Retraction Notice

The Editor-in-Chief and the publisher have retracted this article, which was submitted as part of a guest-edited special section. An investigation uncovered evidence of systematic manipulation of the publication process, including compromised peer review. The Editor and publisher no longer have confidence in the results and conclusions of the article.

LM and TD either did not respond directly or could not be reached.

Study on factors influencing e-commerce in short videos based on artificial intelligence-supported recommendation

Lingxing Meng[a,†] **and Tianyu Dong**[b,*,†]
[a]China University of Political Science and Law, Business College, Department of Law and Business, Beijing, China
[b]China University of Political Science and Law, Business College, Department of Theoretical Economics, Beijing, China

Abstract. Short video platforms, represented by TikTok, are gaining popularity across the world. Although mainly for entertainment and social interactions, short video mobile apps are intensively testing embedded e-commerce in short videos based on artificial intelligence (AI)-supported recommendation in the United States, Europe, China, and other countries and regions. To study users' acceptance of embedded e-commerce in short videos based on AI-supported recommendation, we make an analysis with a number of factors as independent variables, concluding that perceived risk and perceived cost have a significant negative influence on purchase intention, whereas other independent variables have a significant positive influence on purchase intention. In addition, perceived enjoyment and conformity, embodying the entertainment and social features of short video apps, have a significant positive influence on perceived usefulness. We provide a guideline for enterprises to improve functions of the technology and informs public oversight of the technology's development. © *2022 SPIE and IS&T* [DOI: 10.1117/1.JEI.32.3.031805]

Keywords: artificial intelligence; e-commerce in short videos; technology acceptance model; perceived enjoyment; conformity.

Paper 221016SS received Sep. 24, 2022; accepted for publication Nov. 11, 2022; published online Nov. 29, 2022; retracted Jun. 24, 2023.

1 Introduction

Short video apps, especially TikTok, have gone viral around the world. According to economists, TikTok hit over one billion global active users in March 2020 and is witnessing a continuous increase of the number. Sensor tower data reveal that TikTok continued to rank first in global mobile app downloads in 2021. Short videos are mainly for entertainment and social interactions, i.e., achieving high user engagement and retention rates in video watching and sharing using artificial intelligence (AI)-enabled recommendation and distribution. Nevertheless, AI technologies also make it possible for short videos to change the patterns of traditional offline shopping and e-commerce online shopping. Viewers of Tiktok will receive sale recommendations on products relevant to the video content with artificial intelligence technologies to label the videos. For example, a user who is into food and cooking videos would receive shopping links to snacks and kitchen wares at the bottom left corner of these videos; and a zoomer who loves rap and skateboarding would receive links to streetwears. Compared with traditional offline shopping and online e-commerce, short videos provide users with easy access to full details of the products and dig deep into what products the users are interested in through AI technologies. Embedded e-commerce in short videos based on AI-supported recommendation is trying to change the shopping habits of the public.

Since 2020, successively, American, British, and Indonesian TikTokers have begun to enjoy the in-video purchase feature. They can simply click the Amazon links within a short video and complete the purchase of the same or similar products as presented in the video. Bloomberg

*Address all correspondence to Tianyu Dong, 2002060230@cupl.edu.cn

†These authors contributed equally to this work

reported that this year, TikTok is testing in-app sales in Europe to further integrate short videos and shopping and blur the boundary between social media and online shopping. In China, where privacy policy is not that strict, the in-app sales feature has already been tested on a small scale in the end of 2018. To some extent, the feature makes shopping more convenient and therefore is welcomed by users. However, it also poses risks, such as privacy leakage and over-shopping. The question that whether short video app users accept the embedded shopping feature based on AI-supported recommendation and what they would take into account—convenience, privacy, enjoyment, or risk—is worth studying.

2 Use of AI Algorithm in E-Commerce in Short Videos

The application of AI algorithm in short video e-commerce business can be roughly divided into three parts. The first part is to identify and label video content and classify and sketch users' interests. The second part is to distribute and recommend videos intelligently according to label content and user portrait. The third part is to give flow support to the video and live streaming content based on user's feedback.

Short video is a decentralized platform, which means any account has a chance to have millions or even tens of millions of followers. For video creators, the platform will conduct a review of the uploaded video, which is mainly to check whether there are any violations. If there are no violations, the platform will allow contents upload. This is when the content will officially appear in front of the user. For a newly released video by a creator, only by obtaining the traffic support of the short video platform can the creator's video be seen by more people and the products he wants to sell can be introduced by more users.

The platform will give the creator some initial traffic and the platform will judge whether the content of the creator is popular according to the feedback of the initial traffic. If the video is popular, the platform will distribute more traffic, otherwise it will not distribute traffic to the creator. The principle of whether to give traffic is that viewing rate of the video is important than the rate of watching the entire video, and the rate of watching the entire video is important than the likes, and likes is important than the comments and comments is important than the retweets.

First recommend from short video platform based on account of different weights is a small fraction of traffic. If recommended works have great data feedback, platform will determine our content is relatively popular and give a recommendation the second time. If the second recommendation still has a better feedback, platform will recommend the third time. If the feedback is still good, the platform will use a combination of algorithms and human reviewers to see if your content is a hit. If the video is released for a week with low playback, it will be regarded as a low or obsolete title, and the platform will rarely recommend it. If it does not break more playbacks after a month, it will also be regarded as a zombie title.

The platform will set a plate for his video tag library when the user opens the short video platform. For example, you are a 3-year-old child's mother living in a big city with 24 to 35 years old and recently like reading-related content with maternal and child supplies consumption ability is in the high-end price and household consumption ability is low. For people like you, the platform will first grab hundreds of videos that may attract you to stay in the short video and live broadcast room most and then cut them into some small pieces according to a few rules and sort them by highly relevant accounts (accounts you follow and interact with frequently), highly popular accounts (highly popular content that has exploded in the last few hours), and ad-jumping content (paid for by others to show you a ranking) to test your interests

When a user wants to sell products through short videos, the platform will adjust your account model according to the content of each live broadcast and short video release and the types of users you attract to stay and the types of users who have purchase behaviors until the platform determines your account model. Then the platform will try to help you to find suitable viewers and buyers for your account to verify the platform's judgment on your model. This cycle will continue to adjust the platform's model for you until the platform finds your local optimal traffic model, which is the process of the machine learning and then the short video platform will try to give you more traffic. After giving more recommendations, the short video platform will push the good video a higher ranking position every 5 min to ensure that more users can see and come. If the video has a better performance than 80% similar video after 5 min, it means you are selling products that a lot of people like. This is the horse racing mechanism. In this mechanism, all the voting power of content is given to the user, user's stay rate, interaction rate, action of like and follow and comment, product click, and paying, each action gives you real-time bonus points, the higher score means the more users like. This is the basic situation of the use of AI algorithms in short video e-commerce.

From the perspective of short video platform operators, such technical rules can help them improve operational efficiency and gain more profits. But for the users of the application, they can only passively accept such AI technology rules. Do users accept such rules? Do users enjoy staying on the platform to share or watch videos? Can users accept the new situation of short video e-commerce shopping? So the further research is needed.

3 Research Model and Research Hypothesis

Technology acceptance model (TAM) is an extension of the theory of reasoned action (TRA), which is proposed by Davis et al.[1] The model can help us to analyze users' attitude toward e-commerce in short videos and their behavioral intention, as well as factors affecting the use of this feature.

TAM suggests that behavioral intention determines users' specific behaviors and attitudes to use the new technology. Regarding embedded e-commerce in short videos based on AI-supported recommendation, perceived usefulness means the user believes that the feature can help them to purchase what they want; and perceived ease-of-use refers to shopping convenience. Both are factors that eventually would influence users' acceptance of the feature.

3.1 *TAM-Based Hypothesis*

Perceived usefulness refers to the fact that when viewing short videos, AI technologies could recommend items that exactly to users' tastes; and short videos can beat shopping websites in introducing product information and product usage, saving users from going out for shopping or finding what they want in a massive database.

Perceived ease-of-use refers to the fact that users enjoy a convenient shopping experience and professional service within short video apps, just like what they would do in online shopping apps. Meanwhile, shopping in short video apps is more user friendly thanks to more fluent user interface (UIs), and users could complete the purchase while entertaining themselves or socializing with others. TAM-based hypothesis are as follows:

H1: Perceived usefulness has a significant positive influence on purchase intention.
H2: Perceived ease-of-use has a significant positive influence on purchase intention.

3.2 *Perceived Enjoyment-Based Hypothesis*

In studying factors influencing the use of e-commerce, Childers et al.[2] found that enjoyment is one of the factors that make e-commerce a success. The entertainment and social features of short videos give rise to a new user experience. For example, through entertainment, users perceive enjoyment, which may possibly influence shopping decisions and increase perceived usefulness. Such possibility is worth discussing. Hypotheses are as follows:

H3: Perceived enjoyment has a significant positive influence on purchase intention.
H4: Perceived enjoyment has a significant positive influence on perceived usefulness.

3.3 *Perceived Risk-Based Hypothesis*

To use a new feature, a new technology challenging existing lifestyle, it is necessary to take into account perceived risk. Bauer[3] put forward for the first time the concept of perceived risk, defining users' uncertainty toward the quality and user experience of the products as risk. Cox[4] systematically broadened the definition of perceived risk, incorporating in all the uncertainty emerges during the entire shopping process. Regarding the new AI-supported recommendation technology, poor after-sales service and impulsive shopping both constitute risks. Hypothesis is as follows:

H5: Perceived risk has a significant negative influence on purchase intention.

3.4 *Perceived Cost-Based Hypothesis*

Compared with traditional e-commerce, the brand new embedded e-commerce in short videos is more costly. It is well known that short videos are a business to drive traffic by catching people's eyes. As TikTok goes viral, people are spending a lot of time on it. Although users can save time and energy by making purchases based on AI recommendation, they consume energy while being obsessed in viewing short videos. Therefore, it is necessary to conduct a trade-off analysis. Obviously, using short video products would cost users' physical and mental energy. When they consider the cost is too high, they would get rid of such service. In studying user acceptance model, Liu et al.[5] introduced perceived cost, and the empirical results indicate that cost has an influence on perceived value. Hypothesis is as follows:

H6: Perceived cost has a significant negative influence on purchase intention.

3.5 *Perceived Trust-Based Hypothesis*

All product information presented by e-commerce is virtual. Therefore, trust matters. Based on the Hofstede model, Yoon[6] found that trust has an influence on consumer acceptance of e-commerce. A study carried out by Apiradee and Nuttapol[7] also indicates that in social e-commerce, consumer trust in products and sellers has an influence on consumer engagement. Based on social identity theory, Hu et al.[8] constructed the model of audiences' continuous watching intention, finding that audiences' identification with video platforms is positively associated with their continuous watching intention. Hypothesis is as follows:

H7: Trust has a significant positive influence on purchase intention.

3.6 *Conformity-Based Hypothesis*

In the scenario of short video e-commerce, influenced by social environment, users' conformity would lead to conformity consumption behaviors. Shi et al.[9] proved that quantity of participants has a positive influence on users' willingness to pay. In general, the more people around them make purchases in short videos, the more willingly consumers would use the function. Besides, in the perceived enjoyment section, the entertainment and social features of short videos were mentioned, with the former regarded as embodiment of the entertainment feature. Here, conformity embodies the social feature. On this basis, a discussion on the influence of conformity on perceived usefulness can be carried out. Hypotheses are as follows:

H8: Conformity has a significant positive influence on purchase intention.
H9: Conformity has a significant positive influence on perceived usefulness.

4 Scale Development and Data

Building on the R&D results of TAM, and combining the behavioral features of embedded e-commerce in short videos based on AI-supported recommendation, this article designs measurement items for each variable and eventually develops a measurement item list, as shown in Table 1. The questionnaire falls into two parts. The first part focuses on the demographics of the respondents, including gender, age, monthly spending on online shopping, and weekly time spent on short videos. The second part includes the measurement items of all variables in the research model, each rated by the 5-point Likert scale. The survey was conducted online, and 301 copies of effective questionnaire were withdrawn. According to respondents' demographics, there is an almost even split between males (about 50%) and females (about 50%); and the 25 to 35 age group takes the largest proportion (almost 70%), who also constitutes the majority of the audience of TikTok and other short video apps. Most respondents spend \$100 to \$200 on online shopping. And almost half of the respondents spend 4 to 10 hours per week on short video apps.

Table 1 Questionnaire.

Variable	No.	Measurement item	Source
Perceived usefulness	YA1	Short videos help me know better the product appearance and functions	Xue et al.[10]
	YA2	Interest-based recommendation saves my time and increases my shopping efficiency	
	YA3	Products recommended by short videos cover my daily shopping lists	
	YA4	Various kinds of short videos make me realize that I need to purchase more meaningful items	
Perceived ease-of-use	YB1	Interest-based video recommendation mechanism automatically presents me products I am interested in	Benbasat et al.[11]
	YB2	Short video apps make it easy and convenient to pick out and pay for products	
	YB3	The interface of short video platforms is visually pleasing and user friendly	
Perceived enjoyment	YC1	Purchasing within a short video makes me feel like I am interacting with the video creator	Fiore et al.[12]
	YC2	Shopping within favorite short videos is more pleasant	
	YC3	I would buy things out of impulse when my favorite video creator recommends my favorite brand	
Perceived risk	YD1	I am afraid that products recommended by short videos are of bad quality	Jacoby and Kaplan[13]
	YD2	I am afraid that short video-based shopping has a poor after-sales service, for example, poor return policy	
	YD3	I am afraid that I am making impulsive purchases within short videos	
Perceived cost	YE1	Shopping by viewing short videos is a waste of time and energy	
	YE2	I am afraid that the recommendation mechanism would cause privacy leakage	
	YE3	I am afraid that more videos of the same kind would be recommended to seduce me to make unnecessary purchases	
Trust	YF1	I like viewing short videos and have trust in the recommended products	Apiradee and Nuttapol[7]
	YF2	I like the video creators I follow and have stronger interests in the products they recommend	
	YF3	I believe the video creators I follow provide me with reliable product information	
Conformity	YG1	My friends buy things within short videos	Zhang et al.[14]
	YG2	I think it is cool to buy the same products as recommended in short videos	
	YG3	I decide whether buy the recommended products or not based on comments on short videos	
Purchase intention	YH1	I make purchases through the recommendation mechanism of short videos	Chen and Lin[15]
	YH2	I make purchases within videos posted by creators who I follow	
	YH3	I make purchases within videos I like	

Table 2 Test of reliability and validity.

Second-level indicator	Number of terms	Cronbach's alpha	Kaiser–Meyer–Olkin	Statistical significance	Chi-square	Degree of freedom
Perceived usefulness	4	0.892	0.839	0.000	701.463	6
Perceived ease-of-use	3	0.955	0.778	0.000	949.496	3
Perceived enjoyment	3	0.974	0.783	0.000	1347.579	3
Perceived risk	3	0.946	0.763	0.000	875.727	3
Perceived cost	3	0.955	0.775	0.000	958.153	3
Trust	3	0.961	0.780	0.000	1021.791	3
Conformity	3	0.911	0.757	0.000	607.884	3
Purchase intention	3	0.913	0.760	0.000	643.299	3

Table 3 Variable correlation.

Variable		Perceived usefulness	Perceived ease-of-use	Perceived enjoyment	Perceived risk	Perceived cost	Trust	Conformity	Purchase intention
Perceived usefulness	Pearson correlation	1	0.366	0.223	−0.362	−0.337	0.497	0.794	0.738
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Number of cases	301	301	301	301	301	301	301	301
Perceived ease-of-use	Pearson correlation	0.366	1	0.541	−0.300	−0.641	0.167	0.404	0.327
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000	0.000	0.000
	Number of cases	301	301	301	301	301	301	301	301
Perceived enjoyment	Pearson correlation	0.223	0.541	1	−0.136	−0.542	0.080	0.342	0.285
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000	0.000	0.000
	Number of cases	301	301	301	301	301	301	301	301
Perceived risk	Pearson correlation	−0.362	−0.300	−0.136	1	0.298	0.137	−0.398	−0.350
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000	0.000	0.000
	Number of cases	301	301	301	301	301	301	301	301
Perceived cost	Pearson correlation	−0.337	−0.641	−0.542	0.298	1	0.197	−0.446	−0.381
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000	0.000	0.000
	Number of cases	301	301	301	301	301	301	301	301
Trust	Pearson correlation	0.497	0.167	0.080	−0.137	−0.197	1	0.532	0.515
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000		0.000	0.000
	Number of cases	301	301	301	301	301	301	301	301

Table 3 (*Continued*).

Variable		Perceived usefulness	Perceived ease-of-use	Perceived enjoyment	Perceived risk	Perceived cost	Trust	Conformity	Purchase intention
Conformity	Pearson correlation	0.794	0.404	0.342	–0.398	–0.446	0.532	1	0.856
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000		0.000
	Number of cases	301	301	301	301	301	301	301	301
Purchase intention	Pearson correlation	0.738	0.327	0.285	–0.350	–0.381	0.515	0.856	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
	Number of cases	301	301	301	301	301	301	301	301

5 Results

In the fundamental research, Cronbach's alpha value and Kaiser–Meyer–Olkin (KMO) value of 0.70 or higher indicate a good reliability and structure validity of survey data. Results of this article are shown in Table 2.

This article conducts a Pearson correlation analysis of seven factors above. Analysis results are shown in Table 3. Obviously, the seven factors have a significant correlation with purchase intention. For perceived risk and perceived cost, the correlation is negative; whereas for the other five, it is positive.

In addition, regression results of each independent variable and purchase intention as dependent variable are shown in Table 4. Regression results of other hypothesis are shown in Table 5.

Table 4 Regression results with purchase intention as the dependent variable.

Independent variable	Standardized regression coefficient	*T*-value	Statistical significance	Significant or not
Perceived usefulness	0.738	18.933	0.000	Yes
Perceived ease-of-use	0.327	5.982	0.000	Yes
Perceived enjoyment	0.285	5.146	0.000	Yes
Perceived risk	–0.350	–6.468	0.000	Yes
Perceived cost	–0.381	–7.123	0.000	Yes
Trust	0.515	10.393	0.000	Yes
Conformity	0.856	28.625	0.000	Yes

Table 5 Regression results of other variables.

Independent variable/dependent variable	Standardized regression coefficient	*T*-value	Statistical significance	Significant or not
Perceived cost/perceived risk	0.298	5.394	0.000	Yes
Perceived enjoyment/perceived usefulness	0.223	3.949	0.000	Yes
Conformity/perceived usefulness	0.794	22.618	0.000	Yes

Table 6 Summary of hypothesis testing.

Hypothesis	Content	Yes or no
H1	Perceived usefulness has a significant positive influence on purchase intention	Yes
H2	Perceived ease-of-use has a significant positive influence on purchase intention	Yes
H3	Perceived enjoyment has a significant positive influence on purchase intention	Yes
H4	Perceived enjoyment has a significant positive influence on perceived usefulness	Yes
H5	Perceived risk has a significant negative influence on purchase intention	Yes
H6	Perceived cost has a significant negative influence on purchase intention	Yes
H7	Trust has a significant positive influence on purchase intention	Yes
H8	Conformity has a significant positive influence on purchase intention	Yes
H9	Conformity has a significant positive influence on perceived ease-of-use	Yes

The results of hypothesis testing are summed up in Table 6, which, together with the above analyses, confirms the relations between variables of the theoretical model constructed in this article.

6 Conclusion

From the analysis results of statistical significance and regression, perceived usefulness and perceived ease-of-use have an extremely significant positive influence on purchase intention, which also indicates that embedded e-commerce in short videos, as a new form of shopping, is upending traditional shopping pattern in terms of functionality and convenience.[16] Both offline shopping and online e-commerce created by internet and technology companies are not the ultimate shopping patterns. New shopping experiences and features are still emerging. Embedded e-commerce in short videos, by presenting genuine product information in videos, enriching peoples' shopping experience in terms of entertainment and social interactions, and saving people from consuming too much energy on shopping with the help of AI-supported technology, has become a new technology-based shopping pattern that is remarkable and promising.[17]

New experience brought about by the new technology is largely reflected in entertainment and social interactions, factors underpinning perceived enjoyment and conformity in embedded e-commerce in short videos.[18] From the analysis results of statistical significance and regression, perceived enjoyment and conformity are not only positively correlated with purchase intention, but also with perceived usefulness, which, to some extent, indicates that the entertainment and social features of short videos increase users' intention to make purchases on the platforms. This is what makes embedded e-commerce in short videos distinctive from and more successful than traditional e-commerce.[19] After all, for users, products the same as those appear in their favorite videos or products recommended by creators they follow are more attractive. In the process of socializing via short videos, comments on videos, shopping behaviors of the people around, and usage of products purchased online in social interactions all stimulate purchase intention. Significantly different from shopping websites, the process brings about a brand new shopping experience.

The new technology gives rise not only to new features but also to new costs and risks.[20] Significantly, trust is positively correlated with the purchase intention toward embedded e-commerce in short videos, whereas perceived risk and perceived cost are negatively associated with purchase intention. This sheds light on the new uncertainty posed by the new technology, draws attention to legal restraints and corporate responsibilities regarding technology application, and informs companies of better approaches to applying the new technology. First of all, short video apps and e-commerce platforms are indeed two different types of application, and therefore having different focus, as well as distinctive features and styles in terms of product functions. It is necessary for new technology enterprises to think about whether users trust shopping on short video platforms and how to increase the authenticity of products and reliability of after-sales service. Meanwhile, although AI-supported recommendation helps a lot of users to find products they like, the underlying user privacy leakage and over-shopping remains a matter of concern to some consumers. Finally, people, especially zoomers, are spending more time and energy on short videos. Whether they can get corresponding rewards is critical for user retention.

In conclusion, embedded e-commerce in short videos based on AI-supported recommendation, as a new shopping pattern brought about by the new technology, allows people with different needs to enjoy new shopping experience. However, problems emerge as well, such as privacy leakage, energy-draining, and over-shopping, which require improvements in applying the new technology. Enterprises shall keep making improvements in response to the needs of consumers, in particular those of zoomers, so as to provide more diversified shopping options in the future.

References

1. F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User acceptance of computer technology: a comparison of two theoretical models," *Manage. Sci.* **35**(8), 982–1003 (1989).
2. T. L. Childers et al., "Hedonic and utilitarian motivations for online retail shopping behavior," *J. Retail.* **77**, 511–535 (2001).
3. R. A. Bauer, "Consumer behavior as risk," *Market.: Crit. Perspect. Business Manag.* **3**, 13 (2001).
4. D. F. Cox, *Risk Taking and Information Handling in Consumer Behavior*, Harvard University Press (1967).
5. J.-H. Liu, Z.-Z. An, and L.-F. Xu, "An empirical study on the influencing factors of MOOC users' willingness to use," *Higher Educ. Res.* **36**(11), 69–76 (2015).
6. C. Yoon, "The effects of national culture values on consumer acceptance of e-commerce: online shopping in China," *Inf. Manage.* **46**(5), 294–301 (2009).
7. W. Apiradee and A. Nuttapol, "The role of live streaming in building consumer trust and engagement with social commerce sellers," *J. Bus. Res.* **117**, 543–556 (2020).
8. M. Hu, M. Zhang, and Y. Wang, "Why do audiences choose to keep watching on live video streaming platforms? An explanation of dual identification framework," *Comput. Hum. Behav.* **75**(10), 594–606 (2017).
9. X. Shi, X. Zheng, and F. Yang, "Exploring payment behavior for live courses in social Q&A communities: an information foraging perspective," *Inf. Process. Manage.* **57**(4), 102241 (2020).
10. J. L. Xue et al., "See now, act now. How to interact with customers to enhance social commerce engagements," *Inf. Manage.* **57**(6), 103324 (2020).
11. I. Benbasat, D. Gefen, and P. A. Pavlou, "Trust in online environments," *J. Manage. Inf. Syst.* **24**(4), 275–286 (2008).
12. A. M. Fiore, H. J. Jin, and J. Kim, "For fun and profit: hedonic value from image interactivity and responses toward an online store," *Psychol. Market.* **22**(8), 669–694 (2005).
13. J. Jacoby and L. B. Kaplan, "Components of perceived risk in product purchase: a cross-validation," *J. Appl. Psychol.* **59**(3), 287–291 (1972).
14. Y. Zhang, Y. Zhang, and H. Liu, "Research on context-aware service adoption behavior of mobile commerce users," *Inf. Sci.* **36**(3), 87–92, 111 (2018).
15. C. C. Chen and Y. C. Lin, "What drives live-stream usage intention? The perspectives of flow, entertainment, social interaction, and endorsement," *Telemat. Inf.* **35**(1), 293–303 (2018).
16. D. Zulli and D. James, "Extending the Internet meme: conceptualizing technological mimesis and imitation publics on the TikTok platform," *New Media Soc.* **24**(8), 1872–1890 (2022).
17. J. Kream Elizabeth et al., "TikTok sheds light on tanning: tanning is still popular and emerging trends pose new risks," *Dermatol. Surg.* **48**, 1018–1021 (2022).

18. Z. Shan et al., "Analysis of the marketing strategy of Pu'er tea E-commerce," *Int. J. Educ. Econ.* **3**(3) (2020).
19. Coupang Corp., "System and method of sorting apparatus cell allocation for fast E-commerce order fulfillment," Published Online (USPTO 20200265504), Computer Weekly News (2020).
20. UnivDatos Market Insights, "Global subscription E-commerce market is expected to reach US$ 478 Bn by 2025|CAGR: 68%| UnivDatos Market Insights," Medical Letter on the CDC & FDA (2020).

Lingxing Meng is a lecturer in the Department of Law and Business Management, China University of Political Science and Law, is a doctor of business law at Tsinghua University, and is a master of economic law at Renmin University of China. His research interests include corporate governance and legal and commercial management.

Tianyu Dong is a PhD candidate at Business Collage, China University of Political Science and Law and is a master of management at Beijing Institute of Technology. His research interests include innovation management, entrepreneurial management, and corporate ethical responsibility.