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The Effects of Trust, Perceived Risk, Innovativeness, and Deal Proneness on Consumers' Purchasing Behavior in the Livestreaming Social Commerce Context

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Abstract: Livestreaming shopping platforms have emerged as dynamic and innovative channels for e-commerce, mobile commerce, and social commerce, revolutionizing the way consumers engage with online retail. Drawing upon the Technology Acceptance Model 3 framework, this research seeks to provide a comprehensive understanding of the interplay between perceived risk, trust, innovativeness and deal proneness in shaping consumers' purchasing behavior in the livestreaming social commerce context. A snowball sampling method was applied to collect data from 675 Chinese livestreaming customers in December 2022. A PLS-SEM analysis was used to measure the proposed model. The results confirm that the present model has weak explanatory power except for medium predictive accuracy in explaining consumers' purchasing behavior in the livestreaming social commerce context (R^2 = 0.35; Q^2 = 0.31). This research contributes to the social commerce literature by extending the Technology Acceptance Model 3 (TAM 3) to the novel domain of the livestreaming social commerce context, offering insights into the unique drivers of consumers' purchasing behavior. It also provides practical implications for platform developers and marketers aiming to enhance consumer experiences and increase sales performance, thereby increasing economic growth.

Keywords: decision making process; economic growth; live streaming shopping; online consumer; social commerce; TAM3

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Citation: Sun, X.; Pelet, J.-É.; Dai, S.; Ma, Y. The Effects of Trust, Perceived Risk, Innovativeness, and Deal Proneness on Consumers' Purchasing Behavior in the Livestreaming Social Commerce Context. *Sustainability* **2023**, *15*, 16320. https://doi.org/10.3390/su152316320

Academic Editors: Lester Johnson and Ting Chi

Received: 30 September 2023
Revised: 10 November 2023
Accepted: 24 November 2023
Published: 26 November 2023

1. Introduction

The influence of social media on the daily lives of individuals is undergoing substantial transformation. In response to the increasing consumer desire for convenient and immediate online purchasing experiences, firms have begun to recognize and exploit the e-commerce capabilities of these platforms [1]. The utilization of social media platforms allows these consumers to engage in purchasing activities without the need to go away from the platform, hence facilitating a streamlined and expedited customer experience. The confluence of e-commerce and social media has unavoidably given rise to the emergence of social commerce [2]. Therefore, social commerce refers to an online commercial platform that utilizes social media and Web 2.0 technologies to facilitate social interaction and user-generated content [3]. A report shows the global revenue generated via social commerce reached 724 billion U.S. dollars in 2022 and is projected to exceed six trillion U.S. dollars by 2030 [1]. Additionally, it is noteworthy that Asian countries exhibit a notable inclination towards social buying. In 2022, China achieved one of the highest social media shopping rates globally, standing at 84% [2]. In the meanwhile, livestreaming commerce, often known as a subset of e-commerce or social commerce [4], garnered significant consumer attention in the Asia Pacific area starting in 2021 [5]. Notably, the biggest difference is between livestreaming e-commerce and livestreaming social commerce. Users' shopping needs vary on Taobao, the largest livestreaming e-commerce platform worldwide [6], and TikTok, mainland China's dominant social media platform, especially for short-form video content and livestreaming [7]. When livestreaming platforms are implemented, they have various consequences since TikTok is an entertainment short video application and Taobao is an online shopping application [8]. To put it another way, viewers of Taobao livestreaming seek content that is more specialized and focused in order to comprehend a certain product, see product demos, and engage with the anchor. Taobao consumers often have active, not passive, purchasing demands. Users spend a longer average amount of time on TikTok because they want to be amused, which leads them to purchase rapidly and impulsively in response to livestreaming settings and amusing material [9,10].

The use of live streaming as a means to enhance sales performance in China has been embraced by several vendors operating on social commerce platforms, owing to its growing popularity [11]. The livestreaming mode has changed traditional social commerce in several ways. First, traditional social commerce focuses on text and static photos for product information, but livestreaming platforms offer streamers in-the-moment video demonstrations, which improve product understanding; second, through the bullet screen, livestreaming shopping enables prompt client inquiries, with streamers answering in real-time; lastly, the dynamic engagement of livestream purchasing decreases concerns about supplier legitimacy, lowering perceived risks associated with online purchase [11,12]. Therefore, whether in online retail platforms or social media platforms, livestreaming commerce has emerged as a widely adopted shopping channel among Chinese consumers [13].

This particular kind of livestreaming enterprise capitalizes on the substantial fan base it has [14], and the active development of livestreaming shopping calls attention to empirical research. A majority of studies explored the antecedents that impact purchasing intention in the livestreaming shopping environment from various theoretical perspectives, such as IT affordance [11], the elaboration likelihood model [15], signaling theory [16], dual-process theory [17], the SOR framework [18], flow theory [19], social telepresence [20], and perceived value theory [21]. It is critical to comprehend the variables that affect customers' factual behaviors in a livestreaming commerce environment as the number of transactions taking place increases. There were several studies focused on consumers' impulse behavior in the livestreaming shopping context [19–21]. However, the study of the livestreaming shopping behaviors in the context of social commerce is still limited. In addition, prior research suggested that internet shopping behavior is often sensible [22], due to the increased uncertainty and risks consumers encounter in the online shopping environment [23]. Researchers discovered that social commerce via live streaming offers a natural interface for not just human-to-human contact [24], but also human–computer interaction [25]. In addition, people aged 18 to over 40 years old made up the majority of livestream shoppers in China [26]. The intricacy of today's livestreaming commerce environment prompts academics to revisit the fundamentals of online buying behavior. Therefore, it is important to explore what factors influence customers' decision-making processes in the context of livestreaming social commerce. In addition, social commerce encounters substantial challenges, encompassing concerns related to privacy, trust, and ethical considerations [27]. Hence, it is imperative to investigate how perceived risk in the social commerce context affects online consumers' attitudes and actual purchasing behaviors.

By focusing on the consumers' actual purchasing behavior, this pioneering research aims to provide a complete model for understanding customers' decision making processes within the setting of livestreaming social commerce, drawing upon the framework of Technology Acceptance Model 3 (TAM 3). The present study contributes a valuable addition to the existing literature on TAM 3, as well as enhancing the theoretical analysis of consumer actual buying behavior. Furthermore, this study holds the potential to foster sustainability by offering valuable insights into the development of marketing and promotional strategies that can enhance sales performance for merchants. Such strategies, when effectively implemented, can contribute to the broader objective of bolstering economic growth within the Chinese market. This research is structured as follows. In the next section, the authors will provide a brief review of the literature related to TAM3. Following this, hypotheses will be formulated with support from the relevant literature. Subsequently, the methodology employed to test these hypotheses will be presented. After reporting the results from the data analysis, the authors will engage in a discussion of the findings, offer insights into practical and research implications, and finally, present their conclusions.

2. Literature Review and Hypotheses Development

2.1. Technology Acceptance Model 3

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2, [28]) and TAM 3 are widely applied in the field of information systems and technology adoption. The UTAUT2 is a comprehensive theoretical model used to understand and explain the adoption and use of technology by individuals [28]. However, the primary focus of this article is not on technology adoption but on understanding customer behavior in the context of livestreaming social commerce. Thus, TAM3 is a more general framework that can be adapted to various contexts beyond technology.

TAM [29] is designed to anticipate the individual adoption and usage of new IT device, which asserts that people's behavioral intention to use an IT device is driven by its perceived utility and perceived ease of use. Venkatesh and Davis [30] have extended TAM to TAM2 by introducing determinants of perceived usefulness, such as subjective norm, image, job relevance, output quality, result demonstrability, and perceived ease of use, along with the inclusion of two moderators: experience and voluntariness. Venkatesh and Bala [31] developed TAM3, which encompasses four distinct categories: individual variations, system features, social impact, and enabling factors. These categories function as factors that contribute to the perception of usefulness and ease of use. This study also aims to understand the impacts of individual differences; therefore, this study was based on TAM3 [31] as the framework to understand the comprehensive nature of consumers' livestreaming purchasing behavior through a social media application.

2.2. Hypotheses Development

2.2.1. The Relationships among Perceived Risk, Trust and Purchasing Behavior

Perceived risk is often viewed as the inherent likelihood of experiencing negative consequences while engaging in online buying activities, including both the element of ambiguity and the possible severity of outcomes [32]. E-commerce has a higher propensity to engender ambiguity, particularly in areas such as online transactions, shipping and return policies, hence contributing to the perception of risk, in comparison to those of conventional commerce [33]. Perceived risk is taken into account in TAM 3 as an external variable that depicts how consumers perceive possible risks and uncertainties related to adopting a technology or platform [34], such as social commerce, and in turn, leads users to evaluate the trustworthiness of the platform.

Previous studies have shown that a high perceived risk level seems to be inversely associated with consumer confidence in online activities [35,36]. Nevertheless, clients are more likely to establish confidence in a provider if the perceived level of risk remains within a certain range [33]. Customers carefully choose online merchants that they deem to be sufficiently dependable in order to reduce their perceived risk [32]. Hansen et al. [37] state that the influence of perceived risks and consumer trust in online reviews significantly shapes consumer attitudes and behaviors concerning these reviews, with risk-taking directly impacting the intention to trust. This argument has been confirmed by a study by Sun [38], that found that perceived risk positively impacts consumers' trust in livestreaming shopping in China. Furthermore, the positive relationship between perceived risk has been confirmed in online purchase intentions [39,40]. There is sufficient evidence to support a strong association between behavioral intention and usage behavior [41,42]. Therefore, the following hypotheses are presented:

H1. *In the livestreaming social commerce context, perceived risk positively impacts trust.*

H2. *In the livestreaming social commerce context, perceived risk positively impacts consumers' purchasing behavior.*

Trust plays a crucial role in influencing the behavioral intentions and actual use of users under the Technology Acceptance Model (TAM), especially in online activities, such as e-payment [43] and e-learning [44]. Trust has been acknowledged as a vital element in the online environment and has been extensively examined within the realm of e-commerce [45]. Trust is commonly defined as a personal evaluation made by an individual on the reliability, integrity, dependability, and competence of another individual or organization [46]. Consumers are presently extensively using internet technology for duties pertaining to sensitive information [28]. Trust is a crucial and well-recognized notion that plays a significant role in shaping behavioral intention and use behavior across many domains, particularly in the context of electronic environments. While previous studies have shown the significant influence of trust on purchasing behavioral intentions [38,47,48] and purchasing behavior [38,49,50], it remains imperative to consider its relevance within the context of livestreaming social commerce. Therefore, the hypothesis below is presented:

H3. *In the livestreaming social commerce context, trust positively impacts consumers' purchasing behavior.*

2.2.2. The Relationships among Innovativeness, Deal Proneness and Purchasing Behavior

Within the context of TAM3, individual difference factors include personality characteristics and demographics such as gender and age, which possess the potential to impact an individual's views of perceived utility and perceived ease of use [31]. Highly inventive customers are innately curious, value creative discovery, and are thus more inclined to use new goods and services [51]. Individual innovativeness, therefore, is a trait of individual users and may affect how they embrace and utilize technology, which is in line with TAM 3′s enhanced emphasis on individual differences. Although some studies have investigated the influence of consumer innovativeness on usage intentions or behavior [52,53], to gain additional empirical evidence and propose a more comprehensive framework, it is necessary to involve this factor in the current study.

Deal proneness, another user characteristic or preference, is a psychological idea that affects actions connected to value awareness and coupon responsiveness [54]. Consumers who are prone to making deals think about the psychological benefits of doing so and may not care about the implications for their finances [55]. A previous study found that higher innovative consumer tendencies are anticipated to partly impact their propensity to redeem bargains [56]. This finding also has been confirmed by Ghosh [57], who claims that consumers' innovativeness positively impacts their deal proneness. In addition, Martínez-López et a. [58] mentioned that the availability of tools for price comparison encourages consumers to make purchases online rather than via more conventional channels. Therefore, online retailers use several promotions to entice clients to engage in activities or make purchases, and even online marketplaces create a variety of festivals to encourage consumption [59,60]. Therefore, this study presented the hypotheses below:

H4. *In the livestreaming social commerce context, innovativeness positively impacts deal proneness.*

H5. *In the livestreaming social commerce context, innovativeness positively impacts consumers' purchasing behavior.*

H6. *In the livestreaming social commerce context, deal proneness positively impacts consumers' purchasing behavior.*

3. Research Methodology

3.1. Sample

The target audience for this research was mainland Chinese customers who have livestreaming purchasing experiences on social media platforms such as TikTok. To ensure the accuracy of the possible answers, one pre-screening question asked respondents whether they had experienced livestreaming shopping using a social media application for more than a year. If the respondents chose the "no" option, the survey was instantly ended.

A self-administered survey with two components was created to gather data. Age, gender, and prior livestreaming purchasing through a social media app were among the demographic data in the first section; in the second section, seventeen questions on a 7-point Likert scale, from "1 = strongly disagree" to "7 = strongly agree," were used to assess the respondents' psychological characteristics. The scales of previous studies were selected as follows: five items were adapted for trust from Zhou et al. [42] and Xu [61], three items were adapted for perceived risk from Xu [61], three items were adopted for innovativeness from Escobar-Rodríguez and Carvajal-Trujillo [62], three items were adapted for deal proneness from Tak and Panwar [55], and three items were adapted for consumers' purchasing behavior from Zhou et al. [42]. All items are listed in Appendix A.

3.2. Data Collection

There were 27,661 COVID-19 infections in mainland China as of 1 December 2022 [63]; therefore, randomly reaching target respondents in various cities across China posed a considerable difficulty. Faugier and Sargeant [64] mentioned that the snowball sampling technique is considered the most viable strategy in situations when easily available sample frames are not accessible. In addition, data collection was conducted via an online questionnaire hosted on wjx.com. The first sample was initially gathered via snowball sampling from the author's personal contacts on the Chinese mainland. Following that, they were urged to tell their acquaintances about the link. By the end of December 2022, there were 675 valid responses collected. The sample size used in this research meets Taro Yamane formula's statistical standards [65], which asks for at least 399 valid data points when there are 464 million livestreaming users by the end of December 2021 [2]. Therefore, the study followed the standards specified by Taro Yamane for sample representation. The demographic statistics are presented in Table 1. According to Table 1, the preponderance of female respondents (61.3%) in this study does not introduce bias but rather reflects the prevailing trend in the Chinese context. That is, in contrast to male shoppers, female consumers exhibit a higher inclination to engage in online shopping events and embrace emerging functionalities such as social commerce and livestreaming commerce [66]. This indicates that the dataset of this study reflects the gender characteristics observed in the population.

Table 1. Demographic characteristics of the respondents.

Demographic Factors	Descriptive Statistics	
Gender	Male	261 persons (38.7%)
	Female	414 persons (61.3%)
Age	Below 18 years old	102 persons (15.1%)
	18–25 years old	214 persons (31.7%)
	26–30 years old	105 persons (15.6%)
	31–40 years old	125 persons (18.5%)
	41–50 years old	59 persons (8.7%)
	51–60 years old	41 persons (6.1%)
	Above 60 years old	29 persons (4.3%)
Experience	1–3 years	428 persons (63.4%)
	4–6 years	204 persons (30.2%)
	over 7 years	43 persons (6.4%)

3.3. Statistical Analysis

The statistical method employed for data analysis was partial least squares structural equation modeling (PLS-SEM). PLS-SEM was selected due to its suitability for non-normally distributed data and its applicability to exploratory research geared towards prediction and theory development [67]. In this study, PLS-SEM was deemed appropriate as the research aimed to construct a comprehensive model for understanding customer decision-making processes within the livestreaming social commerce context, drawing from the framework of TAM 3. It is worth noting that the data exhibited skewness and kurtosis values within the ranges of −0.583 to −1.020 and −0.286 to 0.708, respectively, indicating that not all variables conformed to a normal distribution. PLS-SEM analysis was performed in SmartPLS 4.0 [68].

4. Results

4.1. Analysis of Measurement Model

Before the structural model's evaluation, all conditions must be met by testing the measurement model [67], which is equivalent to confirmatory factor analysis (CFA) in covariance-based structural equation modeling (CB-SEM, [69]). Since only reflective constructs were used in this research, it is necessary to compute the factor loadings, Cronbach's alpha (CA), composite reliability (CR), average variance extracted (AVE), and discriminant validity [70].

First and foremost, to determine an indicator's dependability, factor loadings were computed, as shown in Table 2, and the factor loadings needed to be above 0.708 to be significant at the 0.05 level [67]. In the meantime, cross-loadings were assessed, and the results showed that each indication loaded more strongly for its specific build than it did for any other construct [71].

Table 2. Factor loadings and cross loadings.

Items	Deal Proneness	Innovativeness	Perceived Risk	Trust	Purchasing Behavior
DP1	**0.97 (277.24)**	0.43	0.44	0.43	0.44
DP2	**0.94 (148.36)**	0.38	0.41	0.39	0.40
DP3	**0.94 (173.86)**	0.39	0.38	0.36	0.41
INT1	0.42	**0.95 (165.60)**	0.35	0.37	0.35
INT2	0.40	**0.93 (154.69)**	0.30	0.37	0.38
INT3	0.38	**0.94 (140.89)**	0.29	0.34	0.34
PR1	0.43	0.34	**0.97 (220.118)**	0.40	0.35
PR2	0.42	0.32	**0.95 (178.29)**	0.35	0.30
PR3	0.38	0.30	**0.94 (134.25)**	0.35	0.30
TR1	0.40	0.36	0.37	**0.96 (200.91)**	0.52
TR2	0.37	0.36	0.34	**0.92 (149.68)**	0.49
TR3	0.40	0.34	0.38	**0.92 (136.58)**	0.50
TR4	0.38	0.35	0.37	**0.90 (109.35)**	0.45
TR5	0.35	0.37	0.32	**0.91 (118.197)**	0.47
PB1	0.41	0.39	0.33	0.53	**0.95 (171.58)**
PB2	0.41	0.32	0.31	0.48	**0.94 (147.26)**
PB3	0.42	0.36	0.32	0.49	**0.94 (182.07)**

Note. DP = deal proneness, INT = innovativeness, PR = perceived risk, TR = trust, PB = purchasing behavior. The bold values are the factor loadings, and the values in the () are T-values.

Table 3 shows the results of an analysis using CA and CR to evaluate the construct's internal consistency reliability. The results demonstrate that all metrics are higher than the necessary threshold of 0.70 [67]. Additionally, AVE was used to test convergent validity, and all results were above the standard threshold of 0.5 [67]. Lastly, discriminant validity was evaluated using two techniques. The Fornell–Larcker criterion [72] was used as the first technique, and Table 3 shows that AVEs fulfill the criteria for discriminant validity since their square root is greater than their correlation coefficient with other constructs.

Because the original Fornell–Larcker PLS technique may exaggerate indicator loadings and underestimate structural model relationships [73], the second technique was used to assess the discriminant validity using the Heterotrait–Monotrait (HTMT) ratio of correlation, a higher-boundary criterion. Given that each concept was independent of the others, the results of the HTMT ratio test were all lower than a threshold of 0.85 [67], indicating that the discriminant validity was good.

Table 3. Reliabilities and correlation of constructs.

Constructs	CA	CR	AVE	Correlation of Constructs and Heterotrait–Monotrait (HTMT) Ratio				
				Deal Proneness	Innovativeness	Perceived Risk	Trust	Usage Behavior
Deal Proneness	0.95	0.97	0.90	**0.95**				
Innovativeness	0.94	0.96	0.88	0.42 (0.45)	**0.94**			
Perceived Risk	0.95	0.97	0.91	0.43 (0.46)	0.33 (0.35)	**0.95**		
Trust	0.96	0.97	0.85	0.42 (0.44)	0.38 (0.41)	0.39 (0.40)	**0.92**	
Purchasing Behavior	0.94	0.96	0.89	0.44 (0.46)	0.38 (0.40)	0.34 (0.36)	0.53 (0.56)	**0.94**

Note. Square root of AVE is presented diagonally; the value within () is the value of the HTMT ratio.

4.2. Multicollinearity and Common Method Bias Assessment (CMB)

To examine multicollinearity, full variance inflation factor (VIF) statistics were used. The results reveal a range of full VIFs with latent variables from 1.42 to 1.93, which are not greater than 3. In essence, this demonstrates that multicollinearity was not a concern [67]. The possibility of common method bias in this research was also examined using the partial correlation procedure [74]. The partial correlation approach tests whether the zero-order and partial correlations are statistically consistent by using a marker variable that is conceptually unrelated to at least one of the conceptual model's core components. Since the TAM model is not conceptually connected to respondents' livestreaming purchasing experiences via social media applications, this marker variable was employed in the present investigation. Following the suggestion in Ringle et al. [75], the correlation matrix demonstrated that neither the dependent variable, consumer purchasing behavior, nor any of the other four constructs were significantly connected to the marker variable. The outcome of the partial correlation process revealed that none of the research correlations had undergone substantial modifications, indicating that common method bias was not a big issue in this study [74].

4.3. Structural Model Analysis

PLS-SEM analysis was performed to assess H1 to H18. The statistics of the latent variables were tested using the PLS algorithm with 300 iterations, and the significance was assessed using bootstrapping (5000 times) [67,76]. The outcomes indicate the relationship between the various constructs, as determined by examining the significance of the path coefficient, the R^2, the Q^2, and the effect size (f^2). According to Figure 1, the findings show that the current model's ability to explain customers' purchase decisions for livestreamed commerce is poor, but its predictive power is medium ($R^2 = 0.35$; $Q^2 = 0.31$). In addition, regarding the outcomes, it can be stated that the main predictors of consumers' purchasing behavior of livestreaming shopping through a social media platform in order of significance are as follows: trust ($\beta = 0.37$, $p < 0.00$, $f^2 = 0.16$), deal proneness ($\beta = 0.20$, $p < 0.00$, $f^2 = 0.04$) and innovativeness ($\beta = 0.13$, $p < 0.00$, $f^2 = 0.02$). Lastly, the results from the model assessment indicate that perceived risk and trust were positively and significantly associated ($\beta = 0.39$, $p < 0.00$, $f^2 = 0.18$); moreover, perceived risk positively impacts consumers' purchasing behavior but not significantly ($\beta = 0.07$, $p = 0.13$, $f^2 = 0.01$). Additionally, innovativeness was found to significantly and positively impact deal proneness ($\beta = 0.42$, $p < 0.00$, $f^2 = 0.22$).

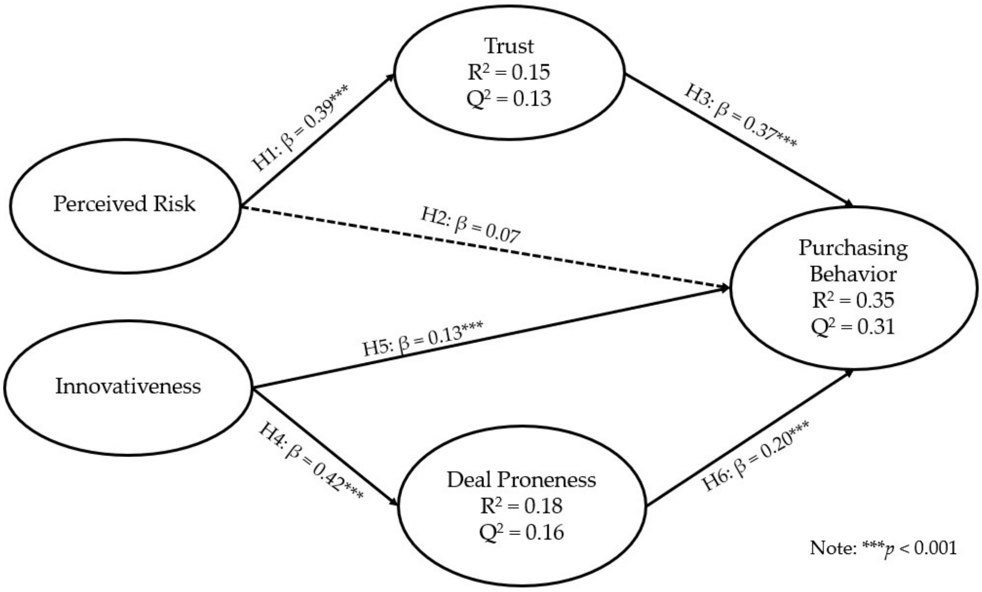

Figure 1. The structural results of the conceptual model.

4.4. Mediating Effects

The mediating functions of trust and deal proneness have been explored in order to more precisely analyze the mediating influence between components in the theoretical framework. After bootstrap estimation (5000 times), mediating effects were investigated based on the regulation carried out and procedures applied by Zhou et al. [42]. That is, total effects, indirect effects and direct effects were used to explore the mediating effects between the components. In the beginning, a basic need for the meaningful presence of mediating effects is the importance of total effects and indirect effects. Additionally, if the direct effects are also important, the mediator is considered a "partial mediator"; otherwise, it is seen as a "full mediator." Table 4 presents that both trust and deal proneness have complimentary partial mediating effects in the proposed model.

Table 4. Mediating effects on the structural model paths.

Path	Effects	Estimate	Bootstrap 5000 Times			Percentile		Conclusion
			S.E	T-Statistics	*p*-Value	Low	Upper	
Perceived Risk → Trust → Purchasing Behavior	Direct Effects	0.39 ***	0.04	9.10	0.00	0.30	0.47	Complimentary Partial Meditation
	Indirect Effects	0.14 ***	0.02	5.98	0.00	0.10	0.19	
	Total Effects	0.21 ***	0.05	4.53	0.00	0.12	0.30	
Innovativeness → Deal Proneness → Purchasing Behavior	Direct Effects	0.13 ***	0.04	2.89	0.00	0.04	0.21	Complimentary Partial Meditation
	Indirect Effects	0.09 ***	0.02	3.72	0.00	0.04	0.13	
	Total Effects	0.21 ***	0.04	4.87	0.00	0.13	0.30	

Note. *** $p < 0.001$.

5. Discussion

In the context of livestreaming social commerce, this research offered a more thorough model based on the framework of TAM 3 [31] to comprehend customer purchase behavior in mainland China. Using 675 valid responses, a PLS-SEM analysis supported the majority of the hypotheses proposed. First and foremost, the analysis presented that consumer-perceived risk positively influences their trust in livestreaming social commerce. This finding is consistent with that pf previous studies by Hong [33] and Ling et al. [39]; however, it contrasts the findings of Kamalul et al. [35] and Park et al. [36]. That is, consumers tend to rely on trust as a coping mechanism in the face of perceived uncertainties and risks. It aligns with the notion of Jiang et al. [32] that in a circumstance of high perceived risks, consumers tend to scrutinize product-related information on social media platforms more diligently in order to minimize potential losses.

Furthermore, the finding reveals a positive relationship between trust and consumer actual purchasing behavior, which is in line with the findings of previous studies [49,50].This indicates that consumers place a premium on the trustworthiness of the platform or technology they are using for their purchasing decisions. They are more likely to engage in online transactions when they perceive the platform as reliable, secure, and credible. This finding aligns with the core tenets of TAM3, which highlights the importance of trust as a key construct. It confirms that trust is not just a byproduct but a fundamental driver of technology acceptance and usage.

Lastly, this study found that consumers' innovativeness significantly and positively impacts their deal proneness, which is in line with a previous study in [57]. It implies that individuals characterized by a higher degree of innovativeness are more inclined to explore and embrace novel offerings in the market. This predictive relationship underscores the potential for innovative individuals to be early adopters, setting trends and influencing market dynamics.

6. Theoretical and Practical Implication

The results from this study provide theoretical contributions to the existing literature on TAM 3, as well as enhancing the theoretical analysis of consumer actual purchasing behavior by providing a comprehensive model. First and foremost, by applying TAM 3 to a new business scenario, livestreaming social commerce, this study explores consumers' actual purchasing behavior by integrating consumers' perceived risk, trust, innovativeness and deal proneness, enriching and extending the literature. Second, this research adjusted the measurement items for constructs in the context of livestreaming social commerce, except for innovativeness, and subsequently validated the connections between these constructs. Finally, the finding provides additional empirical support for the notion that perceived risk positively impacts consumers' trust in the context of livestreaming social commerce.

The main findings of this study also offer practical implications for business and platform providers, as well as marketers. First of all, businesses and platform providers may emphasize trust by investing in strategies to enhance trustworthiness, such as transparent policies, secure payment systems, and authentic user reviews, which can have a direct and positive impact on consumers' purchasing behaviors. Furthermore, they may consider taking an opportunity to foster trust by openly addressing perceived risks and implementing risk mitigation strategies. Furthermore, understanding the dynamics of how perceived risk can enhance trust may enable the development of more targeted trust-building initiatives within technology adoption contexts, ultimately influencing consumer behavior positively. In addition, firms and marketers may find value in targeting innovative consumers, tailoring their strategies to resonate with the preferences and openness to innovation displayed by these individuals, for instance by designing marketing campaigns and launching new products. Lastly, legislative policymakers are encouraged to formulate and enact legislation and regulations tailored to the protection of online consumers' privacy and financial well-being.

7. Conclusions

Livestreaming social commerce has been a vital means to enhance sales performance in China, while previous studies on consumers' actual purchasing behavior on livestreaming social commerce platforms are limited. The study effectively addresses existing gaps in investigating consumers' actual online purchasing behavior by investigating the influence of perceived risk, trust, consumers' innovativeness, and deal proneness. Based on the snowball sampling method, an online questionnaire was conducted in mainland China in December 2022. The findings show that consumers' trust, innovativeness, and deal proneness are significantly related to their actual purchasing behavior in the context of livestreaming social commerce. Furthermore, this research provides additional empirical support for the notion that perceived risk positively impacts consumers' trust in the context of livestreaming social commerce. Through this research, the authors offered new knowledge that can help online shoppers, businesses, platform providers, and marketers to focus on understanding and adapting to livestreaming social commerce for effective marketing strategies, thereby enhancing their competitiveness and sales performance in emerging markets such as China. Drawing from the results, the authors have presented a number of practical implications for merchants, platform providers and policymakers, including consumer segmentation, and online consumers' privacy protection.

8. Limitations and Recommendations for Future Trends

It is important to acknowledge the contributions of this work while considering some limitations. The use of a snowball sampling technique in data collection resulted in a limitation in generalizing the survey findings to the broader population. In future research endeavors, it may be advantageous to use a probability-based approach for data collection, since this methodology has the potential to provide more generalizability. Conversely, the data were acquired via a self-administered questionnaire survey, a method susceptible to the effect of respondents' subjective bias. In future research endeavors, it is conceivable that scholars may use a diverse range of resources in order to enhance the precision and reliability of response measurements. Lastly, the predominant inclusion of respondents under the age of 30 years old in this study poses a limitation, potentially introducing bias and hindering the generalizability of findings. Future studies should aim for a more diverse and representative sample, spanning a broader respondent demographic.

Author Contributions: Conceptualization, X.S. and J.-É.P.; methodology, X.S.; formal analysis, X.S.; investigation, Y.M. and S.D.; resources, S.D.; writing—original draft preparation, X.S. and Y.M.; writing—review and editing, X.S. and J.-É.P.; project administration, X.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board of National Institute of Development Administration (reference no. ECNIDA 2022-0107).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to ethical reasons.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Measurement scales

Consumers' Purchasing Behavior

1. Livestreaming social commerce is my first choice when I need to buy something.
2. I will follow the anchor of the livestreaming social commerce platforms.
3. I will recommend to my friends to use livestreaming social commerce platforms.

Trust

1. I think livestreaming social commerce is trustworthy.
2. I trust the quality of goods purchased on livestreaming social commerce platforms.
3. The livestreaming social commerce platform has a good after-sales service system.
4. The law can fully protect my interest in livestreaming social commerce.
5. I believe that livestreaming social commerce forms can protect my privacy and safety.

Perceived Risk

1. I am worried that commodities provided by livestreaming social commerce platforms do not match the actual situation.
2. I am worried that the quality of products provided by livestreaming social commerce platforms is not good.
3. I am worried that personal information will be leaked by livestreaming social commerce platforms.

Consumers' Innovativeness

1. If I heard about new information technology, I would look for ways to experiment with it.
2. Among my peers, I am usually the first to explore new information technologies.
3. I like to experiment with new information technologies.

Deal Proneness

1. Redeeming coupons and/or taking advantage of promotional deals on livestreaming social commerce makes me feel good.
2. I am more likely to buy brands or patronize service firms that have promotional deals on livestreaming social commerce platforms.
3. Beyond the money I save, redeeming coupons and taking advantage of promotional deals on livestreaming social commerce platforms give me a sense of joy.

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