FACTORS AFFECTING THE URGE TO BUY IMPULSIVELY OF YOUNG CONSUMERS IN HANOI CITY ON SOCIAL COMMERCE SITES

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Abstract: This study aims at analyzing the factors affecting the urge of impulse buying behavior witnessed in young Hanoian consumers in social commerce. These factors are mostly related to social interactions - the outstanding features facilitated by social commerce platforms. The data for this study were randomly collected from the young population of Hanoi via a survey from February to April 2021, of which results indicating that Parasocial interactions (PAR), Social interactions (INT), and Hedonic consumption (HED) positively affect the urge to buy impulsively (URG). The study not only proposes appropriate tactics for businesses to boost sales but also gives advice to young consumers on how to shop appropriately.

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1. Introduction

Vietnam's e-commerce industry has recently made significant progress. With 53% of the population participating in online shopping, Vietnam's e-commerce in 2020 has generated a revenue of more than 11.8 billion USD, which earns Vietnam a place in the list of 10 countries with the fastest growth rate in the world's e-commerce industry (Vietnam E-commerce and Information Technology Agency, 2020). Along with the rapid development of the e-commerce market, the social commerce section is also receiving more attention than ever. According to Vietnam E-commerce White Paper 2020, the percentage of businesses appreciating the effectiveness of social commerce is 40%. The number of regularly active social media accounts in Vietnam in 2020 is 72 million, an increase of 10.8% compared to that of 2019 and equivalent to 73.7% of the total population of Vietnam. Furthermore, the number of people using social media to shop is remarkably high, with up to 95.8% of people surveyed claiming to have shopped at least once on social media platforms (Vinaresearch, 2018). The above figures have highlighted the enormous potential of social commerce in Vietnam, consistent with optimistic forecasts of the future of this field in developed countries around the world (Insider Intelligence & eMarketer, 2021).

In the prospect of retail sellers, social media is a highly efficient mechanism of commerce as they are able to approach and interact with their customers at ease, through the contents generated on this platform. ***Apart from the interaction created by the seller's side, interaction in the community of social media users is considered a common form of social interaction while they share their personal experiences about products or services.*** Meanwhile, many studies have proven that environmental factors, especially social interaction factors, play a significant role in shaping consumption behavior, especially impulsive consumption in social commerce (Xiang *et al.*, 2016; Chen *et al.*, 2016; Chen *et al.*, 2011).

Impulse buying behavior is a classic topic in the fields of behavioral economics, business and marketing, typically as studies by Beatty and Ferrell (1998), Rook (1987), Cobb and Hoyer (1986). However, there have not been many studies on impulse buying behavior selecting the context of social media. By focusing on social commerce, the research is able to emphasize the influence of factors created by social interactions between users, which is unlikely to appear on traditional e-commerce sites. In addition, the authors identified the subjects of the study as young people living in urban areas, in the 18-35 age group, which makes up the majority of social media users in Vietnam and is more susceptible to changes in the real world and social media environment.

Despite the fact that impulse buying behavior has been comprehensively studied worldwide, the number of studies in Vietnam is rather limited and there has been a research gap on impulse buying behavior on social commerce platforms. Therefore, this study aims to answer three questions:

1. Which factors affect the urge to buy impulsively of young consumers in Hanoi city?
2. How do those factors affect the research subjects' urge to buy impulsively?
3. What recommendations can be offered to consumers and retail businesses?

2. Theoretical foundations, hypotheses and research models

2.1 The urge to buy impulsively

Impulsive purchases were first formally defined in DuPont's studies (1948-1965) as unplanned purchases, which are opposed to actual purchases that followed a designated shopping list. Rook (1987) defined that impulse buying occurs "when a consumer experiences a sudden, often strong, and persistent urge to buy something immediately". Parboteeah *et al.* (2009) considered an impulse purchase as a behavior performed subsequent to the interaction between a website and its users. This process has two characteristics: (1) the consumer feels a sudden and urgent desire or urge to purchase online, and (2) the consumer is ultimately tempted to make an online purchase. The most comprehensive definition belongs to Piron (1991): ***Impulsive buying is a purchase that is unplanned, the result of an exposure to a stimulus, and decided on the spot.*** From the above definition, four characteristics of impulsive buying behavior can be drawn: (1) Unplanned buying, (2) Exposure to stimuli, (3) Instantaneous behavior, (4) Post-purchase emotional reaction. Stern (1962) classified impulse buying into four distinct categories, namely pure impulse buying, recall, suggestion, and planned purchase. This contribution is quite important even in this day and age, as most research on impulse buying begins with this classification (Beatty & Ferrell, 1998; Rook, 1987).

Urge to buy impulsively is often referred to an irrational desire and can be seen as an intention to buy without any prior planning (Song *et al*., 2015). According to researchers, impulse buying is a psychological state that consumers experience when being exposed to an object in the shopping environment, such as a particular product or a brand. (Rook, 1987, Dholakia, 2000, Mohan *et al.,* 2013). This means that impulse buying will be a precursor to impulse buying behavior (Betty and Ferrell, 1998) and has been attested to be positively correlated with actual behavior (Hanzaee and Taherikia, 2010; Foroughiet, 2012; Mohan *et al*., 2013).

Although studies have demonstrated that impulse buying occurs after a consumer has an impulse to buy, the observation and quantification of this behavior face many obstacles. Parboteeah *et al.* (2009) showed in their experiment that when consumers are asked to recall an impulsive buying experience or when their actual behavior is monitored, study subjects often respond to a tendency that they feel is consistent with social norms. This will create biases in the study results. In addition, there is a possibility that consumers may not be aware that their shopping behavior is in a state of improvisation. Many studies have suggested impulse buying as a proxy of actual impulse buying behavior in the context of social and online commerce environments (Chen *et al.*, 2016, Parboteeah *et al.*, 2009, Xiang *et al.*, 2016). Therefore, the selection of urge to buy impulsively as representative of impulse buying behavior of consumers in the scope of the study is completely reasonable.

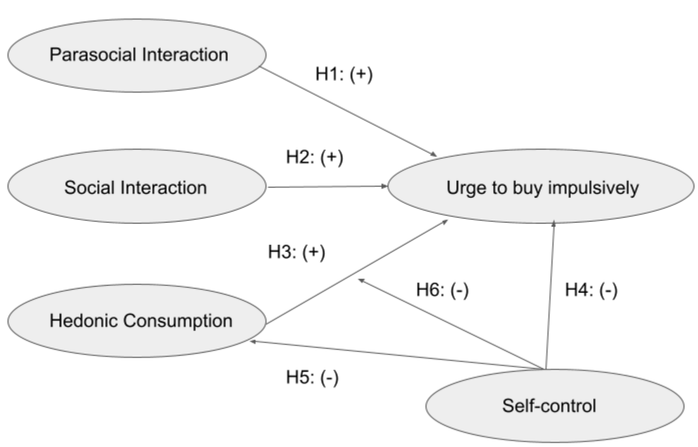
2.2 Social commerce

Social commerce, a phenomenon rooted in social media practices and Web 2.0 technology, has become a widely used tool for socializing and sharing commerce-related information. Social commerce is a combination of e-commerce and social media, of which essence is to conduct all commercial activities by exploiting social capital online on social media (Liang *et al.*, 2011). Social commerce involves many commercial activities that can assist consumers in pre-purchase product evaluation, purchasing decision-making and post-purchase behavior. In this study, the authors refer to social commerce as ***any commercial activity facilitated or conducted through social media platforms under the process of online shopping or interacting between sellers and their clients.*** Sellers optimize the usage of social media platforms to make profits, seek for potential customers, and consumers use social networking platforms to purchase, review and evaluate products.

According to Turban *et al*. (2016), the most significant difference between traditional e-commerce and social commerce lies in the purpose of each business using these platforms. For traditional e-commerce, businesses focus on releasing and distributing products to achieve sales goals. Meanwhile, the purpose of utilizing social commerce is in fact the core value of social media: generating social interactions to increase the transmission of information. Businesses operate on social commerce mainly in the form of approaching and interacting with their potential users. Instead of receiving information generated by the sellers on traditional e-commerce websites, product information is accessible to consumers through comments, feedback, negative or positive reviews of experienced users. This makes social commerce a trustworthy platform to make shopping decisions based on product feedback from people with whom they have established relationships (Lai, 2011). It can be implied that social commerce is characterized by its social and community aspects.

2.3 Research hypotheses

Figure 1. Proposed research model



Source: Author's own compilation

Parasocial Interaction

The influence of Parasocial interactions on consumer behavior has been well studied in the offline context. Parasocial interactions between viewers and TV characters have been shown to influence TV impulse purchases (Park & Lennon, 2006). The authors propose that the impact of Parasocial interaction on consumers' impulse buying behavior on social media is very strong because this interaction can easily be enhanced in the context of social media, as one important feature of social media is to provide users with many images of products and help them interact with many different users. Moreover, social media gives users the opportunity to feel like they are communicating with celebrities and experts. Compared to traditional media channels, where people can only see celebrities and experts on screen, social media can provide a platform for users to interact, thereby forming a relationship that is deemed as two-way but is actually one-way with KOLs. Thus, social media platforms witness a relatively stronger Parasocial interaction between users and KOLs than on TV shows, thereby promoting impulse shopping on this platform.

Therefore, the following hypothesis is proposed:

H_1: Parasocial interaction has a positive impact on Impulse buying tendency.

Social Interaction - E-Word of Mouth & Observational learning

Consumers tend to be influenced by their social interactions with others when making purchasing decisions (Godes *et al.*, 2004). They can learn from or be influenced by the opinions and the actual purchasing decisions of other individuals. According to Arndt (1967), the form of social interaction based on the perspective of others is *word of mouth*. The psychological and economic literature (Bandura, 1977; Bikhchandani *et al.*, 1998) defines the type of action or behavior-based social interaction as *observational learning*. The importance of social interaction has been widely recognized in the e-commerce environment (Hennig-Thurau *et al.* 2004; Park & Kim, 2008; Yap *et al.*, 2013; Lu *et al.*, 2014). Specifically, consumers expect to receive shopping recommendations from people with a high level of expertise and experience as products are becoming more technically complex (Godes *et al*. 2004). This type of information is often referred to as user-generated content and is considered a more reliable source of information than traditional media (Goh *et al.*, 2013).

Therefore, the following hypothesis is proposed:

H_2: Social interaction has a positive impact on Impulse buying tendency.

Hedonic consumption

One of consumers' high-level needs is the need for novelty, variety and surprise (Holbrook and Hirschman, 1982; Hirschman and Holbrook, 1982). Similarly, a number of studies have shown that impulsive purchases satisfy a number of consumers' emotional hedonic desires (Piron, 1991; Rook, 1987; Thompson *et al.*, 1990). In addition, the need for emotional support can also be met by the social interactions taking place during the shopping experience. For example, consumers report feeling ecstatic or energized after experiencing shopping activities in several qualitative studies (Cobb and Hoyer, 1986; Rook, 1987). These studies have partly implied a link between hedonic consumption motivation and impulse buying behavior. Thus, consumers who are motivated to shop based on hedonic needs can engage in shopping activities involving multi-sensory, imaginative, and emotional experiences. Hedonic consumption motivation may be associated with pleasure rather than completing a task (Holbrook and Hirschman, 1982).

Therefore, the following hypothesis is proposed:

H_3: Hedonic consumption has a positive impact on The urge to buy impulsively.

Self-control

Self-control is the tendency to modify or adjust one's own behavior in response to societal demands (Becherer and Richard, 1978). People with a high degree of self-control are willing to adjust their behavior to suit different situations. People with low self-control are less willing to please those around them, instead preferring to live up to their attitudes and values in different situations. Compared to people with low levels of self-control, people with high levels of self-control desire to control their own reactions to stimuli due to the need to appear rational and cautious under the scrutiny of others (Luo, 2005). Consumers often view impulse purchases as having no control over their momentary desires, which leads to negative post-purchase effects, guilt, and unfavorable evaluation of purchasing decisions (Dittmar and Drury, 2000; Rook, 1987; Trocchia and Janda, 2002). Thus, the degree of self-control seems to explain the contrasting interpersonal effects on impulse buying and novelty-seeking tendency when shopping.

Therefore, the following hypotheses are proposed:

H_4: Self-control has a negative impact on the Urge to buy impulsively.

H_5: Self-control has a negative impact on Hedonic consumption.

H_6: Self-control has a negative impact on the relationship between Hedonic consumption and the Urge to buy impulsively.

Urge to buy impulsively

Previous studies on impulse buying have considered the Urge to buy impulsively as a reasonable proxy for impulsive buying behavior. In fact, some researchers have found that the Urge to buy impulsively is a more effective and rational measure of impulsivity than actual impulsive behavior (McGoldrick *et al.*, 1999; Dutta *et al.*, 2003; Beatty & Ferrell, 1998). Therefore, according to the model of Parboteeah *et al.* (2009), in this study, the Urge to buy impulsively, not the actual impulse buying behavior itself, is considered the user's response to stimuli generated by social media. The Urge to buy impulsively is defined as "the state of desire experienced upon encountering an environmental stimulus" (Beatty & Ferrell, 1998). That is, an individual experiences a sudden and spontaneous urge to purchase a product when exposed to a stimulus, and this urge is the result of a state of mind created by the shopping environment (Rook, 1987).

3. Methodology

Initially, I applied the desk research method, investigated the data on the situation of e-commerce, social commerce and the current situation of social networks usage in Vietnam, as well as synthesized previous studies on impulse buying behavior. The collected documents are used as a reference to build a research model in the next step.

In the next step, I applied quantitative research methods, collected primary data through surveys (See Appendix 1) before compiling, analyzing and testing the research model using Excel and R softwares.

Finally, an integrated research method is used to make recommendations and solutions for retail businesses to conduct marketing activities effectively, as well as to raise consumers' awareness in making buying decisions in social commerce platforms from the research results obtained.

4. Research results

4.1 Descriptive statistical results of survey subjects

The study classifies survey participants according to the following criteria: age, gender, education level, total income and monthly allowance. The results of demographic statistics are shown in Table 4.1 below:

Table 1. Characteristics of survey participants

Characteristic	Value ranges	Number of observations	Ratio
Age	From 18 to 25 years old	241	88.93%
	Over 25-35 years old	30	11.07%
Gender	Male	60	22.14%
	Female	209	77.12%
	Other	2	0.74%
Highest academic level	High School Graduate	17	6.27%
	Vocational Intermediate	10	3.69%

	College/ University	233	85.98%
	Master/ Doctorate	7	2.58%
	Other	4	1.48%
Average gross income and allowance per month	Under 1 million VND	26	9.59%
	From 1 to 5 million VND	152	56.09%
	Over 5 – 10 million VND	53	19.56%
	Over 10 - 20 million VND	28	10.33%
	Over 20 million VND	12	4.43%

Source: Author's compilation

From the survey results, it can be seen that most of the respondents are young people between 18 and 25 years old, accounting for 88.93%. The number of respondents from over 25 to 35 years old accounted for only 11.07%. Regarding gender, out of 271 valid questionnaires, female respondents were 3 times more than their male counterparts with the rate of 77.12% and 22.14% respectively. The number of other genders respondents made up the lowest percentage, only 2 people, corresponding to 0.74%.

The classification of survey participants by education level shows that the majority of respondents are at College/ University, accounting for 85.98%, with 233 answers. The proportion of people at other education levels such as High School Graduate, Vocational

Intermediate, Master/ Doctorate answering the questionnaire is relatively low with 38 options, accounting for only 14.02%.

Average total income and allowance per month is divided into 5 levels: Under 1 million VND/month, From 1 to 5 million VND/month, Over 5 to 10 million VND/month, Over 10 to 20 million VND/month and Over 20 million VND/month. Since the survey respondents are mainly college/ university students, who are still studying full-time, incomes and allowances mostly range from 1 to 5 million VND/month, with a corresponding number of 152 people, which accounted for 56.09%. The two groups with incomes below 1 million VND/month and over 10 - 20 million VND/month account for 9.59% and 10.33% respectively. Meanwhile, only 4.43% of survey participants have an income of over 20 million VND/month.

Table 2. Characteristics of using social networks of surveyed subjects

Group	Value ranges/ buckets	Number of people	Ratio
Average time using social media in a day	Less than 1 hour	13	4.8%
	From 1 to 3 hours	131	48.3%
	Over 3 to 6 hours	91	33.6%
	Over 6 hours	36	13.3%
Number of KOLs followed on social media	Under 50 accounts	200	73.8%
	From 50 to 100 accounts	51	18.8%
	Over 100 to 200 accounts	13	4.8%

	Over 200 to 300 accounts	3	1.1%
	Over 300 to 500 accounts	2	0.7%
	Over 500 accounts	2	0.7%

Source: Author's compilation

The amount of time respondents spend on social networks is calculated based on the number of hours that each individual accesses the Internet and uses social media applications in a day. According to the survey, there are 13 out of 271 respondents with a duration of less than 1 hour, accounting for 4.8% of the total respondents. The percentage of respondents with the time of using social networks between 1 and 3 hours a day is relatively high (48.3%) with 131 individuals participating in the survey. The number of respondents with that from over 3 to 6 hours is 91 people, accounting for 33.6%. Meanwhile, there are 36 respondents using social networks for more than 6 hours, reaching 13.3%.

The number of KOLs accounts that survey respondents follow is mainly under 50 accounts, making up 73.8%, 4 times more than the number of survey participants following from 50 to 100 KOLs accounts. The remaining participants who follow over 200 KOLs accounts are minor, with only 7 people, accounting for only 2.5% of the total survey respondents.

4.2 Preliminary assessment results of the scale

The study uses the CFA (Confirmatory Factor Analysis) method to pre-determine the factor structure and verify the psychometric structure of a previously developed scale. To better interpret the factor loadings, I requested the standardized solution instead of the defaulted marker method. The following syntaxes in statistical R programming language will explain my choice better.

The syntaxes for the CFA method are as follows:

Figure 2. CFA method syntaxes

```
# I ran a one-factor CFA with items PAR1, PAR2, PAR3
# as indicators of PAR (para-social interaction)
PAR  <- ' f  =~ PAR1 + PAR2 + PAR3'
onefac3items_PAR <- cfa(PAR, data=CB_new)
# Marker method (default the estimation of the first item is 1, which is PAR1)
summary(onefac3items_PAR)
# Standardized method: to better interpret the factor loadings
summary(onefac3items_PAR, standardized=TRUE)
```

Source: Author's compilation

The first line is the model statement. Here I named my factor **f**, which is indicated by 3 items **`PAR1`**, **`PAR2`** and **`PAR3`** whose names come directly from the dataset. I stored the model into object **`PAR`**. The second line is where I specified that I wanted to run a confirmatory factor analysis using the **`cfa`** function, which is actually a wrapper for the **`lavaan`** function. The model to be estimated is **`PAR`** and the dataset to be used is **`CB_new`**; storing the output into object **`onefac3items_PAR`**. Finally, the upcoming lines request textual output for **`onefac3items_PAR`**, listing for example the estimator used, the number of free parameters, the test statistic, estimated means, loadings and variances with 2 different methods namely marker method and standardized method.

Table 3. Latent variable "**`PAR`**" CFA result

```
lavaan 0.6-9 ended normally after 19 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                         6

  Number of observations                           272

Model Test User Model:

  Test statistic                                 0.000
  Degrees of freedom                                 0

Parameter Estimates:
```

```
  Standard errors                                 Standard
  Information                                     Expected
  Information saturated (h1) model              Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  f =~
    PAR1              1.000                               0.315    0.449
    PAR2              2.231    0.445    5.015    0.000    0.703    0.704
    PAR3              1.727    0.337    5.124    0.000    0.544    0.678

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .PAR1              0.393    0.039   10.167    0.000    0.393    0.798
   .PAR2              0.504    0.104    4.863    0.000    0.504    0.505
   .PAR3              0.348    0.064    5.450    0.000    0.348    0.540
    f                 0.099    0.032    3.134    0.002    1.000    1.000
```

Source: Author’s compilation

Interpretation: For one standardized deviation in Parasocial interaction, item **PAR1, PAR2, PAR3** go up by 0.449, 0.704 and 0.678 standard deviation points respectively. The item **PAR2** has the highest absolute value which implies that this item has the strongest magnitude to the latent variable **PAR**, compared to the other two items.

Doing the same with the other latent variables, I had the results that all my items are in the range of [0.4;0.8] which indicates that my scales are fully able to explain my latent variables. (See Appendix 2)

4.3 Structural regression results

4.3.1 Method 1: Bootstrapping

In order to test the hypotheses $\mathbf{H_1}$ to $\mathbf{H_5}$, (the hypothesis $\mathbf{H_6}$ will be tested in the Moderation Analysis section), I ran a structural regression using the Bootstrapping method as follows.

Figure 3. Structural Regression

```
# I ran the SEM
ConsumerBehav_SEM <- '
# Measurement model
PAR  =~ PAR1 + PAR2 + PAR3
INT  =~ INT1 + INT2 + INT3
HED  =~ HED1 + HED2 + HED3
CON  =~ CON1 + CON2 + CON3
URG  =~ URG1 + URG2 + URG3

# Structural regressions
URG ~ PAR + INT + HED + CON
'

fitSEM <- sem(ConsumerBehav_SEM, data=CB_new)
summary(fitSEM, standardized=TRUE, fit.measures=TRUE)
```

Source: Author's compilation

Here, I specified my measurement model as the observed variables (eg. "`PAR1`", "`PAR2`", etc.) help measuring the latent variable (eg. "`PAR`"). Then, I tested how these exogenous latent variables namely "`PAR`" (parasocial interaction), "`INT`" (social interaction), "`HED`" (hedonic consumption), "`CON`" (self-control) affect the endogenous latent variable "`URG`" (urge to buy impulsively) using the function `sem`.

Table 4. Structural Regression results with Bootstrapping method

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
URG ~						
PAR	1.230	0.287	4.290	0.000	0.490	0.490
INT	-0.319	0.114	-2.797	0.005	-0.229	-0.229
HED	0.370	0.090	4.093	0.000	0.331	0.331
CON	0.211	0.151	1.395	0.163	0.105	0.105

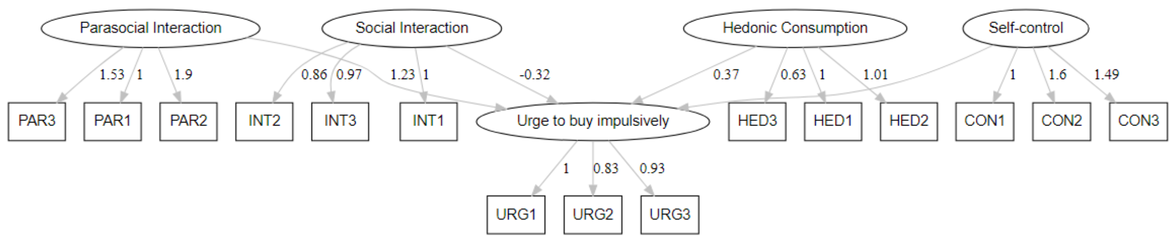
Source: Author's compilation

Interpretation

As can be seen from Table 4, **PAR** has the biggest impact on **URG** with $\beta = 1.230$, followed by **HED** with $\beta = 0.370$, and **CON** surprisingly has a positive impact on **URG** with $\beta = 0.211$. **INT**, unexpectedly has a negative impact on **URG** with $\beta = -0.319$.

The following path diagram shows the coefficients of each variable, but only the paths pass the significant threshold of **`alpha=0.05`**.

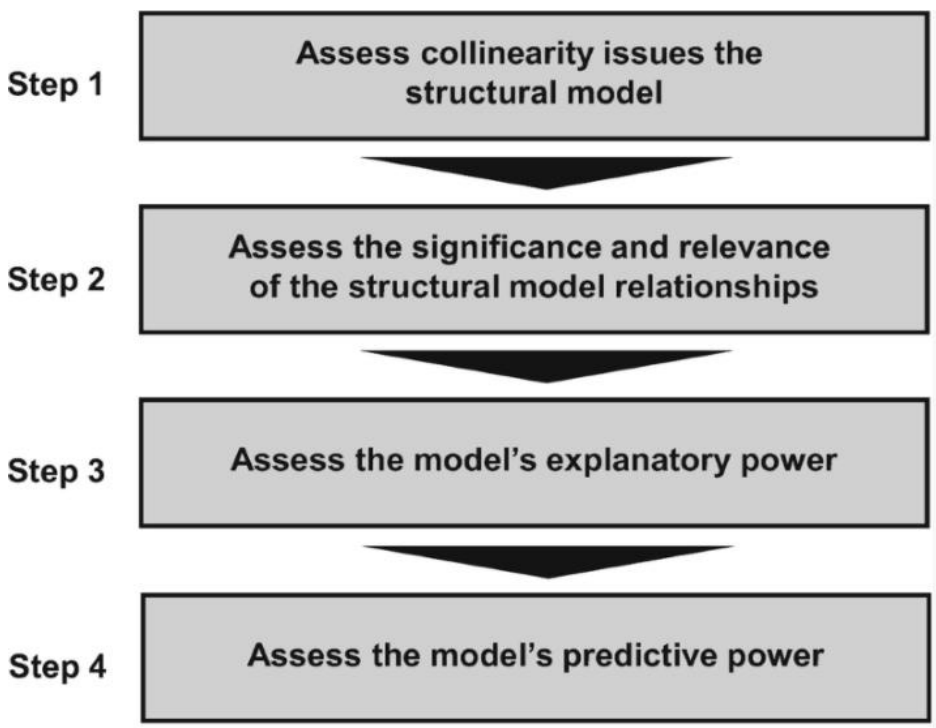
Figure 4. Path diagrams



Source: Author's compilation

4.3.2 Method 2: OLS

Figure 5. Structural Model Assessment Procedure



Source: Hair, Hult, Ringle, & Sarstedt, 2022.

Table 5. Rules of thumb for structural model assessment

Criterion	**Metrics and thresholds**

Collinearity	Critical collinearity issues likely occur if VIF ≥ 5 Collinearity issues are usually uncritical if VIF = 3–5 Collinearity is not a problematic issue if VIF < 3
Significance and relevance of the path coefficients	Apply bootstrapping to assess the significance of the path coefficients on the ground of *t*-values or confidence intervals Assess the magnitude of path coefficients Assess the *f2* values for each path and check that they follow the same rank order as the path coefficient magnitude
R2 value	R2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak. However, R2 values have to be interpreted in the context of the model and its complexity. Excessive R2 values indicate that the model overfits the data
PLSpredict	Focus on one key target construct in the analysis Set *k* = 10, assuming each subgroup meets the minimum required sample size Use ten repetitions Compare the RMSE (or the MAE) values produced by PLS-SEM with those produced by the LM for each indicator. Check if the PLS-SEM analysis (compared to the LM) yields lower prediction errors in terms of RMSE (or MAE) for all (high predictive power), the majority or the same number (medium predictive power), the

	minority (low predictive power), or none of the indicators (no predictive power) Use the DA approach to generate predictions in mediation models

Source: Hair, Hult, Ringle, & Sarstedt, 2022.

Estimating a sequence of regression equations yields structural model coefficients for relationships between constructs. Strong correlations of each set of predictor constructs might bias point estimates and standard errors, hence structural model regressions must be checked for potential collinearity issues (Sarstedt & Mooi, 2019). This procedure is similar to evaluating formative measurement models, except that the variance inflation factor (VIF) values are calculated using the construct scores of the predictor constructs in each regression in the structural model. Collinearity concerns across predictor constructs are more likely when VIF values are more than 5, however collinearity can also exist at lower VIF values of 3–5 (Becker, Ringle, Sarstedt, & Völckner, 2015; Mason & Perreault, 1991). When collinearity is an issue, creating higher-order structures is a common solution. That is why I need to assess this issue in the very first step.

Figure 6. VIF values for structural model

```
> # I inspected the structural model collinearity VIF
> summary_con_beh_est$vif_antecedents
urg :
  par   int   hed   con
1.190 1.144 1.219 1.176

hed :
con
  .
```

Source: Author’s compilation

As can be seen from Figure 6, all VIF values are clearly below the threshold of 5. Therefore, I can conclude that collinearity among predictor constructs is likely not a critical issue in the structural model, and I can continue examining the result report.

Next, in the structural model assessment procedure, I need to evaluate the relevance and significance of the structural paths. The results of the bootstrapping of structural paths can be accessed by inspecting the **`bootstrapped_paths`** element nested in the **`summary_boot_con_est`** object.

Figure 7. Path coefficient estimates, significance, and confidence intervals

```
> # I inspected the structural paths
> summary_boot_con_beh_est$bootstrapped_paths
               Original Est. Bootstrap Mean Bootstrap SD T Stat.
par  ->  urg           0.306          0.309        0.055   5.509
int  ->  urg           0.043          0.065        0.064   0.672
hed  ->  urg           0.276          0.269        0.061   4.555
con  ->  hed           0.311          0.328        0.071   4.382
con  ->  urg           0.128          0.129        0.067   1.895
               2.5% CI 97.5% CI
par  ->  urg     0.198    0.416
int  ->  urg    -0.074    0.177
hed  ->  urg     0.151    0.384
con  ->  hed     0.195    0.465
con  ->  urg    -0.007    0.255
```

Source: Author’s compilation

From Figure 7, Self-control (denoted by "**`con`**"), surprisingly, has a strong positive impact on Hedonic consumption ("**`hed`**") (0.311) and a low but still positive impact on the Urge to buy impulsively ("**`urg`**") (0.128). Parasocial interaction ("**`par`**") and Hedonic consumption ("**`hed`**") also has a relatively strong positive effect on the Urge to buy impulsively ("**`urg`**") (0.306 and 0.276 respectively). On the contrary, Social interaction ("**`int`**") exerts a much lower impact on the Urge to buy impulsively ("**`urg`**") as evidenced in path coefficient estimates of 0.043.

I also found that several relationships are significant, including three of the exogenous driver construct relationships (**`par -> urg, t = 5.509; hed -> urg, t = 4.555; con -> hed, t = 4.382; con -> urg, t = 1.895`**). At the same time, however, one exogenous driver relationship is not statistically significant (**`int -> urg, t = 0.672`**).

In Step 3 of the structural model assessment procedure, I needed to consider the model's explanatory power by analyzing the R-squared of the endogenous constructs and the f2 effect size of the predictor constructs. To start with, I needed to examine the R-squared values of the endogenous constructs. Hair (2022) also suggested that researchers can also assess how the removal of a selected predictor construct affects an endogenous construct's R^2 value. This metric is the f^2 effect size and is similar to the size of the path coefficients. More precisely, the rank order of the relevance of the predictor constructs in explaining a dependent construct in the structural model is often the same when comparing the size of the path coefficients and the f^2 effect sizes.

Figure 8. Path coefficient estimates, R2, adjusted R2 values and *f* 2 effect sizes

```
> # I inspected the model R-squared
> summary_con_beh_est$paths
          urg   hed
R^2     0.298 0.097
AdjR^2  0.287 0.093
par     0.306     .
int     0.043     .
hed     0.276     .
con     0.128 0.311
> # I inspected the effect sizes (##explain what is effect sizes)
> summary_con_beh_est$fSquare
      par   int   hed   con   urg
par 0.000 0.000 0.000 0.000 0.112
int 0.000 0.000 0.000 0.000 0.002
hed 0.000 0.000 0.000 0.000 0.093
con 0.000 0.000 0.107 0.000 0.026
urg 0.000 0.000 0.000 0.000 0.000
```

Source: Author's compilation

As can be seen from Figure 8, only "**hed**" has the explanatory power to the dependent "**urg**" but at very low percent, only 9.7%. Figure shows the f2 values for all combinations of endogenous constructs (represented by the columns) and corresponding exogenous (i.e., predictor) constructs (represented by the rows). "**par**" has a medium effect size of 0.112 on "**urg**"; "con" has a medium effect size of 0.107 on "**hed**". On the contrary, "**int**" is considered to have no effect on "**urg**" (0.002).

Step 4 in the structural model assessment procedure (See Figure 5) is the evaluation of the model's predictive power. To do so, we first have to generate the predictions using the `predict_pls()` function. Table lists this function's arguments.

Table 6. A list of arguments for the `predict_pls()` function

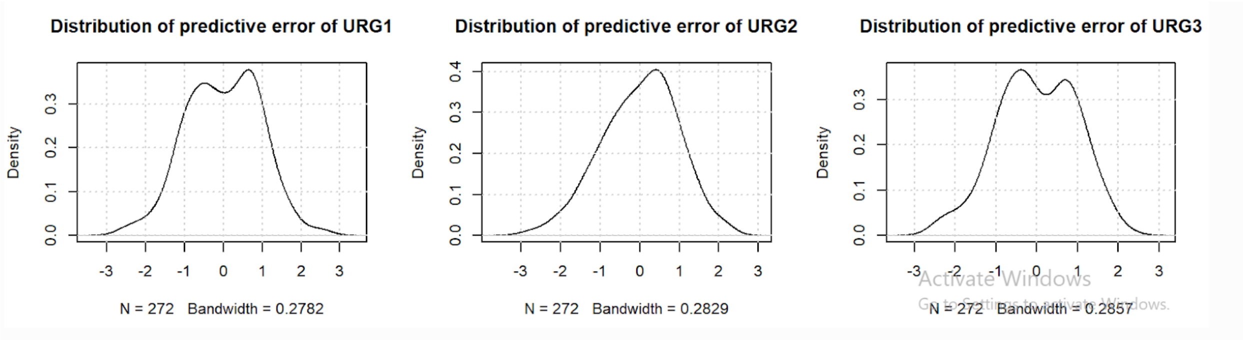
Argument	Value
`model`	The PLS model, which contains the structural and measurement models used to generate predictions
`technique`	The predict_DA option for direct antecedent (DA) approach or predict_EA for the earliest antecedent (EA) approach (predict_DA is set as default)
`noFolds`	Number of folds to employ in the *k*-fold process, NULL is default whereby leave-one-out cross-validation (LOOCV) is performed
`reps`	Number of replications to run (NULL is default whereby the k-fold cross-validation is performed once)
`cores`	The number of cores to use for parallel processing

Source: Hair, Hult, Ringle, & Sarstedt, 2022.

I ran the **PLS**predict procedure with $k = 10$ folds and ten repetitions and thus set `noFolds = 10`, and `reps = 10`. In addition, I used the `predict_DA` approach. Finally, I summarized the **PLS**predict model and assigned the output to the `sum_predict_con_beh_est` object.

The distributions of the prediction errors need to be assessed to decide the best metric for evaluating predictive power. If the prediction error is highly skewed, the MAE is a more appropriate metric than the RMSE. In order to assess the distribution of predictive error, I used the `plot()` function on the object `sum_predict_con_brh_est` and specified the **`indicator`** argument to the indicators of interest. I focused on the key outcome construct **`URG`** and evaluated the indicators **`URG1`**, **`URG2`** and **`URG3`**.

Figure 9. Distribution of prediction error for indicators **`URG1`**, **`URG2`** and **`URG3`**



Source: Author's compilation

The result in Figure shows that while the first plot of "**`URG1`**" and the third plot of "**`URG3`**" merely have no tail, the second plot of "**`URG2`**" has a short left tail and therefore, is slightly negatively skewed, the prediction error distributions are rather symmetric, especially for the second plot. I, consequently, used the RMSE for the assessment of prediction errors.

I can investigate the RMSE and MAE values by calling the **`sum_predict_con_beh_est`** object.

Figure 10. Prediction metrics for outcome construct items

```
PLS in-sample metrics:
      URG1  URG2  URG3  HED1  HED2  HED3
RMSE 0.916 0.936 0.950 0.860 0.912 0.730
MAE  0.762 0.762 0.786 0.646 0.738 0.513

PLS out-of-sample metrics:
      URG1  URG2  URG3  HED1  HED2  HED3
RMSE 0.947 0.963 0.972 0.870 0.924 0.741
MAE  0.786 0.781 0.807 0.653 0.747 0.520

LM in-sample metrics:
      URG1  URG2  URG3  HED1  HED2  HED3
RMSE 0.880 0.923 0.920 0.761 0.808 0.622
MAE  0.735 0.752 0.759 0.596 0.633 0.467

LM out-of-sample metrics:
      URG1  URG2  URG3  HED1  HED2  HED3
RMSE 0.942 0.990 0.975 0.813 0.872 0.675
MAE  0.785 0.803 0.801 0.637 0.683 0.501
```

Source: Author's compilation

Analyzing the **URG** construct's indicators (See Figure 10), we find that the PLS path model has lower out-of-sample predictive error (RMSE) compared to the naïve LM model benchmark for two indicators (sections: **PLS out-of-sample** metrics and **LM out-of-sample metrics**): **URG2** (PLS, 0.963; LM, 0.990), and **URG3** (PLS, 0.972; LM, 0.975, except for the indicator **URG1** (PLS, 0.947; LM, 0.942). Accordingly, I could conclude that the model has a pretty high predictive power.

4.3.3 Moderation analysis result

The term "moderation" refers to a situation in which the relationship between two constructs is not constant and is influenced by the values of a third variable known as the moderator variable. The strength, or even the direction, of a relationship between two constructs in a model is changed by the moderator variable (or construct). Here, I want to test how the latent variable "**CON**" (referred to self-control) can affect the relationship between the variable "**HED**" (hedonic consumption) and the variable "**URG**" (urge to buy impulsively) as specified in the hypotheses section.

Chin, Marcolin, and Newsted's (2003) two-stage technique excels in terms of parameter recovery and statistical power, according to simulation studies (e.g., Becker, Ringle, & Sarstedt, 2018; Henseler & Chin, 2010). Furthermore, because it is the only strategy applicable when the exogenous construct or the moderator is set formatively, this approach provides a lot of flexibility.

The two-stage approach is based on the explicit use of PLS-SEM's strength in estimating latent variable scores (Becker et al., 2018; Rigdon, Ringle, & Sarstedt, 2010). The two stages are as follows:

- Stage 1: To obtain the scores of the latent variables, the main effect model (i.e., without the interaction term) is estimated. These will be saved for Stage 2 analysis.
- Stage 2: The exogenous construct and moderator variable latent variable scores from Stage 1 are compounded to form a single item that is used to test the interaction term. All other latent variables are represented using single items from their Stage 1 latent variable scores.

Becker et al. (2018) investigated the impact of various data treatment techniques on the performance of the two-stage approach. The findings suggest that standardizing the indicator data and the interaction term, rather than working with unstandardized or mean-centered data, improves parameter recovery. By removing the variable's mean from each observation and dividing the result by the variable's standard error, standardization is achieved. (Sarstedt & Mooi, 2019). Therefore, I applied the two-stage approach with standardized data when conducting moderator analysis.

Table 7. Bootstrapping results of structural model

Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	2.5% CI	97.5% CI
par -> urg	0.295	0.300	0.056	5.224	0.189	0.412
int -> urg	0.049	0.068	0.063	0.780	-0.056	0.184
hed -> urg	0.283	0.278	0.058	4.853	0.169	0.389
con -> hed	0.311	0.322	0.070	4.455	0.181	0.450
con -> urg	0.133	0.129	0.064	2.070	-0.003	0.255
hed*con -> urg	0.059	0.063	0.051	1.152	-0.026	0.170

Source: Author’s compilation

<u>Interpretation</u>

As can be seen in the table above, the interaction term (**`hed*con`**) has a positive effect on **`urg`** of **0.059**, whereas the simple effect of **`hed`** on **`urg`** is **0.287**. Jointly, these results suggest that the relationship between **`hed`** and **`urg`** is **0.287** for an average level of self-control level. For higher levels of self-control (i.e., for every standard deviation unit increase of **`con`**), the relationship between **`hed`** and **`urg`** increases by the size of the interaction term (i.e., 0.287 − 0.059 = **0.228**). On the contrary, for lower levels of self-control (i.e., for every standard deviation unit decrease of **`con`**), the relationship between **`hed`** and **`urg`** decreases by the size of the interaction term (i.e., 0.287 − (−0.059) = **0.346**).

5. Discussion and implications

5.1 Discussion

The research results indicate the level and role of each factor contributing to the formation of the urge to buy impulsively of consumers in social commerce. Here I mainly use the results of the OLS SEM instead of the Bootstrapping method for implications as I have proved that the second approach has no issue of collinearity usually met with structural models, not to mention it has quite high predictive power.

The OLS SEM suggested that Parasocial interaction and Hedonic consumption can have a relatively strong impact on the Urge to buy impulsively, while Social interaction between buyers and sellers has no statistically significant impact on the temptation to buy impulsively. Self-control, surprisingly, cannot help consumers "control" their impulse buying tendency but somehow, positively impact the temptation.

5.2 Implications

5.2.1 Implications for consumers

Solutions to reduce the impact of Parasocial interaction (the impact of KOLs) on the Urge to buy impulsively

As can be seen from the research results, the more interactions a consumer has with an attractive person on social media, the more likely he will buy the products promoted by this KOL even if he does not plan to purchase beforehand. Therefore, social media users need to remain alert when accessing information on these platforms. It is necessary to distinguish the difference between advertising information and objective information (especially posts that seem to be objective product reviews but are in fact paid by the business retailers). Another thing to consider is to maintain a critical mindset towards the flow of information consumers on social media, as well as perceive the fact that comparing yourself to others is unreasonable and avoid buying recommended products with the desire to bridge the gap between consumers and KOLs.

Solutions to reduce the impact of Hedonic Consumption

Impulsiveness is an integral part of the human personality, but this does not suggest that consumers cannot control this impulsive tendency. If consumers can clearly identify the impact of this negative personality on their irrational purchasing decisions, this instinct can be completely suppressed. Some effective methods in the short term can be mentioned as (1) Setting a time to consider the purchase decision. Two of the four factors characterizing Impulsiveness, according to Whiteside and Lynam (2001) are a sense of urgency, lack of perseverance and thereby lead to the urge to buy goods immediately to satisfy the search of novelty. (2) Designing a spending plan, set aside a separate budget for hedonic shopping. In addition, in the long term, consumers should seriously consider learning to manage their personal finances and be determined to change their impulse buying habits.

5.2.2 Implications for retail businesses

Solutions to promote Parasocial interaction between KOLs and consumers

The expertise of the brand's representative should be a top priority. Businesses should utilize KOLs who have knowledge and experience with their product line, because usually a KOL specializing in a certain field will have experience sharing personal views about that product line, creating a sense of objectivity to the content they post. Posts may also include personal information, such as daily activities to increase followers' similarity to KOLs. Vivid personal narrative articles can stimulate a positive attitude of the reader, generate empathy, and capture the reader's attention more easily. Moreover, aesthetic taste has also been shown to be effective in increasing engagement. In addition, trust has also been shown to have a certain effect in increasing Parasocial interactions. Once the consumer trusts the KOL, the intention to buy the product recommended by that KOL will be formed quickly (Floh and Madlberger, 2013). Trust in a KOL will be formed and strengthened through articles introducing products with high quality, objectively and closely related to the potential needs of consumers.

6. Conclusion

The research has made certain contributions on both scientific and practical aspects. Scientifically, research contributes four basic findings. Firstly, it has constructed and proved the appropriateness of the research model in order to evaluate the impulse buying urge of young people in Hanoi city based on the integration of previous researches and related theories. Secondly, the research has verified the reliability and relevance of the new scale through experimental research data. Thirdly, by analyzing empirical data, the study has successfully evaluated different levels of factors that affect the Urge to buy impulsively through social networks. Finally, the study can be a practical reference for future researchers to establish models evaluating long-term effects of this impulse buying behavior. In terms of practice, the results also provide useful suggestions for individuals or businesses doing e-commerce, especially through social networking platforms in Vietnam.

However, certain limitations still remain within the scope of the research as the observational sample is relatively modest and not highly representative, which results in failures in testing some of the initial hypotheses. The dependent variable Urge to buy impulsively is an appropriate representation but cannot completely replace Impulsive buying behavior for its inability to guarantee the execution of the actual behavior. Moreover, some important variables have been omitted from the research model, therefore, further researchers are highly encouraged to make amends to the existing research model in order to enhance its practicality.