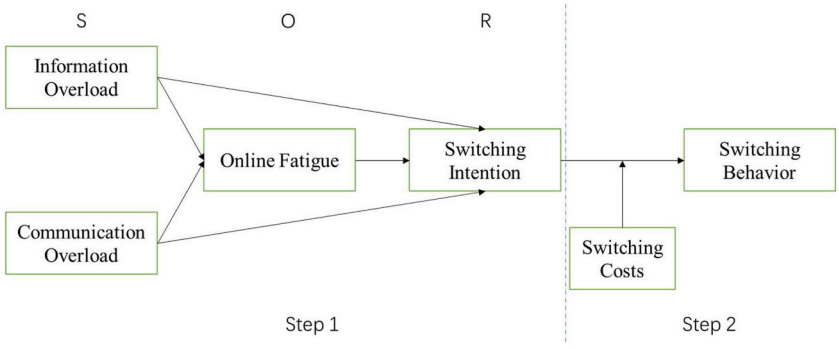

Fig. 1. Research framework.

H5. Online fatigue positively influences switching intention.

H6. Online fatigue mediates the relationship between information overload and switching intention.

H7. Online fatigue mediates the relationship between communication overload and switching intention.

2.5. Switching cost

Switching cost is a multidimensional concept that can vary according to the research context and product characteristics [43]. Chang et al. [23] defined switching costs as the customer-perceived procedural and relational costs associated with transitioning from physical to mobile stores. Researchers and practitioners have paid increasing attention to the role of switching costs in determining customer behavior, however, in the process of adopting new technology, a user is in the stage of comparison and hesitation. Therefore, it is difficult to determine the impact of the conversion cost during initial use [44]. Li et al. [45] studied the effects of inertia and switching costs on customer retention and identified the latter as the one-off costs paid by customers to switch from one hotel to another. Both, financial and procedural switching costs, affect customer retention positively. However, the effects of each cost dimension on customer retention are vague. Balakrishnan et al. [22] indicated a significant positive relationship between switching cost and resistance. Bölen [43] used procedural and financial switching costs to study the intention to switch from traditional watches to smartwatches; it was revealed that relative advantage and financial switching costs significantly influence the behavioral intentions of traditional wristwatch users to switch to smartwatches. Furthermore, financial switching costs mediated the effects of relative advantage and perceived product lifetime on the intention to switch. This study defines switching costs as all the costs that a consumer must bear when changing the currently frequented social commerce platform. This study proposes that switching costs influence the relationship between the intention and behavior to switch. Thus, the following hypothesis is proposed:

H8. Switching costs negatively moderate the effect of switching intention on switching behavior.

3. Research methodology

This study adopted a cross-sectional survey design approved by the ethics committee of Sanquan College of Xinxiang Medical University (SQ2021YQJH05). The survey was conducted anonymously through an online platform, and informed consent was obtained from all participants involved in the study.

3.1. Sample and data collection

This study investigated the platform-switching behavior of consumers in social commerce. Non-probability sampling was used because the sampling frame was unavailable. Purposive sampling techniques were employed to ensure that the samples were consistent with the research objectives. The inclusion criteria for the respondents were as follows: (1) they must be social commerce users, (2) they must have made at least four purchases on social commerce platforms (i.e., social media), and (3) they must have used at least two social commerce platforms. Eligible respondents were asked to select the social commerce platforms they were using–for example, Douyin, Weibo, and Xiaohongshu–and to complete the questionnaire based on their selections. The survey questionnaire consisted of two parts: the first part gathered the demographic characteristics of the participants, including gender, age, education level, and monthly income, while the second part comprised questions related to all constructs in the conceptual model. The survey was conducted in China and data were collected through an online survey platform in December 2023. After filtering out invalid responses, 477 valid responses were obtained. Typically, a sample size greater than 200 is considered sufficient to test a model [46]. Table 1 presents the participants' descriptive statistics. From a demographic perspective, 43.19 % of the users were male, and 56.81 % were female. Users holding a bachelor's degree comprised 68.3 % of the sample; further, those aged 18–29 years accounted for 43.40 % of the sample. Additionally, 40.88 % of the participants reported an income ranging from 5000 to 10,000 ¥.

Table 1
Demographics of research samples.

Field	Category	Frequency	Percentage
Gender	Male	206	43.19 %
	Female	271	56.81 %
Age (years old)	18–29	207	43.40 %
	30–39	191	40.04 %
	40–49	43	9.01 %
	50 and above	36	7.55 %
Education	High school and below	17	3.56 %
	Vocational college	35	7.34 %
	Bachelor	326	68.34 %
	Master and above	99	20.75 %
Income	Less than 5000 ¥	132	27.67 %
	5000–10,000 ¥	195	40.88 %
	More than 10,000 ¥	150	31.45 %

3.2. Measurement of constructs

The constructs employed in this survey were derived from previously validated, well-established scales. The content was modified based on the research context to ensure the validity of the survey items. All constructs were measured reflectively using a 5-point Likert scale. Specifically, information overload (IO) was adapted from Lin et al. [37], communication overload (CO) was adapted from Cao and Sun [29], online fatigue (OF) was adapted from Cao et al. [47], switching cost (SC) was adapted from Sun et al. [48], switching intention (SI) was adapted from Ye et al. [10], and switching behavior (SB) was adapted from Fang and Li [49]. Appendix A presents the constructs and measurement parameters.

3.3. Data analysis

This study employed structural equation modeling (SEM) to analyze the data. SEM is a common method used in social science research, which allows for the simultaneous exploration and validation of multiple statistical relationships through visualization. Complex models can be simplified and discussed effectively by employing SEM, especially the relationships between latent structures (factors), achieved through path coefficients and measurement models [50]. Specifically, we used SPSS and AMOS software to perform the data analysis. First, confirmatory factor analysis (CFA) was performed to analyze the research model. Second, overall model fit was assessed, using various goodness-of-fit indices, such as chi-square to the degrees of freedom ratio (χ^2/df), root mean square error of approximation (RMSEA), root mean square residual (RMR), goodness of fit index (GFI), normed fit index (NFI), tucker-lewis index (TLI), and comparative fit index (CFI). Subsequently, SEM was used in AMOS to test the direct and mediating effects between the variables. Additionally, the moderating effect was tested using the “Process” procedure in SPSS software.

4. Results

4.1. Common method variance

Given that this study employed a single data-collection method, common method bias may be a concern. We conducted Harman’s single-factor test to address this [51]. The results indicated that the variance among users did not exceed 50 %. This suggested that the common method bias was not a significant concern in this study.

4.2. Measurement model

In this study, Cronbach’s α and composite reliability (CR) were employed to measure the reliability of the model. As shown in Table 2, Both α and CR have values greater than 0.7, indicating a high level of reliability for the model. Furthermore, the average variance extracted (AVE) for the study measures surpassed 0.5, signifying good convergent validity of the model. The square roots of the AVE values for each construct exceeded the inter-construct correlations, supporting discriminant validity (see Table 3). In summary, the measurement model used in this study demonstrated sufficient data fit, high reliability, and robust convergent and discriminant validity.

Table 2
Confirmatory factor analysis.

Construct	Items	Standard load	Cronbach’s α	CR	AVE
Information Overload (IO)	IO1	0.842	0.905	0.906	0.707
	IO2	0.867			
	IO3	0.828			
	IO4	0.827			
Communication Overload (CO)	CO1	0.814	0.835	0.838	0.633
	CO2	0.812			
	CO3	0.759			
Online Fatigue (OF)	OF1	0.799	0.844	0.846	0.647
	OF2	0.799			
	OF3	0.815			
Switching Intention (SI)	SI1	0.791	0.842	0.845	0.644
	SI2	0.812			
	SI3	0.804			
Switching Cost (SC)	SC1	0.803	0.834	0.837	0.631
	SC2	0.778			
	SC3	0.802			
Switching Behavior (SB)	SB1	0.808	0.862	0.863	0.678
	SB2	0.858			
	SB3	0.803			

Table 3
Discriminate validity: Pearson's correlation coefficient.

	IO	CO	OF	SI	SC	SB
IO	**0.841**					
CO	0.589***	**0.796**				
OF	0.628***	0.549***	**0.804**			
SI	0.562***	0.542***	0.547***	**0.803**		
SC	−0.349***	−0.317***	−0.338***	−0.627***	**0.794**	
SB	0.654***	0.646***	0.615***	0.696***	−0.568***	**0.823**

Notes: ***p < 0.001; the square root of the AVE is displayed on the diagonal.

4.3. Hypothesis testing

The SEM model (see Fig. 2) and model fit indices were examined using the AMOS software. Table 4 presents the results of the study. The measurement model fitting indicators (χ^2/df = 2.757; GFI = 0.950; RMSEA = 0.061; RMR = 0.065; CFI = 0.971; NFI = 0.956; TLI = 0.962) suggest that the data fit is satisfactory. All aforementioned metrics met the criteria for model fitting, supporting a robust model fit.

This study employed AMOS software for the path analysis of the SEM, and the results are presented in Table 5. Both, information and communication overload, demonstrated positive effects on online fatigue, with coefficients of 0.469 and 0.272, respectively. Furthermore, they positively affected switching intentions, with coefficients of 0.266 and 0.250, respectively. Therefore, statistical evidence supported H1, H2, H3, and H4. Additionally, the significant effect of online fatigue on switching intentions, with a coefficient of 0.243, supported H5.

To examine the mediating role of online fatigue, this study performed a bootstrapping procedure (5000 subsamples) in AMOS. The results, as shown in Table 6, indicate that online fatigue mediates the relationship between information overload and switching intentions, with a mediation effect value of 0.099. Similarly, online fatigue mediates the relationship between communication overload and switching intentions, with a mediation effect value of 0.056. Therefore, H6 and H7 were supported. Serial mediation analyses were conducted to gain deeper insight and improve the explanatory power of the model. The modified model (see Fig. 3) still met the SEM requirements, and the analysis results are presented in Table 7. The serial mediation effects of IO-OF-SI-SB and CO-OF-SI-SB were significant, with effect values of 0.038 and 0.022, respectively.

The moderation effect was assessed through the "Process" procedure in SPSS software using 5000-subsample bootstrapping. To examine the moderating effect of switching costs, we employed the three-step method recommended by Baron et al. [52]. As shown in Table 8, the effect of the interaction term SI × SC is significant. Fig. 4 further illustrates the negative moderating effect of switching costs on the relationship between switching intention and switching behavior Therefore, H8 was supported.

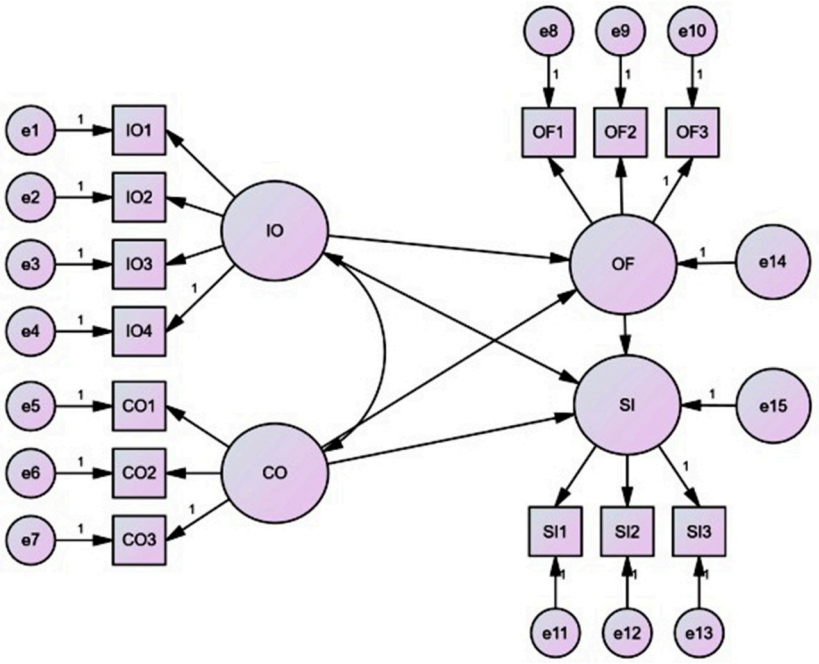

Fig. 2. Structural model for the first step.

Table 4
Fit indices for the measurement model and structural model.

Indicators	χ^2/df	RMSEA	RMR	GFI	CFI	NFI	TLI
Standard criteria	<3	<0.10	<0.05	>0.9	>0.9	>0.9	>0.9
Value	2.757	0.061	0.065	0.950	0.971	0.956	0.962

Table 5
Path analysis results.

Hypothesis	Path	Estimate	S.E.	C.R.	p	STD Estimate
H1	IO→OF	0.394	0.050	7.938	***	0.469
H2	IO→SI	0.230	0.057	4.054	***	0.266
H3	CO→OF	0.224	0.048	4.628	***	0.272
H4	CO→SI	0.212	0.053	4.006	***	0.250
H5	OF→SI	0.251	0.068	3.698	***	0.243

Note: ***p < 0.001.

Table 6
Mediation effects of online fatigue.

Effects	Path	Estimate	Confidence interval	p
Total effects	IO→SI	0.329	[0.221, 0.436]	***
	CO→SI	0.268	[0.165, 0.383]	***
Mediation effects	H5: IO→OF→SI	0.099	[0.034, 0.177]	***
	H6: CO→OF→SI	0.056	[0.017, 0.116]	***
Direct effects	IO→SI	0.230	[0.111, 0.361]	***
	CO →SI	0.212	[0.110, 0.329]	***

Notes: ***p < 0.001.

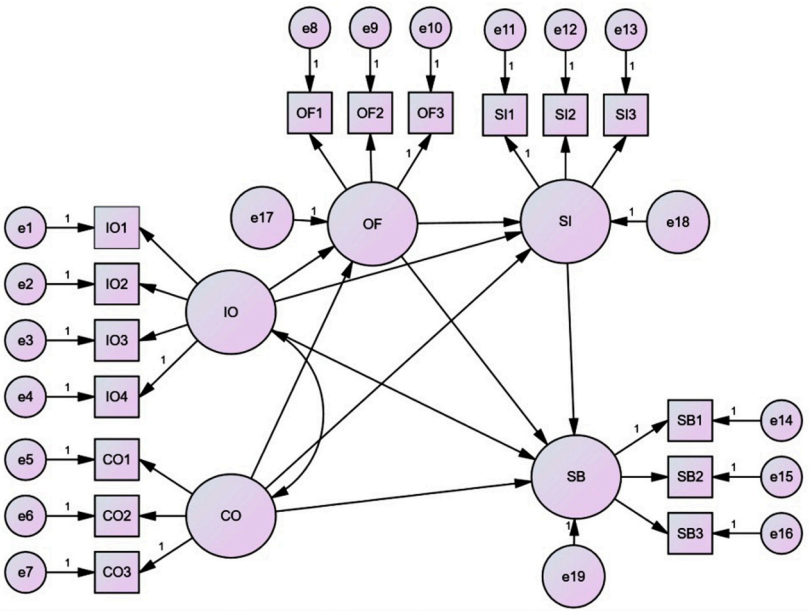

Fig. 3. Serial mediation model.

5. Discussion

5.1. Discussion of results

This study investigated the platform-switching behavior of consumers in the context of social commerce, proposing a model based on SOR. Platform overload (i.e., information and communication overload) and online fatigue were incorporated into the SOR model

Table 7
Serial mediation analysis.

Effects	Path	Estimate	Confidence interval	p
Total effects	IO→SB	0.377	[0.264, 0.249]	***
	CO→SB	0.356	[0.238, 0.499]	***
Mediation effects	IO→OF→SB	0.064	[0.012, 0.136]	0.015
	IO→SI→SB	0.086	[0.038, 0.162]	***
	IO→OF→SI→SB	0.038	[0.014, 0.078]	0.002
	CO→OF→SB	0.037	[0.007, 0.085]	0.013
	CO→SI→SB	0.083	[0.040, 0.149]	***
	CO→OF→SI→SB	0.022	[0.007, 0.052]	0.002
Direct effects	IO→SB	0.195	[0.084, 0.315]	0.001
	CO→SB	0.217	[0.102, 0.351]	***

Notes: ***p < 0.001.

Table 8
Moderating effect results (dependent variable: SB).

	Model 1		Model 2		Model 3	
	B	p	B	p	*B*	p
Constant	2.415	***	2.415	***	2.354	***
SI	0.62	***	0.488	***	0.457	***
SC			−0.236	***	−0.232	***
SI × SC					−0.093	0.007
R^2	0.35		0.39		0.4	
Adjusted R^2	0.348		0.388		0.396	
F	*F* (1,475) = 255.571 ***		*F* (2,474) = 151.746 ***		*F* (3,473) = 105.033 ***	

Notes: ***p < 0.001.

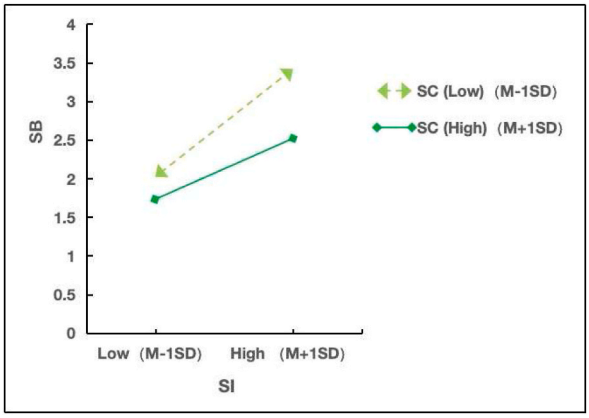

Fig. 4. Moderating effect of switching costs.

as new stimuli and the organism's internal state (i.e., emotional reaction), respectively, to understand consumers' behavioral responses (i.e., platform-switching intention and behavior). Hypotheses H1-H7 were supported, demonstrating the suitability of the SOR in the current research context. Additionally, switching costs were included in the research model to understand the gap between intention and behavior. H8 was supported, indicating the moderating role of switching costs, and providing deeper insights into real-world scenarios. A more detailed discussion of these results is provided below.

First, the results demonstrate that an overload of both, information and communication, positively and directly affects online fatigue in social commerce. This echoes the findings of Pang and Ruan [15,16], who documented similar effects of overload on user discontinuation intentions in the context of WeChat. The direct link between overload types and online fatigue underscores the pressing need for social commerce platforms to develop mechanisms to filter or reduce the influx of information and communication demands, potentially through personalized algorithms or user control features, as suggested by Lin et al. [37].

Second, information overload, communication overload, and online fatigue positively and directly affect the platform-switching intentions of consumers. These findings align with the propositions of Hattingh et al. [33] and Lin et al. [37], who discussed the detrimental impact of overload on user behavior in digital environments. This reinforces the importance of designing social commerce environments that are aware of the cognitive and emotional capacities of users, thereby preventing the escalation of overload to the

point of inducing switching intentions.

Third, online fatigue mediates the effects of information and communication overloads on platform switching intentions. This mediation effect highlights the critical role of emotional states in processing overloads and translating it into behavioral intentions. This is consistent with the findings of Liu et al. [36], who observed the mediating role of social media fatigue in the relationship between perceived information overload and discontinuation intention among Generation Z users in the United Kingdom.

Furthermore, additional serial mediation analysis shows that the effects of information and communication overload on platform-switching behavior are serially mediated by online fatigue and switching intention. In other words, information and communication overload can sequentially influence switching behavior through line fatigue and switching intention. This serial mediation underscores the complex interplay between the cognitive and emotional processes that precede the actual behavioral outcome of platform-switching.

Lastly, switching costs negatively moderate the effect of switching intention on switching behavior. This implies that switching intention may not lead to switching behavior in the context of social commerce, if consumers perceive the cost of switching platforms to be relatively high. This finding illustrates the practical barriers to actualizing switching intentions as behaviors, as identified by Balakrishnan et al. [22], who explored the moderating effects of switching costs on technology adoption. This suggests that even when users have a strong intention to switch platforms owing to overload and fatigue, the perceived costs associated with switching can deter actual behavior, indicating a critical area for intervention by platform designers and marketers.

5.2. Theoretical implications

This study is theoretically significant in several aspects. First, to understand consumers' platform switching behavior, information overload, communication overload, and online fatigue were included in the research model as negative factors related to social media usage, theoretically adding value to the social commerce literature. This inclusion not only broadens the scope of factors considered in studying platform-switching behavior, but also emphasizes the psychological impacts of social commerce environments. This highlights the significance of these negative factors in consumers' decision-making processes, suggesting a critical re-evaluation of platform design and user experience strategies to mitigate such overloads. Thus, theoretical frameworks within social commerce and user behavior studies can be expanded to incorporate these dimensions, providing a richer understanding of user engagement and retention challenges.

Second, the SOR model was applied to the social commerce context to understand consumers' platform switching behavior and reveal the process of consumers' emotional responses during platform switching in social commerce. This application illustrates the versatility of the model and its capacity to encapsulate the complex dynamics of user interactions within digital platforms. By detailing organismic responses to specific stimuli and their consequent effects on user behavior, this study reinforces the relevance of the SOR model in digital consumer behavior research. This opens avenues for further research on how various stimuli unique to the digital and social commerce landscape can influence user responses and behaviors, encouraging a deeper investigation into the nuances of the SOR framework in online settings.

Third, the investigation and analysis were extended from intention to behavior. The results of the additional mediation analysis demonstrate the mechanism by which information and communication overload sequentially influence platform switching behavior through online fatigue and switching intention, providing empirical evidence for this theorization. Furthermore, the exploration of the moderating effect of switching costs highlights the gap between intention and behavior in the current research context. This consideration enriches the theoretical discourse on platform switching by integrating practical constraints into the model, thus offering a more comprehensive understanding of the factors influencing consumer behavior in social commerce environments.

5.3. Practical implications

This study offers actionable insights for social commerce platform developers and marketers. First, understanding the detrimental effects of information and communication overload is of paramount importance for platform developers. This overload leads to increased user fatigue, contributing to a higher propensity for platform switching. To address this issue, developers are advised to enhance platform functionality by incorporating features that enable users to customize their information intake. Such features may include advanced filters for prioritizing content, or tools that allow users to manage the flow of communication effectively. Implementing innovative solutions, such as interactive mini-games or engaging in technological experiences, can also alleviate user fatigue, making social media platforms more enjoyable and less overwhelming.

Second, marketing professionals should acknowledge the significance of users' emotional experiences during campaigns. The push for marketing content should be balanced and targeted to avoid exacerbating information and communication loads. Strategies, such as personalized marketing, incentivized engagement, and the promotion of special events, can maintain user interests without overwhelming them. Implementing rewards for interaction, exclusive offers to loyal fans, and active engagement strategies can foster a more positive user experience, thus reducing the likelihood of platform switching owing to fatigue.

Third, the findings on the gap between switching intentions and actual switching behavior underscore the critical role of switching costs. Marketers and platform operators should consider these costs when devising strategies for retaining users. Offering exceptional after-sales services, competitive pricing, and immersive social experiences can strengthen user loyalty, thereby diminishing the drive to switch services. Recognizing the different facets of switching costs, including time, financial, and emotional investments, allows for the development of targeted interventions aimed at enhancing user satisfaction and platform commitment.

5.4. Limitations and future work

This study had certain limitations. First, the sample's restrictions to a single country may have limited the generalizability of the findings. Future research should consider multicountry comparisons to explore the impact of cultural and geographical differences on platform-switching behavior, thus enhancing the applicability of the study across diverse contexts. Second, most of the respondents were young. This demographic focus raises questions about the applicability of the findings to older segments of the population, who may exhibit different social commerce behaviors and reactions to platform overload and online fatigue. Future studies could include a broader age range to understand age-related differences in platform-switching behavior. Third, this study did not focus on feature differences between social commerce platforms. Given that platform features can significantly impact the user experience, overlooking this aspect means that the study may not fully capture the nuances of how specific platform characteristics influence overload and fatigue. Future research could examine the role of platform features in shaping user perceptions and behaviors to provide deeper insights into the design of more user-friendly social commerce environments.

6. Conclusion

This study illuminated the complex dynamics of platform switching behavior within the realm of social commerce by employing a robust SOR model framework to dissect the interplay between information overload, communication overload, and online fatigue, and their cumulative effect on users' switching intentions and behaviors. By integrating the novel aspects of switching costs and extending the model's applicability from intention to actual behavior, this research not only deepens our understanding of the psychological and practical factors driving users towards alternative platforms, but also underscores the critical need for designing user-centric social commerce environments. Future studies should explore the cross-cultural and cross-age applicability of these findings and further dissect the role of platform-specific features in shaping user experiences and behaviors.

Data availability statement

Data will be made available on request.

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CRediT authorship contribution statement

Wenjing Fan: Writing – original draft, Investigation, Formal analysis, Conceptualization. **Syuhaily Osman:** Methodology, Funding acquisition. **Norzalina Zainudin:** Methodology. **Pinyi Yao:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e31603.

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