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Chapter: Human Capital, Entrepreneurial Dynamics, and Consumer Behavior as Investment in Human Development

Influence of Customer's Self-comments Versus Others' Comments on the Customer's Subsequent Repurchase Behaviour

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Annotation. User-generated content (UGC) is an important type of customer feedback that provides reference for a future customer's purchase decision and acts as a guideline for corporate marketing strategies. This research verifies the influence of a customer's previous self-comments and others' comments on the former's future repurchasing behavior. To obtain observations on customers' real purchases, we cooperate with one company that sells its product through the Amazon platform to get transaction data and collect comments and ratings directly from the platform. Excluding missing data, in the first round of data collection there are 1,366 transactions from this company's focal products during the years 2019 to 2022. After following up on any repeat purchase behavior from those customers in the next year, final repurchase orders make up 139 repeat transactions. This research uses the Large Language Model (LLM) to transform customers' text comments by natural language processing (NLP) into a score. Empirical results reveal that customers are both concerned about their own previous experiences and others' comments and focus more on the text content rather than the title of the comments. For the moderating effect of product types, the more negative the contents of others' comments and previous comments on utilitarian products are, the less a customer will repurchase from the brand. One interesting finding is that when making repurchase decisions, others' comments outweigh a customer's self-comments.

Keywords: customer's repurchase behavior, user-generated content (UGC), customer's self-comments, others' comments, ratings.

JEL classification: M16, M30, M31, O30.

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Introduction

Research Background

Electronic commerce has been growing rapidly in recent years via a significant climb in online sales, whereas traditional retail sales are declining. As Digital Commerce 360 notes, online sales exhibited record-breaking growth in 2020 of 31.8% year-on-year, or two times bigger than their growth in 2019. During the onset of the COVID-19 pandemic in 2020, many brick-and-mortar stores were forced to close, thus spurring the big rise in online shopping. Indeed, small retailers that used to do business in a traditional way are now struggling from facing a large number of available products and architectures (Aulkemeier *et al.,* 2016). By embracing omnichannel retailing, small- and medium-size enterprises (SMEs) are aiming to transform their business and adapt to global changes in the digital era (Lo, Nguyen, 2024).

Research Motivations

There are two main routes that SMEs can choose to outsource e-commerce. They can rely on large providers that sell all kinds of products such as Amazon and eBay or on smaller specialized online marketplaces, like Zalando for fashion and Sephora for beauty products. Selling products on online platforms assist SMEs in trading across regions and countries in a relatively effortless way and at attracting even more potential customers (Lo, Chien, 2024). Another important aspect is that online platforms often provide wide-ranging complementary services that are particularly attractive and beneficial for SMEs that lack resources, including logistics, customer services, and data analytics. On the positive side, SMEs can lower their overall operating costs by reducing labor and other costs in many areas. Moreover, slicker and more streamlined operations improve work efficiency and increase productivity. With its speed of growth from year to year, as of 2021 Amazon is now the world's largest Internet company, online marketplace, AI assistant provider, cloud computing platform, and live-streaming service as measured by revenue and market share.

Based on its successful platform, Amazon has opened its business to third-party retailers, most of which are SMEs, in order to extend its market share. On Amazon, a seller can choose whether to have a 1st-party relationship or a 3rd-party relationship. In the former, sellers act as wholesalers to send inventory to Amazon. They lose the main control of their products, but cooperating with Amazon could increase brand trust on account of Amazon's powerful credibility. As for 3rd-party relationships, sellers sell products directly to consumers via the Amazon marketplace, acting as retailers and independent operators. All logistics services and after-sales services are conducted by 3rd-party sellers, giving SMEs more self-control. For example, SMEs can maintain control of their products and pricing, enabling them to price in real-time against competitors. From Amazon's estimations, its 3rd-party sellers account for around 60% of all products on its platform. In 2020, approximately US$80.5 billion profit was earned by 3rd-party seller services, increasing nearly 50% over 2019. After COVID-19 spread throughout the world in 2020, offline consumption fell greatly, with the result that over 200,000 SMEs started selling their products on Amazon.

Amazon owns a wide range of 3rd-party sellers that compete with each other on its platform over price strategy and customer loyalty. Amazon's concept is a price model based on keeping prices as low as possible for all buyers. Knowing that Amazon promises its customers that they could buy products at the lowest price helps many consumers to be loyal to Amazon and exhibit relatively good trust toward it. The next step for SMEs is typically to build their own relationships with their customers and figure out a way to keep and maintain loyal customers.

Research Purposes

Using online techniques to promote products and services in order to attract more customers internationally, SMEs are now able to expand company or product information, gain potential customers, and maintain relationships with loyal customers, thus improving customer management systems via Internet platforms. How to attract and manage online customers and increase customer loyalty and attract repurchase customers are important for companies that sell products over online platforms. Operating in the Internet of Things (IoT) era, SMEs must adopt an online platform and form channels between service providers and consumers (Lo & Campos, 2018). Online user comments on social media platforms provide valuable feedback and evaluation functions (Jiang, 2024; Rostamzadeh *et al.,* 2024). Companies should monitor their interaction with consumers and share information among consumers more systematically (Lo *et al.,* 2020; Yu *et al.,* 2017).

Customers communicate with each other on digital platforms through online comments. Most customers make a purchase decision after referencing previous customers' comments, which are terms user-generated content (UGC) (Vollero *et al.,* 2023). For most companies, UGC thus provides valuable information for companies to understand customers' options. The first objective of this study is to explore how other customers' comments influence a customer's purchasing behavior.

Companies naturally hope to attract loyal customers and not just one-time transactions. Therefore, repurchasing behaviors are especially essential and a challenge for firms to analyze. Our second research objective is to examine repurchase customers and how their own previous shopping experiences in a company or brand influence their future shopping behavior. Walther *et al.* (2009) noted self-generated versus other-generated statements, which are both important communication outlets for users. Based on this statement, this research examines the influence of a customer's previous self-comments and others' comments on the customer's repurchasing behavior.

Most related literature focuses on purchase intention or perception data (Costa, Pillo, 2024; Lo *et al.,* 2020; Nicolescu, Ripa, 2024). This research highlights real purchase behavior with comments and ratings written on the Amazon platform, constituting one of the major contributions of this paper. Furthermore, when customers make a repurchasing decision, this research tries to evaluate whether a customer's self-comments on previous shopping experiences or other customers' comments will be a bigger factor in such a decision.

In summary, this research empirically analyzes peer and self-comments provided by customers and their influences on any subsequent repurchase behavior through data extracted from Amazon's platform. Section 2 discusses the fundamental theory for formulating the hypotheses. Section 3 explains the research methodology, data collection and analysis, and variable construction for empirical analysis. Section 4 presents our results and evaluates the findings. Section 5 offers a conclusion, discussion, implications, and contributions for companies in the digital era.

1. Literature Review

1.1 International Expansion in the Digital Era of SMEs

International business theories have presented different approaches to internationalization that mainly encompass large companies. However, the use of digital technologies also creates new opportunities for small- to medium-size enterprises (SMEs) to expand their businesses and be successful in foreign markets (Lo, Chien, 2024). International businesses are experiencing increasing growth in the global economy via the fast development of e-commerce. Furthermore, entrepreneurs are more comfortable with technology and more reactive to innovations, making them engage outside of domestic markets and thereby benefit from international trade without limited resources (Yoo *et al.,* 2012). The reason why entrepreneurs are so successful in this rapid growth era can be credited to communication technology (Ziyae *et al.,* 2014). Therefore, the emergence of born-digital companies is mainly driven by their digitalization. Born-digital companies leverage digitalization across their value chains in the internationalization path (Vadana *et al.,* 2021). Facing uncertain and challenging environments, many businesses have to alter their strategic planning and decision-making process with efficiency and precision in order to stay ahead of intense competition.

In the early stages of internationalization, SMEs lack both market knowledge and experiential knowledge. First, they generally choose is exporting products through agents, and this allows for low business risk and low commitment, but high flexibility. After being involved in exporting activities, their knowledge of entering global markets rises gradually. Thus, the increase in export activities allows SMEs to commit more resources to international markets. Second, SMEs accumulate market-specific knowledge with considerable experience and well-developed international institutional arrangements, which help them continue to export extensively without agents - namely, wholly-owned sales. Nevertheless, exporting incurs demand uncertainty, a greater number of sellers, and more barriers to entry. Nguyen (2012) stated that demand uncertainty is typically resolved after SMEs enter a market and learn that they cannot gain profit. The venture ends in failure and exit from the market. Nonetheless, SMEs always seek new channels that can create sales and profits to maintain company values.

We now provide some successful cases showcasing how SMEs leverage online platforms for international expansion. The first case is 3:35 PM Milk Tea, founded by Mr. Chiu in 1991 from Taiwan. Its product are on the Amazon platform and explored by North American, European, and Asia buyers. The second case is OKtea, founded in 2009 in Taiwan, which sells bubble milk teas, milk teas, and different kinds of teas all over the world through Rakuten (from Japan), Shopee (from Singapore), Coupang (from South Korea), Amazon, and company website. The third case is HANYU Food International Corporation, founded by Mr. Yang in 1986, which is a food processing company that sells products through Shopee, MOMO, PCHome, and Buy 123 platforms. These cases offer valuable real-world perspectives for SMEs under a resource restriction that are still successfully expanding onto the international market and fostering customer loyalty through Internet platforms.

1.2 Customer Repurchasing Behavior on Digital Online Platforms

Customer relationship management (CRM) is a step in which businesses can gain insight into their customers' purchase behavior and thereby modify their working operations to ensure that all customers are services in the best and most optimal way. This technology helps companies manage their relationships and interactions with customers who stay connected with them and further improve their profitability.

Technological revolutions around the world have led to another new step for businesses that is called service-oriented architecture (SOA). SOA is an architectural style that supports the integration of business processes as linked services that may be accessed when needed over a network (Mehta *et al.,* 2006). Service orientation can be described as a way of thinking in terms of services and service-based development as well as the outcomes of services. SOA enables internal and external systems to interact and integrate with each other to grow with changes and varying needs. By allowing services to communicate, companies can accomplish more complicated tasks requiring the functionality of multiple services (Karlsson, 2018). SOA also plays an important role in electronic commerce to fulfill plenty of business requirements and implement business processes.

There are many aspects that can influence what customers want and pursue and will react to during their decision-making procedure, such as past shopping habits, purchasing behavior, brands they prefer (Abbas, 2023), or retailers they trust. A purchase decision is a result of a combination of these factors. Entrepreneurs get the chance to develop a new strategy by recognizing and understanding what factors influence changes in customers' purchasing behavior. Consumer buying behavior implies actions that customers take online or offline before purchasing a product or service. These processes may include consulting search engines, engaging with social media posts, or a variety of other actions. It is valuable for marketers to understand these processes, because they help businesses better tailor their marketing strategy to attract more potential customers or regain lost customers.

In an Internet environment, online customers' emotional and cognitive reactions are very important, since they are all required in the context of online shopping. How to retain customers is a critical task for a successful business. Along with the increase in the amount of online shopping, this market has improved by leaps and bounds and is now more familiar to customers, turning it into a mature market. Every company hopes that all customers will visit their website or store more than just once. Given this situation, companies know how important it is to keep their customers satisfied and create a positive relationship with companies or brands.

Electronic word-of-mouth (E-WOM) provides important clues on customers' previous purchasing experiences (Lee, Koo, 2012; Gallardo-Garcia *et al.,* 2024; Kerse, 2024). From the perspective of marketing, although the cost of retaining old customers is five times higher than developing new customers, nowadays the main task of e-commerce businesses has been transformed from attracting new customers and improving the growth rate of customers to enhancing repurchase intention. Lee *et al.* (2008) suggested that a growth rate of 5% in customer retention could raise profit anywhere from 25% to 75%. For an organization to maintain its profitability stream, it must develop strategies that advance customer retention (Almohaimmeed, 2019). Therefore, it is necessary to identify the influencing factors of online customers' repurchase intention, thus properly managing a firm's relationships with its loyal customers.

1.3 Hypotheses' Development

Does a previous shopping experience really influence customers' future repurchasing behavior? The emotional reaction of customers in the Internet environment is regarded as the most crucial factor that influences their repurchase intention and leads us to this in-depth exploration. In general, this research argues that if customers are willing to make a second purchase through online shopping, then they are somehow satisfied with the online shopping experience and the products they received, feel wise about using online shopping, and agree to the use of online shopping in order to their demands. Based on the above studies, this research hypothesizes that one's own past experience impacts repurchase behavior.

H1-1: A customer's self-previous overall comments influence the customer's repurchase behavior.

By the same token, in each comment, the content part covers more cues of satisfaction with products or services than the comment's title. Because of the diversity of online consumer comment formats, comments can range from simple recommendations with simple evaluative texts to attribute-specific comments with factual keywords. More sufficient information in the comments provides more understandable and believable recommendations (Abumallohet *et al.,* 2024). By this logic and reasoning, this research proposes the following hypothesis.

H1-2: The content of a customer's self-previous comments has a greater effect on the customer's repurchase behavior than the title.

The stronger the negative emotion expressed in the content is, the more negative effects there are that result in restraining one's willingness to purchase from the same brand or company again. In a similar way, customers tend to not repeat a purchasing behavior when their past experience is negative, giving evidence that the content of their previous comments includes depressed and frustrated words. This suggests the following hypothesis.

H1-3: The negative content of a customer's self-previous comments has a stronger negative effect on the customer's repurchase behavior.

This research places a strong weight on one's own previous experiences, and negative impressions place a hold on one's willingness to generate repeat purchase behavior. While customer dissatisfaction is measured in terms of the fulfillment of the gap between expectation and actual experience, a higher expectation will result in higher disappointment. However, during the purchasing process, many consumers are pleased to evaluate product attribute-value information and recommendations from numerous information sources. Indeed, satisfied customers do not always retain the same brand, and unsatisfied customers do not always switch to another brand. No matter what, customer churn happens repeatedly in an e-business context all the time (Ke *et al.,* 2021). From an experienced customer's view, searching and shifting to alternatives bring the risk of selecting another unfamiliar brand. The underlying switching cost becomes an impediment for unsatisfied consumers to churn and shift to another brand (Ke *et al.,* 2021), resulting in giving a second chance to the previous brand.

The majority of the literature has shown that customer reviews are based more on the WOM theoretical stream. Internet shoppers could share information and shopping experiences with those who have the same interest online. Many consumers ask friends and family for recommendations before buying. In this case, consumers are likely to refer to others' experiences of the product for decision-making. Even though their previous experiences may be unpleasant, customers will open their arms to give a second chance rather than turn to an unfamiliar product. Therefore, this research proposes the following hypothesis from the view of concern about others' comments.

H2-1: Other customers' overall comments influence a customer's repurchase behavior.

Chan *et al.* (2015) noted in the Internet era that customers can have peer-to-peer and peer-to-firm interactions. On the Amazon platform, customers can communicate with sellers via comments and ratings. Taking a further step, when customers leave comments, they provide information to future customers for references. As indicated in previous sections, higher word counts represent stronger helpfulness and are accompanied by greater relevance, reliability, understandability, and sufficiency.

H2-2: The content of other customers' comments has a greater effect on a customer's repurchase behavior than the title.

In the minds of basic consumers, an increase in negative comments raises the riskiness of the product and decreases the desire of buying it. It goes without saying that negative comments definitely are an important factor to take into account since comments are typically written by experienced consumers and can be counted as credible reviews. Negative comments can easily be used to observe how many people have already bought the product and how many of them are unsatisfied with the product. Studies showed that more experienced reviewers enhance the linear impact on review helpfulness (Agnihotri, Bhattacharya, 2016). When viewing their comments, one is less likely to encounter fake ones, and the sentiments are a true reflection of their emotion. Thus, we put forward that negative contents have a stronger negative influence on one's willingness to repeat a purchase behavior.

H2-3: The negative content of other customers' comments has a stronger negative effect on a customer's repurchase behavior.

1.4 Moderating Effect of Product Types

Different types of products (such as utilitarian or hedonic) result in different customer purchase behaviors (Shao, Li, 2021; Sameeni *et al.,* 2022). In the context of discussing customer repurchase behavior, we also take two product types into consideration and whether or not they moderate the relationship between customers' previous comments and customer repurchase behavior.

H3-1: The relationship between customers' self-previous overall comments and a customer's repurchase behavior is moderated by product types.

As utilitarian products' main target is to meet demands and needs (Shao, Li, 2021), a negative impression does not diminish as time goes by. A bad experience does make one lose confidence in the products or services and lose interest in them. There is more than literal truth to the saying that "you never get a second chance to make a first impression". Thus, on the basis of the previous hypothesis, we suggest that the content plays a more vital role than the title in each comment, and the moderator leads to the next hypothesis.

H3-2: For utilitarian products, the content of customers' self-previous comments has a greater effect on a customer's repurchase behavior than hedonic products.

Based on the result of a previous study, when customers are pursuing hedonic goals, negative ratings are more vulnerable to being discounted than positive ratings. Therefore, consumers may refute such negative ratings of hedonic products (Chu *et al.,* 2015). As a consequence, we suggest that the negative content of utilitarian products has a stronger influence than hedonic products.

H3-3: For utilitarian products, the negative content of customers' self-previous comments has a stronger negative effect on a customer's repurchase behavior than hedonic products.

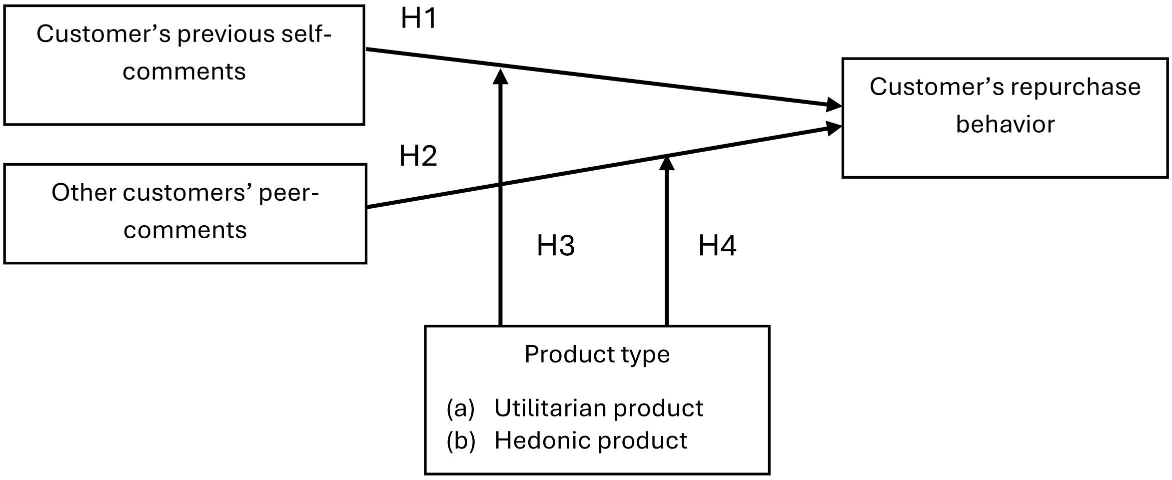
Two types of products give rise to different circumstances of aspects of customer repurchase behavior. Hedonic products provide individuals with unique experiences that are incomparable to other products (Shao, Li, 2021). Utilitarian products are often related to people's basic needs, have more alignable attributes, and are more easily involved in comparisons with other products (Shao, Li, 2021). Accordingly, as stated in the previous hypotheses, we come up with the following.

H4-1: The relationship between other customers' overall comments and a customer's repurchase behavior is moderated by product types.

When viewing other customers' viewpoints, the word depth of the comments makes an important point to compare with one's own previous experience. The more words there are, the more detailed is the actual usage feeling that is shared in the comments for everyone to take as reference. As described, utilitarian products' focal point is to fulfill a task or mission, and information in the content most likely contains others' viewpoints on the degree of accomplishing the functional tasks.

H4-2: For utilitarian products, the content of other customers' comments has a greater effect on a customer's repurchase behavior than hedonic products.

The literature is always curious about what other customers think. If one's previous experience was negative, then what might the reason be that other customers would give the same product a diametrically opposed comment? Online consumers consider different comments on products they are interested in to grasp other consumers' perceptions of them and thus reduce product-related uncertainty.



Source: This study.

Figure 1. **Research Framework**

Hedonic products hinge on one's preference for brands, taste, or appearance. Thus, the first impression of products or brands will not easily be dismissed by others. However, peers can influence utilitarian products whose goals are to meet basic needs. Thus, we suggest that others' negative contents of utilitarian products have a stronger negative effect than hedonic products. *Figure 1* illustrates the research framework.

H4-3: For utilitarian products, the negative content of other customers' comments has a stronger negative effect on a customer's repurchase behavior than hedonic products.

2. Methodology

2.1 Data and Sample

In this research we use an empirical approach to gather real transaction data from company A. Capturing real transactions is one advantage of an empirical study to test more in-depth and to evaluate the entire process that a customer has gone through. It is more reliable, because it represents real data and not just perception data. Empirical studies do require a lot more effort to collect customer transactions in a company and collaborate those transactions with Amazon's online comments. Efforts are made to collect data from different sources to avoid possible common-method biases.

2.2 Raw Transaction Data from Company A

The records of orders are an important asset of every company. All companies possess a database to keep all order records, for marketing, inventory management, providing experiences that customers will cherish, and so on. Customer data management is the organized storage and retrieval of customer data so that it is usable for business. With these records, a company can easily do customer data analytics to predict customers' behavior so that it can make decisions accordingly.

This research needs to match a customer's comments on Amazon and the order records from company A to clarify who bought the product and who left the comment and to further figure out among them who made a second or more purchase action. First, we use the customer ID and customer name of the comments we downloaded from Amazon free downloader to match with the order records from company A. Based on reviewers' names and IDs, the items they bought, and the time of the comment, we find out which matches the order records. Second, we mark the customer ID of those who have bought the product and left a comment to check if they have made a second purchase. The reason for using customer IDs rather than customers' name is to make sure that they use the same account to do the second purchase. There is no need to insist that the receiver should be the same person, although the names may be more repetitive in nature.

To obtain the utilitarian and hedonic products from company A, the time interval of the research sample spans from 2017 to 2022. We need to follow up on their subsequent repurchase behavior over those products. Utilitarian products in company A are household furniture. When customers purchase furniture, they are concerned more about product utility. Hedonic products, consumed for happiness purposes, are desirable objects that bring pleasure and enjoyment and tend to be impulse purchases. For analysis, we choose sports equipment. This amounts to a total of 2,897 orders from company A. The next step is bases on customer ID to identify whether customers made a second purchase over this brand and gave a comment on their first purchase experience between 2017 to 2022 on Amazon's platform. After removing those who did not give comments or did not repurchase during those time periods, the final sample consists of 139 orders. The final samples are based on combining the record of the orders from 2017 to 2022 from company A and the comments left on Amazon within this time to find those orders that match the condition.

Table 1. Sample descriptions in empirical analysis

Product type	Product name
Hedonic Product	Adjustable Dumbbell Set (40 Pounds)
Hedonic Product	Bench Press Rack for Full Body Strength Workout
Hedonic Product	Multifunctional Adjustable Utility Weight Bench for Full Body Workout
Utilitarian Product	Multifunctional Book and Toy Storage Cabinet
Utilitarian Product	2-Cube/4-Cube/6-Cube Sturdy Room Organizer
Utilitarian Product	4/6/8 Cube Room Organizer Shelf, Storage Divider, Book Cabinets

Source: this study.

We take fitness equipment as a hedonic product in this study. The reasons why people exercise are to enhance or maintain physical fitness and overall health and wellness. We find that sometimes people exercise not to lose weight, but to improve mental health by reducing anxiety, depression, and negative mood and improving self-esteem and cognitive function. Exercise briefly enhances one's mood and puts minds in a more positive state, providing one with a sense of accomplishment that boosts confidence. Thus, we can say that doing exercise brings enjoyment and accomplishment. It is all about an emotional reaction and can be influenced by one's preference. Although detailed specifications could be shown on the website in the area of product information, its perceptions and opinions after actual use vary from person to person. It is hard to base analysis on others' experiences to define one's viewpoints. We retrieve online reviews for six products, where *Table 1* shows their detailed descriptions.

2.3 Amazon Free Downloader

The Amazon comments we use in this research only focus on those that are recognized as "Verified Purchase" in company A. This means a customer has indeed made a purchase and then left a comment and rating of that product. These kinds of reviews are also called "feed book". Comments data are collected from Amazon free downloader (see *Table 2*).

Table 2. Comments data collected from Amazon free downloader

Variables	Description of variables
ID	Customer's ID on Amazon.
Username	Customer's name on Amazon.
ProfileURL	URL of customer's profile on Amazon.
Rate	Scale of the rate that customers give to this product. (1 to 5)
RateText	Text version of the rate. (3.0 out of 5 stars)
Format	Format of the customer bought of this product.
Title	Title of the comment.
Content	Content of the comment.
Helpful	Helpful votes of this comment.
Date	Date this comment was left.
Thumbnails	A small picture of an image or page of this comment on a computer screen.
Images	Pictures of images or pages of this comment.
Video	Videos of pages of this comment.
Verified	Rating and comment left after a real purchase.
ReviewURL	URL of the review on Amazon.

Source: this study.

For the comments, this research uses the Large Language Model (LLM), which is a kind of artificial intelligence (AI). We transform the text comments by natural language processing (NLP) into a score and let the text generated by the user (i.e., customer) present a score for their text comments and to empirical test the models. The literature has also adopted this method to analyze customers' online comments (Lo, Chien, 2024).

This study develops two sets of hypotheses and examines them through Statistical Package for Social Science (SPSS) software, version 22. The raw data from company A are checked for completeness before being coded.

2.4 Measurements

Table 3 present all variables used in the research framework and the definition of each variable. The dependent variable is the price of a repurchase order (re-price). The definition of repurchase means that a customer should have bought from company A more than once. We assume that customers take into consideration their previous experience and others' comments. Therefore, there are two sources for a total of 16 independent variables concerning comments. The moderator (p-type) is the product type being either utilitarian or hedonic.

Table 3. Descriptions of variables

Variable	Description	Sourced from
re-price	Amount of repurchase order	Company A
year	Year t of the order	Company A
tit-neg-pre	Average negative score of the title of previous comment in year t-1	Amazon
tit-neu-pre	Average neutral score of the title of previous comment in year t-1	Amazon
tit-pos-pre	Average positive score of the title of previous comment in year t-1	Amazon
tit-com-pre	Average compound score of the title of previous comment in year t-1	Amazon
con-neg-pre	Average negative score of the content of previous comment in year t-1	Amazon
con-neu-pre	Average neutral score of the content of previous comment in year t-1	Amazon
con-pos-pre	Average positive score of the content of previous comment in year t-1	Amazon
con-com-pre	Average compound score of the content of previous comment in year t-1	Amazon
tit-neg-other	Average negative score of the title of others' comments in year t-1	Amazon
tit-neu-other	Average neutral score of the title of others' comments in year t-1	Amazon
tit-pos-other	Average positive score of the title of others' comments in year t-1	Amazon
tit-com-other	Average compound score of the title of others' comments in year t-1	Amazon
con-neg-other	Average negative score of the content of others' comments in year t-1	Amazon
con-neu-other	Average neutral score of the content of others' comments in year t-1	Amazon
con-pos-other	Average positive score of the content of others' comments in year t-1	Amazon
con-com-other	Average compound score of the content of others' comments in year t-1	Amazon
p-type	1 for utilitarian product; 0 for hedonic product	Company A

Source: this study.

As to the control variable, because our data are composed of multi-year repurchasing data, to avoid the confounding effect of time issue, we control the year variable. The year of orders range from 2017 to 2022, in which the year 2017 is coded as "1", 2018 is coded as "2", 2019 is coded as "3", 2020 is coded as "4", 2021 is coded as "5", and 2022 is coded as "6". When it comes to repurchasing, the time series should be expended so as to test customer behavior appropriately.

2.5 Keyword Extraction

We use Python to calculate the scores of text evaluation with human language data for application in statistical natural language processing. Thinking logically, words can be recognized as being positive or negative, and whether they include some emotional or critical keywords that reflect sentimental feelings. Natural language processing (NLP) is a field that focuses on making natural human language usable by computer programs. NLP is a powerful technology that helps derive immense value from data.

Natural Language Toolkit (NLTK) is a Python package that one can use for NLP to create visualizations of unstructured data and human-readable text. NLTK is the most popular package in education and research. It has led to many breakthroughs in text analysis and helps to analyze things very easily. With this excellent data library, we are able to require a specific combination of algorithms. Through building Python programs to work with NLTK, there is a suite of libraries and programs for symbolic and statistical natural language processing for English written in the Python programming language to give each comment's title and content an accurate score, making it obtainable and defined in different levels.

Each comment is composed of two parts: title and content. For these two parts, we utilize the NLP method to score these two parts separately in Python. The processes are divided into several parts. We set up each title and content of comments into: (1) Lowercase: change the text of comments into lowercase letters; (2) Tokenization: split up the text by sentence to work with smaller pieces of text; (3) Stop-word removal and spelling correction: stop words are words that need to be ignored, by filtering them out of the text when processing them, besides correcting all mistakes; (4) Stemming: a text processing task in which you reduce words to their root, which is the core part of a word; and (5) Emotion list: words or sentences are usually labeled positively or negatively according to a polarity score, which can then help extract the emotions behind these words.

3. Results and Discussion

3.1 Results

We turn now to evidence on customer repurchase behavior from previous comments and other customers' comments. *Table 4* presents descriptive statistics (i.e., means and standard deviations) and the correlation matrix among the variables. Correlation analysis results demonstrate the correlation coefficient between the independent and dependent variables, and so the independent variables included in the regression analysis are appropriate. There is no serious multicollinearity among independent variables.

Table 4. Correlation matrix of the variables

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Pearson Correlation	1. year	5.108	1.081	1.000																		
	2. p-type	0.760	0.427	-.211*	1.000																	
	3. re-price	57.175	79.503	0.032	.247**	1.000																
	4. tit-neg-pre	0.102	0.237	0.131	-0.031	-.217*	1.000															
	5. tit-neu-pre	0.517	0.358	-0.119	-0.001	0.037	-.235**	1.000														
	6. tit-pos-pre	0.381	0.380	0.031	0.02	0.101	-.403**	-.795**	1.000													
	7. tit-com-pre	0.237	0.387	-0.01	0.045	.240**	-.691**	-.441**	.847**	1.000												
	8. com-neg-pre	0.065	0.113	0.05	-0.068	-.236**	.381**	0.152	-.381**	-.455**	1.000											
	9. com-neu-pre	0.713	0.183	0.06	0.058	-0.048	0.137	.195*	-.269**	-.198*	-0.102	1.000										
	10. com-pos-pre	0.222	0.205	-0.081	-0.014	.173*	-.332**	-.258**	.450**	.426**	-.460**	-.837**	1.000									
	11. com-com-pre	0.337	0.536	-0.08	0.089	.392**	-.483**	-.340**	.528**	.654**	-.736**	-.227**	.608**	1.000								
	12. tit-neg-other	0.139	0.200	0.044	-.396**	-.280**	.183*	-0.001	-0.113	-0.154	0.134	0.091	-0.166	-.180*	1.000							
	13. tit-neu-other	0.511	0.120	-.337**	.239**	-0.113	-0.132	0.076	0.011	0.003	-0.036	-.191*	.191*	0.05	-.475**	1.000						
	14. tit-pos-other	0.387	0.184	.337**	.391**	.285**	-0.028	-0.038	0.053	0.06	-0.117	0.052	0.018	0.071	-.713**	0.003	1.000					
	15. tit-com-other	0.163	0.302	0.137	.616**	.355**	-0.141	-0.025	0.112	0.161	-0.144	-0.015	0.093	.173*	-.955**	.169*	.807**	1.000				
	16. com-neg-other	0.087	0.094	0.069	-.603**	-.343**	.207*	0.022	-0.15	-.212*	.189*	0.061	-0.158	-.235**	.968**	-.381**	-.653**	-.928**	1.000			
	17. com-neu-other	0.710	0.082	-0.07	.604**	.262**	-0.049	-0.086	0.112	0.123	-0.008	-0.006	0.009	0.122	-.522**	0.14	.373**	.574**	-.554**	1.000		
	18. com-pos-other	0.203	0.084	-0.01	0.091	0.13	-.185*	0.059	0.06	0.119	-.205*	-0.063	.169*	0.146	-.581**	.292**	.371**	.485**	-.586**	-.351**	1.000	
	19. com-com-other	0.246	0.487	0.02	.623**	.330**	-0.163	0.014	0.09	0.149	-0.147	-0.041	0.117	.176*	-.950**	.356**	.737**	.944**	-.949**	.462**	.618**	1.000

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Source: this study.

Table 5 presents the linear regression results of our research framework. Model 1 provides the control variables. Model 2 adds the independent variables about a customer's previous self-comments and others' comments. Model 3 further tests the moderating effects of the product types.

Table 5. Regression results

	Model 1				Model 2				Model 3			
Variable	β	SE	t	Sig.	β	SE	t	Sig.	β	SE	T9	Sig.
Constant	0.354	0.129	2.753	**	6.342	2.985	2.124	**	3.872	4.586	0.844	
Control variable												
Year	0.023	0.039	0.575	**	0.095	0.049	1.953	**	0.029	0.078	.374	†
Independent variable												
tit-neg-pre					0.04	0.254	0.159		-0.198	0.567	-0.349	
tit-neu-pre					-0.483	0.217	-2.223		0.316	0.518	0.609	
tit-com-pre					0.379	0.284	1.332	†	-0.55	0.697	-0.79	
con-neg-pre					-0.241	0.553	-0.437	†	-1.555	1.446	-1.075	†
con-neu-pre					-0.348	0.244	-1.425		-0.052	0.503	-0.104	
con-com-pre					-0.333	0.133	2.499	*	-0.105	0.283	-0.372	
tit-neg-other					-5.105	2.382	-2.143	*	-2.751	4.388	-0.627	
tit-neu-other					-2.926	1.186	-2.467		-1.815	1.914	-0.948	
tit-pos-other					0.663	0.467	-1.421	†	0.284	1.005	0.282	
tit-com-other					-2.902	1.327	-2.186	*	-1.97	2.116	-0.931	*
con-neu-other					-3.233	2.373	-1.362	***	-1.347	3.38	-0.398	
con-pos-other					5.114	2.694	-1.898	*	-4.291	5.115	-0.839	†
con-com-other					-8.177	0.434	2.715	***	-5.168	0.764	1.529	†
Interacting term												
tit-neg-preXp-type									-0.516	0.944	-0.546	
tit-pos-preXp-type									-0.683	0.686	-0.995	
tit-com-preXp-type									1.598	0.89	-1.796	†
con-neg-preXp-type									-5.98	0.768	1.275	***
con-pos-preXp-type									-1.675	1.556	1.077	*
con-com-preXp-type									0.309	0.576	0.537	
tit-neg-otherXp-type									0.559	0.328	1.705	*
tit-com-otherXp-type									-0.007	2.072	-0.004	
con-pos-otherXp-type									-0.455	2.546	-0.179	
con-com-otherXp-type									-9.387	2.091	0.185	***

Notes: significance level for *** is p-value < 0.005, for ** is p-value <0.01, and for * is p-value <0.05. : p-value <0.1 (one-tailed). N = 139.

Source: this study.

In model 2 the tested models show the importance of one's previous comments or others' comments. Both of them are statistically significant at a level of 0.05% or above. Therefore, Hypotheses 1-1 and 2-1 are supported. This indicates that when it comes to discussing the repurchase behavior, customers may take both their previous purchase experience and others' comments into consideration.

We next further examine the effect of content in previous self-comments and others' comments on customer repurchase behavior in H1-2 and H2-2. We reveal that both are supported in this research, whereby the significant effect of the content is higher than the title. Although the results of previous comments only show marginal significance, they explain the stronger influence of WOM.

Hypothesis 1-3 argues that the significant effect of the negative content of previous comments (β = -0.241, significant level at † for p < 0.1) exceeds the positive effect and is supported in this research. Hypothesis 1-3 claims that the negative content of others' comments has a stronger negative effect on repurchase behavior. Although there is no significant level on the negative score, by taking notice of the compound score of others' comments (β = -8.177), we understand that the negative implication of this means that negative contents might have greater effects than positive contents. Therefore, H2-3 is supported in this research.

In model 3, Hypotheses 3 and 4 test the moderating effects of product type to appeal to whether the product types of utilitarian and hedonic products will influence customer repurchase behavior. In Hypotheses 3-1 and 4-1, the effects of customers' previous comments and others' comments are all supported as in model 3. There are even some significant signs showing that the contents and the titles do influence customer repurchase behavior.

Hypotheses 3-2 and 4-2 are formulated in relation to product types. The content part of utilitarian products having a stronger influence versus the part of the title is supported and accepted. When discussing the interacting term, model three reveals that only the contents have statistical significance at a level of 0.05%. The significant level of the content explains that reading the content is more helpful and has a more powerful influence than the title.

The negative attitude from negative contents (β = -5.98, significant level at *** for $p < 0.005$) weakens consumers' willingness to repurchase the product, which also supports Hypothesis 3-3. Compared with hedonic products, the more negative the content of utilitarian products is, the less a customer will repurchase the same brand or the same product. The effect of negative reviews is quite important. Current data does not fully support Hypothesis 4-3, but the compound score of the contents of others' comments has a significant level of 0.05%. The β value of the contents of others' comments is -9.387, which tends to be negative. The negative compound score directly points out on the whole that the content expresses more negative attitudes toward a product or brand. Hypothesis 4-3 is partially supported by the overall compound score.

3.2 Discussions

The hypotheses' testing results of the research framework are illustrated in *Table 6*.

Table 6. Summary of hypotheses' testing results

	Hypothesis	Statistical Results
H1-1	A customer's self-previous overall comments influence the customer's repurchase behavior.	Supported
H1-2	The content of a customer's self-previous comments has a greater effect on the customer's repurchase behavior than the title.	Supported
H1-3	The negative content of a customer's self-previous comments has a stronger negative effect on the customer's repurchase behavior than the title.	Supported
H2-1	Other customers' overall comments influence a customer's repurchase behavior.	Supported
H2-2	The content of other customers' comments has a greater effect on a customer's repurchase behavior than the title.	Supported
H2-3	The negative content of other customers' comments has a stronger negative effect on a customer's repurchase behavior.	Supported
H3-1	The relationship between a customers' self-previous overall comments and the customer's repurchase behavior is moderated by product types.	Supported
H3-2	For utilitarian products, the content of customers' self-previous comments has a greater effect on a customer's repurchase behavior than hedonic products.	Supported
H3-3	For utilitarian products, the negative content of customers' self-previous comments has a stronger negative effect on a customer's repurchase behavior than hedonic products.	Supported
H4-1	The relationship between other customers' overall comments and a customer's repurchase behavior will be moderated by product types.	Supported
H4-2	For utilitarian products, the content of other customers' comments has a greater effect on a customer's repurchase behavior than hedonic products.	Supported
H4-3	For utilitarian products, the negative content of other customers' comments has a stronger negative effect on a customer's repurchase behavior than hedonic products.	Partially Supported*

Notes: H4-3 is partially supported due to overall (compound) score of the comment's content.

Source: this study.

Here, the first and the second sets of hypotheses discuss the effect of one's previous comments on customer repurchase behavior. The third and the fourth sets of hypotheses explore the effect of other customers' comments on customer repurchase behavior.

Conclusions

Concluding Remarks

Consumers' previous online shopping experience and overall satisfaction can show up in their online comments and ratings. In this research, we prove that customers tend to not repeat a purchasing behavior when their past experience is negative. Moreover, we speculate that those who have a higher negative attitude toward a product or brand need more time to cope with negative stimuli and restore their emotional system to a stable state. This means that a bad experience from their previous shopping significantly lowers their willingness to repurchase the same brand.

In our research model we subsequently put customers' previous comments and others' comments into an in-depth exploration at the same time. From the results of our research, we find that the significant level of others' comments exceeds one's previous comments, meaning an individual is easily influenced and controlled by others. Word-of-mouth (WOM) is a popular topic that has been discussed for a long time and is an action that can be described as a group phenomenon of exchanging comments with each other (Bone, 1992). WOM is a preferred factor that customers generally rely on and can significantly affect their perceptions (Athanassopoulos *et al.,* 2001). Moreover, it is widely accepted in traditional marketing research (Lee *et al.,* 2008).

We observed that comments not only influence one's repurchase behavior, but also impact others' purchase behavior. From the company's perspective, encouraging customers to leave a comment can suggest that it is achieving long-term goals to ensure sustainable growth. Positive comments build positive brand credibility and create stronger trust for other customers. However, as previously stated, except for negative comments, the company should also focus on neutral comments to find out what underlying cues are hidden. Online comments can either positively or negatively link with sales growth. SMEs main target is thus to figure out how to perfectly manage the relationship with their customers. To sum up, SMEs should comprehensively understand their customers, supplementing their all-around review management to build brand-positive images.

Limitations and Future Research Directions

Different products could influence a customer's purchasing behavior. Customers only buy products that they need presently, but all products have their own life cycle. Taking furniture as an example, one seldom buys it twice within just two months, even if one is fully satisfied with the brand or product and has left a five-star rating and relatively positive comments. Other research has found that customer retention rate differs across product categories. As a result, future research can work on this to discuss what kind of product category has a lower retention rate and under this circumstance what kinds of marketing strategies should be conducted to attract customers a second time to visit their brand for the long term. If the next purchase decision is far from a customer's last purchase, then SMEs should dedicate themselves to maintaining good relationships with existing customers and building loyalty connections.

Online customer feedback management plays an increasingly important role for businesses (Katsiuba *et al.,* 2023). The related literature focuses on the effects of customers' online comments on their future repurchase behavior. Research can also further focus on the different characteristics of the comments, such as their length (Wei *et al.,* 2022; Peng *et al.,* 2024). For companies, the next step is how to respond to those comments. In the new trend of generative AI or merchant replies (Wei *et al.,* 2022), companies' responses can be separated into two categories: AI-generated and human-written responses (Katsiuba *et al.,* 2023). Which type of response performs better is worth exploring in future research.

Other marketing research has mainly focused on purchase intentions (Lo *et al.,* 2020). To avoid the gap between intention and real purchase behavior, this research acquires real transaction data from Amazon to explore the influence of online comments. Based on other works about purchase behavior (Lo and Chien, 2024), to advance understanding of customer loyalty, this research generates the repurchase behavior of online customers. Future research can also focus on other outcome variables such as product sales (Peng *et al.,* 2024; Zhao *et al.,* 2024) or industrial customers (Zhu and Zhang, 2023) further comprehensively explore the new phenomenon.

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KLIENTO KOMENTARŲ IR KITŲ VARTOTOJŲ ATSILIEPIMŲ ĮTAKA KLIENTO PAKARTOTINIAM PIRKIMUI

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Santrauka. Naudotojų kuriamas turinys (angl. *User-Generated Content, UGC*) yra svarbi klientų atsiliepimų forma, kuri padeda būsimiems vartotojams priimti pirkimo sprendimus ir veikia kaip gairės įmonių rinkodaros strategijoms. Šiame tyrime nagrinėjama kliento ankstesnių komentarų ir kitų vartotojų komentarų įtaka kliento būsimam pakartotiniam pirkimui. Norėdami gauti duomenis apie realius klientų pirkimus, tyrėjai bendradarbiavo su įmone, kuri savo produktus parduoda per platformą „Amazon". Iš jos tiesiogiai surinkti sandorių ir komentarų duomenys. Pašalinus trūkstamus duomenis, pirmojo duomenų rinkimo etapo metu buvo gautos 1366 šios įmonės pagrindinių produktų transakcijos, atliktos 2019–2022 m. Po metų buvo stebimi tų pačių klientų pakartotiniai pirkimai ir nustatytos 139 pakartotinės transakcijos.

Tyrime naudotas Didysis kalbos modelis (angl. *Large Language Model, LLM*). Taikant natūralios kalbos apdorojimo (angl. *Natural Language Processing, NLP*) metodus, pirkėjų komentarų tekstai buvo paversti į vertinimo balus. Empiriniai rezultatai atskleidė, kad klientai atsižvelgia tiek į savo ankstesnę patirtį, tiek į kitų vartotojų komentarus, tačiau daugiau dėmesio skiria pačiam komentaro turiniui, o ne jo antraštei. Nustatyta, kad kuo neigiamesnis kitų ar paties vartotojo komentarų turinys apie utilitarius (praktinius) produktus, tuo mažesnė tikimybė, kad klientas vėl pirks iš tos pačios prekės ženklo. Įdomu tai, kad priimant pakartotinio pirkimo sprendimus kitų klientų komentarai yra paveikesni nei paties vartotojo ankstesni atsiliepimai.

Reikšminiai žodžiai: kliento pakartotinio pirkimo elgesys; vartotojų kuriamas turinys (UGC); kliento komentarai; kitų komentarai; įvertinimai.