Factors Affecting Social Commerce Victimization of a Thai University's Students

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Abstract

This research examines victimization in social commerce among undergraduate students by employing quantitative analytical methods on a survey of 400 participants. The study explores how demographic characteristics, purchasing behaviors including order frequency and value, decision-making factors such as vendor trustworthiness, recognized social value, and awareness of others' victimization, along with risk perceptions including product feature, financial, psychological, and privacy risks, affect victimization rates and financial consequences. Utilizing both descriptive and inferential statistical techniques, such as Pearson correlation coefficients and multiple regression, the study identifies significant relationships. It reveals that factors like order value significantly impact financial losses, whereas vendor trustworthiness has minimal effect. Additionally, the research employs causal regression-based forecasting to recommend future spending limits based on past victimization experiences, aiming to enhance online financial safety. The findings underscore the urgency of developing targeted educational programs and government-led initiatives to foster safer online behaviors, highlighting the complex nature of social commerce victimization and advocating for comprehensive strategies to mitigate its effects.

Keywords: 1) Victimization 2) Social commerce 3) Purchasing behaviors 4) Decision-making factors 5) Risk perceptions

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Introduction

The popularity of online trading, or e-commerce, has been steadily increasing worldwide, with a notable surge during the COVID-19 pandemic. As of January 2024, Thailand's total population is 66.04 million people according to the Bureau of Registration Administration (2024). Concurrently, Thailand now boasts 63.21 million internet users, constituting approximately 95.71% of the national population. Additionally, there are 49.1 million social media users or 74.35% of the total population. These statistics highlight an increasing trend in digital engagement over the past decade. (DataReportal, 2023).

Based on research (Kiadrasamee, 2015, pp. 26-60), approximately 40.74% of the sample group who made online purchases mainly fell within the age range of 21-25 years which aligns with the student age demographic. This correlation is further substantiated by Tuachob (2019, pp. 195-205) indicating that the online shopping behaviors of undergraduate students, belonging to the Gen Z and Gen Y ages of 18-23 years, is evolving together with rapid technological advancements. These students are proficient at swiftly mastering new technologies. However, their online purchasing decisions are entwined with diverse forms of perceived risks (Mitchell, 1982, pp. 80-88).

In the early study of risk perception, researchers often diverge it into two dimensions: uncertainty and divergent outcomes, which consumers may encounter during transactions (Bauer, 1960, pp. 389-398; Cox and Rich, 1964, pp. 32-39). Risk perception, being multidimensional, has been utilized by researchers to explain the varied consumer behaviors observed in purchasing. Moreover, researchers have delved deeper into consumer-centric factors such as financial, psychological, social, or temporal risks (Jacoby and Kapland, 1972, pp. 382-393).

With the rapid evolution of communication technology, the emergence of e-commerce has transformed how goods and services are bought and sold over the internet. Despite the continued growth of e-commerce, the increasing incidence of complaints and fraud in online transactions highlights the tendency of consumers to underestimate the importance of careful product selection and self-protection against the inherent risks (Suchitt, 2021, pp. 97-242). Moreover, the widespread use of social media has triggered a significant increase in transactions through platforms referred to as social commerce or s-commerce (Hirankasi and Klungjaturavet, 2021).

The e-commerce sector is a vital component of the Thai economy, significantly influencing entrepreneurs who often rely on social media for advertising. According to DataReportal (2023), the most popular social media platforms in Thailand include Facebook, LINE, Instagram, and X or Twitter. As a result, s-commerce has become the dominant distribution channel. In response to this shift, several government bodies such as the Ministry of Digital Economy and Society, the Office of the National Digital Economy and Society Commission, and the Department of Internal Trade are actively involved in regulation and oversight. They have established the Online Complaint Center to tackle issues related to online transactions and enhance consumer trust.

Throughout 2021, a total of 37,584 complaints were lodged concerning online transactions. The predominant issues were non-receipt of ordered items, accounting for 47.7% of complaints, and receipt of items not as described, which made up 30.6%. Other complaints included receiving damaged items at 4.6%, delayed delivery at 0.8%, and illegal products at 1.2%. A significant majority of these complaints, 82.1%, originated from Facebook purchases, while other platforms like websites, Instagram, e-marketplaces, and X/Twitter accounted for smaller fractions of the total complaints (Electronic Transactions Development Agency, 2022).

Research on consumer behaviors on online platforms (Kiadrasamee, 2015, pp. 26-60) showed that product features, distribution channels, and technology acceptance significantly enhance purchasing decisions. Privacy maintenance (Sutthisirimongkol, 2019, pp. 35-78) was identified as a key factor in online buying choices. Surveys in Bangkok highlighted the importance of psychological and social factors in shaping consumer behaviors. Purchasing behaviors of undergraduate students in Phutthamonthon, Nakhon Pathom were investigated (Tuachob, 2019, pp. 195-205) across three universities. The majority of respondents had an average monthly income between 3,001 and 5,000 baht and spent over four hours daily online. Their online shopping experience was moderate, with cosmetics and skincare products being the most frequently purchased items, typically bought at least once a month via online apps.

Risk perceptions in Facebook shopping (Anothip, 2013, pp. 38-58) showed product liability as the greatest risk, followed by financial, temporal, psychological, and social risks. Another study (Kutin, 2016, pp. 31-58) on Generation Y in Surat Thani found moderate risk perceptions, with product liability most frequently cited. Product liability and financial risks greatly influenced online purchasing decisions, decreasing with increased shopping experience (Forsythe and Shi, 2003, pp. 867-875). Risk perceptions varied by product type (Griffin and Viehland, 2011, pp. 1-6); airplane tickets had high safety risks, while clothing had high product liability and psychological risks. Comparing Chinese and British consumers (Sims and Xu, 2012, p. 25), Chinese consumers had higher perceptions of financial, product liability, and physical risks, highlighting the need for culturally tailored marketing strategies.

Factors that influence victimization in pyramid schemes were explored (Photjanalawan, 2017, pp. 56-171) through interviews and surveys with 396 individuals who had been victims in Thailand. Her research differentiated pyramid schemes into three distinct types: direct solicitation, membership-driven models, and using social media for recruitment. The findings identified several key factors that increase the likelihood of victimization, including: 1) victim characteristics, 2) belief systems, 3) victimization patterns aligned with Buddhist principles, 4) lifestyle habits, 5) daily routines, 6) opportunities, 7) coercion, 8) social support, 9) capabilities, 10) personal values, and 11) goals/objectives.

Meanwhile, victimization within the online beauty products was investigated (Suchitt, 2021, pp. 37-58), focusing on challenges related to law enforcement, compensation, and product quality control. The findings indicated that victimization was frequently connected to societal values placed on beauty, the probability of becoming a victim, and the victims' behaviors. The study suggested preventative strategies, including refining legal frameworks, and increasing collaboration with various agencies.

In this research, the aim is to explore factors that influence victimization in s-commerce. It primarily targets undergraduate students, a demographic deeply engaged in digital life and online shopping (Tuachob, 2019, pp. 195-205). Key variables include the total number of victimizations and the total amount of victimization money, alongside various identified types of victimization. The research examines influencing factors such as demographic features, purchasing behaviors, decision-making aspects, and risk perception.

The methodology combines survey techniques with quantitative data analysis and includes causal regression-based forecasting to estimate the optimal amount an individual should spend in future orders based on past losses on s-commerce.

Methodology

The population in this study comprises undergraduate students from a large Science and Technology faculty at a Thai university in Bangkok, hosting 3,678 students enrolled in various scientific disciplines. For the sample size n, this study employs the Yamane formula: $n = N/(1+Ne^2)$ where the population size N = 3,678 and the margin of error e = 0.05, and hence n = 361. However, to account for potential non-responses and robustness in the data analysis, 400 samples are collected using a simple random sampling method, given that all students in the population are from the same generation and share similar lifestyles. Each student is assigned a unique number from 1 to 3,678.

Since the typical response rate is not 100%, 450 random numbers are generated. A comprehensive 5-section questionnaire is used to gather data on the respondents' demographic characteristics, purchasing behaviors, decision-making aspects, risk perception, and victimization. To ensure the content validity, the questionnaire has been reviewed by three experts in the relevant fields. Each question has achieved an Index of Congruence (IOC) of at least 0.67. It confirms that the questions are well-suited to meet the research objectives (Thaweerat, 1997, pp. 106-107). Finally, 412 questionnaires are returned, and after removing those with outliers or incomplete data, the final count of usable responses stands at 400.

In this study, quantitative data analysis methods, encompassing both descriptive and inferential statistical techniques, are employed. Descriptive statistics provide foundational insights into the dataset. For inferential analysis, independent-samples t-test compares the means of two distinct groups. If the p-value is less than or equal to a significance level, typically set at 0.05, the null hypothesis: the means are equal, $\mu_1 = \mu_2$, is rejected in favor of the alternative, suggesting significant evidence that the group means differ.

For comparing three or more groups, one-way Analysis of Variance (ANOVA) is utilized to test for significant differences across group means. The null hypothesis states that all group means are equal, $\mu_1 = \mu_2 = \ldots = \mu_k$, while the alternative one states that at least one group mean is different.

When the p-value is less than or equal to α, the null hypothesis is rejected, signifying that statistically significant, not all group means are equal, and hence at least one group significantly differs from the others, warranting further investigations to determine the specific groups that differ.

Pearson's correlation coefficient *r* is used to assess the strength and direction of the linear relationship between two continuous variables. The coefficient ranges from -1 to +1, with values near the extremes indicating a strong linear relationship.

The significance of the correlation is typically tested using a t-test, where the null hypothesis H_0: $\rho = 0$ suggests no true correlation between the variables. This test determines whether the observed correlation is statistically significant.

Multiple regression analysis is used to explore the relationship between a dependent variable and two or more independent variables. The purpose is to explain the behavior of the dependent variable based on the influences of independent variables. The overall model fit is evaluated by adjusted R^2 which offers a more precise measure than R^2. Adjusted R^2 decreases unless a new variable significantly enhances the model's explanatory power.

Lastly, regression-based forecasting is a vital analytical tool that leverages historical data to predict future of a dependent variable

Results and Discussion

To explore factors influencing victimization in social commerce (s-commerce), this study presents results from descriptive statistics. Additionally, insightful findings from inferential analyses on two key variables—the total number of victimizations and the total amount of money lost—are provided. Finally, a regression-based forecast is included to estimate the optimal amount one should spend on future orders.

1. Descriptive Statistics

Table 1 shows that the majority of the 400 respondents are female, making up 55 percent of the sample. The predominant age group is from 20 to 23 years old, representing 54 percent of the respondents.

Additionally, a significant proportion of the sample, approximately 43.2%, are first-year college students. In terms of academic disciplines, Mathematics and Statistics emerge as the most popular fields of study, accounting for 29.3% of the respondents. Chemistry and Biology follow as the second most common fields, each comprising 20.0% of the sample.

Table 1 Participants' demographic characteristics.

Demographic factor	Frequency	Percentage	Demographic factor	Frequency	Percentage
Gender			Collage Year of Study		
Male	180	45.0%	Year 1	173	43.2%
Female	220	55.0%	Year 2	80	20.0%
			Year 3	78	19.5%
			Year 4	61	15.3%
			Year 5 onward	8	2.0%
Age			Academic Discipline		
Less than 18 years	3	0.8%	Computer/IT	72	18.0%
18 to 20 years	151	37.8%	Mathematics/Statistics	117	29.3%
20 to 23 years	216	54.0%	Physics/Electronics	66	16.5%
More than 23 years	30	7.4%	Chemistry/Biology	80	20.0%
			Other Sciences	65	16.2%

Table 2 shows the frequency and percentage usage of each s-commerce platform. TikTok leads as the most preferred platform by 186 participants, representing 46.5% of the sample. Facebook follows closely with 166 participants, accounting for 41.5% of the sample. Instagram (IG) and X/Twitter are preferred equally by 18 participants, making up 4.5%. Line is least preferred by 12 participants, constituting 3.0%. This distribution indicates a significant preference for TikTok and Facebook for conducting s-commerce activities.

Table 2 Preferred s-commerce platforms.

Platform	Frequency	Percentage
Facebook	166	41.5%
Tiktok	186	46.5%
Instagram (IG)	18	4.5%
Line	12	3.0%
X/Twitter	18	4.5%

In addition, two other significant variables include the average number of monthly purchase orders and the average amount spent per order, both analyzed on a scale measurement basis.

Table 3 shows that the minimum number of monthly purchase orders is 1, with a maximum of 100, and an average of 4.14. The standard deviation (SD) is 7.81, indicating a wide variation in the purchase frequency.

Regarding the amount of money spent per order, the minimum spend is 100 baht, and the maximum goes up to 30,000 baht. The average expenditure stands at 606.27 baht, with a substantial SD of 1,754.67. This large deviation highlights significant differences in spending behavior, with some participants making much larger transactions than others.

Table 3 Participants' purchasing behaviors.

Purchasing Behavior	Min	Max	Mean	SD
Average number of monthly purchase orders	1	100	4.14	7.81
Average amount of money spent per order (in baht)	100	30,000	606.27	1,754.67

For the other two influencing factors—decision-making in s-commerce purchases and risk perception—a 5-level Likert scale is utilized to collect responses. This scale includes ratings from 5, representing "most agree," down to 1, indicating "least agree", with intermediate options of 4, 3, and 2, for "strongly agree," "moderately agree," and "slightly agree", respectively. To interpret the results, it is categorized into five equal class intervals (CI) by CI = (highest value – lowest value)/number of classes, and thus CI = (5–1)/5 = 4/5 = 0.8. A specific range of attitudes representing each class interval is interpreted in Table 4.

Table 4 Mean score range interpretations.

Mean score	Interpretation
4.21 – 5.00	most agree
3.41 – 4.20	strongly agree
2.61 – 3.40	moderately agree
1.81 – 2.60	slightly agree
1.00 – 1.80	least agree

The decision-making factors explored include vendor trustworthiness, recognized social values, and awareness of others' victimization. Table 5 shows a general consensus among respondents on these factors, with an overall mean 3.84, signaling strong agreement. A detailed examination reveals that awareness of others' victimization receives the highest level of agreement at 4.07, followed by vendor trustworthiness at 3.81, while recognized social values receives the lowest agreement score at 3.64. Each decision-making factor scores within the class interval of 3.41 to 4.20, indicating robust agreement across the board.

The SD associated underlines variation in participant responses. Vendor trustworthiness and awareness of others' victimization exhibit similar SDs of 0.673 and 0.679, respectively, suggesting moderate consistency. In contrast, recognized social value shows the highest variability with an SD of 0.739, reflecting a wider range of opinions. Nevertheless, the overall average SD for all factors is 0.569, indicating relatively uniform agreement across all factors.

Table 5 Participants' decision-making and risk perception factors.

	Mean	SD
Decision making: Average	3.84	0.569
Vendor trustworthiness	3.81	0.673
Recognized social value	3.64	0.739
Awareness of others'	4.07	0.679
Risk perception: Average	3.30	0.649
Product features	3.48	0.641
Financial risks	3.54	0.702
Psychological risks	2.73	0.955
Privacy risks	3.46	0.849

Table 5 also outlines the risk perception factors: product features, financial risks, psychological risks, and privacy risks. The mean scores reveal participants' perceptions of each risk. Product features are rated with a mean of 3.48, suggesting strong agreement, supported by a low SD of 0.641, indicating consensus among responses. Financial risks are perceived slightly higher, with a highest mean of 3.54 and an SD of 0.702, showing consistent concern.

Psychological risks receive the lowest mean score of 2.73, coupled with the highest SD of 0.955, reflecting a wide range of opinions and potentially less uniform understanding. Privacy risks are rated with a moderate mean of 3.46 and a higher SD of 0.849, indicating varied perceptions. Collectively, the average mean score for all risk perceptions is 3.30, with an SD of 0.649, suggesting a moderate perception, despite some variability in the intensity.

Table 6 Victimization outcomes.

Victim. outcome	Min	Max	Mean	SD
#Victim.	1	10	2.01	1.40
Victim. baht	60	76,800	1,439.87	4,409.98

Table 6 details two primary metrics: the total number of victimizations (#Victim.) and the total victimization money (Victim. baht). The number of victimizations ranges from 1 to 10 incidents, with an average of 2.01 and an SD of 1.40, implying a spread in the victimization frequency. Meanwhile, the total amount lost to victimization ranges widely from 60 to 76,800 baht. The mean is 1,439.87 baht, accompanied by a large SD of 4,409.98, indicating a substantial disparity in the financial loss across individuals.

Table 7 outlines the various types of victimization encountered by participants. The most common type involves items received not as described or advertised, with 319 incidents or 61.35% of all cases, followed by damaged products, with 97 incidents or 18.65%. Not receiving the products at all is reported in 86 cases or 16.54%. The least frequent issue is receiving illegal or counterfeit products with merely 18 instances or 3.46%. This data highlights the occurrence of misrepresentation and quality issues in s-commerce as experienced by the participants.

Table 7 Various types of victimization.

Victimization type	Frequency	Percentage
Products not received	86	16.54%
Received items not as described	319	61.35%
Damaged products	97	18.65%
Illegal or counterfeit products	18	3.46%

2. T-tests and one-way ANOVA analyses

In this section, inferential statistical analyses are performed on the demographic features and purchasing behaviors.

Inferences based on demography

Inferential analyses begin with independent-samples t-tests to identify statistically significant variations in victimization experiences among participants, differentiated by gender, age groups, college levels, and academic disciplines.

Table 8 summarizes the differences in victimization experiences between male and female participants based on the total number of victimizations and the total amount of victimization money.

Table 8 Independent-samples t-test on the total number of victimizations by gender.

Victimization number (Y1)	N	Mean	Standard deviation	F	Sig.
Male	180	1.98	1.37	0.038	0.846
Female	220	2.04	1.42		
			Equal variances assumed (t)	-0.377	0.706
Victimization value (Y2)	**N**	**Mean**	**Standard deviation**	**F**	**Sig.**
Male	180	1,932.94	6,079.97	5.06	0.025*
Female	220	1,036.45	2,203.41		
			Equal variances not assumed (t)	1.880	0.061

For the number of victimizations, the analysis includes 180 males and 220 females. The mean number of victimizations reported by males is 1.98, with an SD of 1.37, while females report a slightly higher mean of 2.04, with an SD of 1.42. The independent-samples t-test with a 0.05 significance level indicates no statistically significant difference between genders, as shown by a t-significance of 0.706, with equal variances assumed given the high F-significance of 0.846.

Additionally, Table 8 shows that males has a higher mean of victimization amount at 1,932.94 baht, compared to females at 1,036.45 baht. The SDs for both groups are high, with males at 6,079.97 and females at

2,203.41, indicating a broad range. The F-test shows a 0.025 significance level, suggesting that unequal variance. Subsequent t-tests show a t-significance of 0.061, indicating no significant difference in means.

Table 9 One-way ANOVA on the victimization number and money.

Victimization number (Y1)	N	Mean	SD	F	Sig.
Age				0.314	0.815
Less than 18 years	3	1.67	0.58		
18 to 20 years	151	1.94	1.20		
20 to 23 years	216	2.07	1.57		
More than 23 years	30	2.00	1.02		
Collage year of study				1.345	0.253
Year 1	173	1.88	1.25		
Year 2	80	1.93	1.13		
Year 3	78	2.15	1.41		
Year 4	61	2.31	2.00		
Year 5 onward	8	2.00	0.76		
Academic discipline				0.804	0.523
Computer/IT	72	2.25	1.61		
Mathematics/Statistics	117	1.96	1.53		
Physics/Electronics	66	2.08	1.17		
Chemistry/Biology	80	1.89	1.33		
Other Sciences	65	1.94	1.18		
Victimization value (Y2)	N	Mean	SD	F	Sig.
Age				5.21	0.002
Less than 18 years	3	1,166.67	1,588.50		
18 to 20 years	151	1,325.96	2,297.36		
20 to 23 years	216	1,107.73	1,925.57		
More than 23 years	30	4,432.00	14,228.71		
Collage year of study				1.75	0.138
Year 1	173	1,280.75	2,172.79		
Year 2	80	1,063.25	1,511.66		
Year 3	78	2,266.67	8,912.00		
Year 4	61	987.87	1,555.76		
Year 5 onward	8	4,032.50	7,280.57		

Victimization number (Y1)	N	Mean	SD	F	Sig.
Academic discipline				0.56	0.692
Computer/IT	72	1,543.89	2,798.75		
Mathematics/Statistics	117	1,141.97	1,535.98		
Physics/Electronics	66	2,051.52	3,139.68		
Chemistry/Biology	80	1,544.00	8,572.94		
Other Sciences	65	1,111.69	2,620.01		

Table 9 presents the results of a one-way ANOVA to examine the victimization number based on age, year of study and academic discipline to discern any significant differences in their experiences of victimization.

Age Groups: Participants are divided into four age categories. Those aged less than 18 years have the lowest mean victimization number at 1.67, while those aged 20 to 23 years report the highest mean at 2.07. The F-value of 0.314 with a 0.815 significance level suggests no statistically significant differences in victimization numbers across different ages.

Year of Study: Fourth-year students report the highest mean victimization number at 2.31, whereas first-year students report the lowest at 1.88. The F-value for this group is 1.345 with a 0.253 significance level, indicating that the year of study does not significantly affect the number of victimizations.

Academic Discipline: Computer/IT participants report the highest mean victimization number at 2.25, while Chemistry/Biology report the lowest at 1.89. With a 0.804 F-value and a 0.523 significance, the results show no significant differences in victimization numbers across different fields.

Overall, the ANOVA results across age, year of study, and academic discipline do not show any statistically significant differences in the total number of victimizations, indicating that these demographic and academic disciplines do not play a decisive role.

Table 9 also provides a one-way ANOVA analysis on the total amount of victimization money categorized by age, year of study, and academic discipline.

Age Groups: The group aged more than 23 years reports a significantly higher mean victimization amount of 4,432.00 baht, with a very large SD of 14,228.71, suggesting extreme variations in the amounts lost. The youngest group, less than 18 years, although small in sample size (n=3), has a mean of 1,166.67 baht. The F-value of 5.21 and a p-value of 0.002 indicate that there are statistically significant differences in the total victimization amounts across different age groups, most of which belong to Generation Y (Kutin, 2016, pp. 31-58).

Year of Study: Students in their fifth year onward report a high mean victimization amount of 4,032.50 baht. This elevated average could be influenced by the small sample size (n=8). Third-year students report the second highest mean of 2,266.67 baht, whereas fourth-year students have the lowest at 987.87 baht. However, the F-value of 1.75 and a p-value of 0.138 suggest that these differences are not statistically significant.

Academic Discipline: Physics/Electronics students report a higher mean victimization amount of 2,051.52 baht. Conversely, Mathematics/Statistics and Other Sciences report some of the lowest averages, at 1,141.97 baht and 1,111.69 baht, respectively. Despite these variations, the F-value of 0.56 and a p-value of 0.692 indicate no statistically significant differences in victimization money across the different academic disciplines.

The analysis highlights significant variations in victimization amounts across age groups, with notable differences in financial impact based on the age of participants. In contrast, the college year of study and academic discipline do not show significant differences, indicating that these factors might not strongly influence the financial extent of victimization experienced in social commerce.

Inferences based on preferred platforms

Table 10 details the results of a one-way ANOVA on the same two target variables, categorized by participants' preferred platforms. For the total number of victimizations (Y1), Facebook users report an average of 2.01 victimization incidents with an SD of 1.46. TikTok users experience slightly fewer, averaging 1.95 with an SD of 1.28. Instagram users report the fewest, averaging 1.78. Line and X/Twitter report more frequent victimizations, with averages of 2.58 and 2.61, respectively. Despite these differences, the 1.57 F-value and a 0.182 significance indicate no statistically significant differences in the victimization numbers across the platforms.

In terms of the total amount of victimization money (Y2), Facebook users report a significantly higher average loss of 1,698.61 baht, with a very large SD of 6,243.39, suggesting a wide range of loss amounts. TikTok users report lower average losses of 1,171.61 baht. Instagram users experience even lower losses averaging 1,022.22 baht, while Line users encounter the highest average losses of 3,358.33 baht. X/Twitter users report the lowest average losses at 964.44 baht. The 0.98 F-value and 0.421 significance level indicates no significant differences in the victimization money across different s-commerce platforms.

The ANOVA results demonstrate variability in both the number of victimizations and the financial impact among users of different platforms, although these differences do not reach statistical significance. This suggests that while user experiences can vary notably, these variations are consistent within the range of typical user experiences across these platforms.

Table 10 One-way ANOVA by platform.

Preferred Platform	N	Mean	SD	F	Sig
#Victim. (Y1)				1.57	0.182
Facebook	166	2.01	1.46		
Tiktok	186	1.95	1.28		
Instagram	18	1.78	1.11		

Preferred Platform	N	Mean	SD	F	Sig
Line	12	2.58	1.38		
X/Twitter	18	2.61	2.00		
Victim. baht				0.98	0.421
Facebook	166	1,698.61	6,243.39		
Tiktok	186	1,171.61	2,380.82		
Instagram	18	1,022.22	1,265.17		
Line	12	3,358.33	3,854.50		
X/Twitter	18	964.44	871.07		

3. Inferences on victimization outcomes

In this section, Pearson correlation coefficients between each target variable and the influencing factors are presented. Regression analyses are conducted to show how these factors collectively impact each of the target variables. This comprehensive approach allows us to explore both individual and combined effects, providing a robust analysis of the factors affecting the outcomes.

Table 11 presents Pearson correlation coefficients between outcome variables—the number of victimizations (Y1) and the total amount of victimization money (Y2)—and nine influencing factors including the number of monthly orders (X1), the amount spent per order (X2), vendor trustworthiness (X3), recognized social value (X4), awareness of others' victimization (X5), product feature risks (X6), financial risks (X7), psychological risks (X8), and privacy risks (X9).

The table shows that the strongest correlation among the influencing factors is between product feature risks (X6) and financial risks (X7), with a coefficient of 0.691, followed closely by the correlation between financial risks (X7) and privacy risks (X9) at 0.649, both significant at the 0.01 level.

Table 11 Pearson correlation coefficients of all variables

Correlation	X1	X2	X3	X4	X5	X6	X7	X8	X9	Y1	Y2
X1	1	-0.004	0.038	0.070	0.015	0.025	-0.010	0.014	0.054	-0.020	0.014
X2		1	0.084	0.094	0.036	.104*	0.091	.103*	0.097	0.067	.906**
X3			1	.596**	.429**	.370**	.293**	0.021	.167**	0.016	0.054
X4				1	.469**	.349**	.323**	.218**	.263**	0.030	0.077
X5					1	.411**	.434**	.121*	.296**	0.074	0.020
X6						1	.691**	.513**	.542**	0.007	0.059
X7							1	.527**	.649**	-0.019	0.042
X8								1	.541**	-0.029	0.081
X9									1	0.038	0.075
Y1										1	.134**

Correlation	X1	X2	X3	X4	X5	X6	X7	X8	X9	Y1	Y2
Y2											1

Note: *Significant at the 0.05 level **Significant at the 0.01 level

Conversely, the weakest correlation is between the average amount spent per order (X2) and psychological risks (X8), at 0.103, significant at the 0.05 level. Importantly, all correlations between these factors range from 0.103 to 0.691, remaining below 0.8, thus indicating an absence of multicollinearity.

Table 11 also reveals that most of the relationships between the nine factors and the number of victimizations (Y1) are weak. Similarly, the correlations between these factors and the total victimization money (Y2) are also generally weak with the exception of the money spent per order (X2) highly correlating with Y2 at 0.906, significantly at the 0.01 level, suggesting a strong direct relationship with the monetary losses.

Table 12 Multiple regression analysis on the victimization number (Y1) and value (Y2)

	Adj. R^2	F	Sig.		Adj. R^2	F	Sig.
Victimization number (Y1)	-0.003	0.866	0.556	**Victimization value (Y2)**	0.819	201.995	0.000
Coefficients	β	*t*	*Sig.*	***Coefficients***	β	*t*	*Sig.*
(Constant)	1.628	3.068	0.002	(Constant)	985.729	1.387	0.166
Orders (X1)	-0.005	-0.529	0.597	Orders (X1)	9.303	0.770	0.442
Order Spent (X2)	0.000	1.364	0.173	Order Spent (X2)	2.286	42.294	0.000
Vendor trustworthiness (X3)	-0.055	-0.391	0.696	Vendor trustworthiness (X3)	-111.144	-0.594	0.553
Social value (X4)	0.022	0.171	0.865	Social value (X4)	65.821	0.385	0.700
Awareness of others (X5)	0.197	1.530	0.127	Awareness of others (X5)	67.028	0.389	0.698
Product feature risks (X6)	0.040	0.243	0.808	Product feature risks (X6)	-135.044	-0.610	0.542
Financial risks (X7)	-0.220	-1.364	0.173	Financial risks (X7)	-287.376	-1.330	0.184
Psychological risks (X8)	-0.077	-0.784	0.433	Psychological risks (X8)	33.821	0.258	0.797
Privacy risks (X9)	0.158	1.374	0.170	Privacy risks (X9)	96.759	0.627	0.531

The regression analysis in Table 12 examines the influence of various operational and psychological factors on the victimization numbers. The analysis yields an adjusted R-squared slightly negative at -0.003, suggesting that the model may not effectively predict victimization based on these predictors.

The constant term in our analysis is significantly different from zero ($p = 0.002$), indicating a baseline level of victimization numbers when all other variables are held constant. However, most of the predictor variables do not significantly influence the victimization numbers. Both the number of monthly orders (X1) and the money spent per order (X2) have coefficients close to zero and are not statistically significant, showing that neither the order frequency nor value significantly impacts victimization numbers.

Similarly, vendor trustworthiness (X3) and recognized social value (X4) do not significantly predict victimization, suggesting that they do not materially affect the likelihood of being victimized. Meanwhile, awareness of others' victimization (X5) displays a slightly positive coefficient, indicating a potential correlation with increased victimizations, although this relationship is not statistically significant.

As for the risk factors, product feature risks (X6) and privacy risks (X9) are associated with positive coefficients, suggesting that higher perceptions of these risks could potentially increase victimizations. However, these findings are not statistically significant. Conversely, financial risks (X7) and psychological risks (X8) show negative coefficients, implying that increased awareness or concern about these risks might reduce victimizations, yet these results also fail to reach statistical significance.

Table 12 also shows that the regression analysis on the total amount of victimization money (Y2) exhibits a substantial explanatory power, with the adjusted R2 at 0.819, suggesting that approximately 81.9% of the variance in the victimization amount can be explained by the predictors used.

In terms of individual predictors, the constant term is quite significant. The most statistically significant predictor is the amount spent per order (X2) with a coefficient of 2.286, indicating that for each unit increase in the order value, the victimization amount increases by 2.286 baht.

However, other variables such as X1 and X3 through X9 do not show a significant impact on the amount of money lost. These variables' coefficients are not statistically significant, indicating that they do not contribute significantly to predicting the victimization amount.

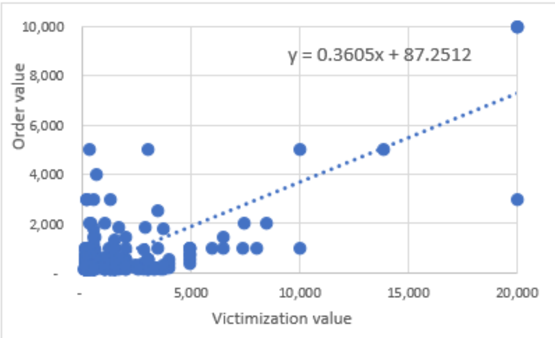
4. Regression-based forecasting

To further derive more insights from the past collected data on the total amount of money an individual lost to victimization and the average amount spent per order, a causal regression forecast is implemented to predict the optimal spending amount per order for an individual based on the money he/she lost to victimization. In this context, the predicting variable is the total amount of money lost to victimization, and the target variable is the average amount of money an individual spends per order.

This forecasting approach will provide valuable information for those who have been deceived in s-commerce transactions, helping them to set spending limits and avoid excessive expenditures online. The forecasted amount will suggest an optimal spending limit per order to guide their future purchases, aiming to enhance their financial safety in online environments.

To implement this, let x be the total amount of money lost to victimization in baht (Victimization value) and y be the average amount of money spent per order or (Order value). Figure 1 illustrates their scatter plot including a dotted regression line y = 0.3605x + 87.2512, which indicates that order value increases at a moderate rate of 0.3605 when the victimization value increases. This relationship is statistically significant, as supported by the sig. F and P-values.

The graph also shows that most data points cluster at the lower end of victimization values, indicating that most participants report lower losses due to victimization. However, as the victimization value increases, we see fewer data points, but these show higher average spending per order, reaching up to nearly 10,000 baht for those who have been victimized by as much as 20,000 baht.



		Adj. R Square	0.8203
F	1,822.20	***Sig. F***	0.0000
	Coefficients	***t-Stat***	***P-value***
Intercept	87.2512	2.229792	0.0263
Victim. Value (x)	0.3605	42.68719	0.0000

Figure 1 Victimization value and statistics.

Figure 1 also shows a high adjusted R2 at 82.03%, indicating that the model explains a significant portion of the variance in spending behavior. An F-value of 1,822.20 and a p-value of 0.0000 confirm that the model is statistically significant. This suggests a very strong relationship between the amount of money lost to victimization and subsequent spending behavior.

The coefficients of the intercept and victimization value (x) are 87.2512 and 0.3605, respectively. Their P-values also show statistically significant impact of past victimization on future spending per order.

An application of this regression analysis in real-life scenarios is demonstrated. Consider an individual who suffered a financial loss on s-commerce, by the formula y = 0.3605x + 87.251, where x is the victimization value or the total amount lost, they can determine a prudent spending limit for future transactions to minimize further financial damage.

For example, if one has incurred an s-commerce loss of 500 baht, inserting this amount into the formula results in a suggested spending limit of approximately 267.48 baht per order. This method offers a useful tool for s-commerce victims, enabling them to control their future expenses. By adhering to these calculated spending limits, individuals can maintain safer financial boundaries and potentially lower the risk of experiencing further loss.

Conclusion and Suggestion

This study explores the dynamics of victimization in s-commerce among undergraduate students, analyzing key variables like the total number of victimizations and monetary losses alongside factors such as demographics, purchasing behaviors, decision-making aspects, and risk perception. Employing methods such as descriptive statistics, t-tests, one-way ANOVA, correlation, and multiple regression analysis, together with causal regression forecasting to predict future spending based on past losses.

The demographic analysis of 400 respondents reveals a slight majority are female, predominantly aged 20 to 23, with significant numbers studying Mathematics, Statistics, Chemistry, and Biology.

In terms of purchasing behaviors, TikTok and Facebook emerge as the most preferred platforms among the respondents. The data on decision-making factors show a strong consensus on awareness of others' victimization and recognized social values, despite some variance in opinions. Additionally, risk perception factors like product features and financial risks are seen as significant, similar to the findings of the study on Facebook shopping risk perceptions (Anothip, 2013, pp. 38-58). Psychological and privacy risks are also noted, though perceptions of these risks vary.

The study also documents the financial impact of victimizations, noting substantial variability in the amount lost, with common issues including non-receipt of products and misrepresentation. These findings underscore the challenges and risks in s-commerce, stress widespread concerns about product integrity and reliability, shaping a comprehensive view of the factors influencing s-commerce victimization.

This study also investigates victimization rates and financial losses by gender, demographic factors, and preferred s-commerce platforms. The analysis finds no significant differences in rates between genders. However, males report a higher average financial loss than females, although further tests show that these differences indicate a notable but not statistically confirmed disparity by gender.

Demographically, the study employs one-way ANOVA to examine victimization by age, academic year, and discipline, finding no significant differences across these variables in both the victimization rates and the financial impact. Regarding platforms, Facebook and Line users generally report higher financial losses, but not statistically significant. This suggests that while there are observed differences in victimization experiences across various demographics and platforms, individual experiences within these categories can vary widely.

Moreover, this research explores the relationship between various factors and victimization in s-commerce through Pearson correlation and regression analysis. The correlation analysis indicates the strongest links between product feature risks and financial risks, and financial risks and privacy risks, demonstrating significant relationships. Conversely, the weakest correlation is between the amount spent per order and psychological risks, with all correlations staying below 0.8, suggesting an absence of multicollinearity. Additionally, while most relationships between the factors and victimization rates are weak, a notable strong correlation between the amount spent per order and the monetary loss is observed.

The regression analysis focusing on the total amount of victimization money reveals a significant explanatory power with a high R2, with the order value being the most significant predictor. This model suggests that increases in order value lead to proportional rises in victimization amounts. Lastly, a causal regression forecast using data from 400 individuals predicts recommended spending limits post-victimization, providing practical guidelines for victims to manage financial risks more effectively.

Research findings indicate that students' awareness of others' victimization is perceived at a moderate level. Consequently, it is crucial to provide students with access to educational resources on psychological and sociological conditions related to social media addiction and criminal behaviors to mitigate their risk of becoming victims. Additionally, there is a proposed need for government-led initiatives to raise public awareness about the impacts of crime. These initiatives should be executed through well-coordinated communication campaigns, enhancing societal understanding and fostering community support.

Moreover, students should exercise caution when using social media, prioritizing the protection of personal data and adopting secure online behaviors. This includes verifying the credibility of sources through thorough research and user feedback reviews, as well as avoiding suspicious links to prevent potential fraud. In cases of online victimization or privacy breaches, it is crucial for students to report these incidents to relevant authorities, such as financial institutions or internet security agencies, to obtain necessary remedies. Notably, the university should incorporate these preventive measures into relevant courses. The adoption of secure payment methods during online transactions is also recommended to minimize financial risks and ensure a clear understanding of refund processes.

Last but not least, future research could explore longitudinal trends in s-commerce victimization among university students, analyze demographic-specific vulnerabilities, and assess the psychological impacts. Platform-specific studies could reveal unique risks, and evaluating educational programs and government-led campaigns could guide future efforts to enhance online safety and reduce victimization rates.

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