A Predictive Model on a Consumer's Impulsive Buying Intention Towards Facebook Live Online Selling Using Binary Logistic Regression

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Abstract

During the COVID-19 crisis, the digital economy expanded. Due to COVID-19 restrictions, people have become more reliant on online buying. Many businesses shifted their approach to online platforms, thus engaging more customers. The live-stream shopping campaign in the Philippines is continuously growing due to more social media interaction with consumers. Small independent merchants have shifted to Facebook Live Selling, which shows real-time video, as a direct selling technique. This study examined the factors influencing impulse buying behavior amongst consumers in Facebook Live Selling. Three hundred eighty-four (386) respondents, ages 18 to 55 participated in the online survey that consisted of their demographics and questions based on the internal and external factors affecting the impulsiveness of a consumer towards buying in Facebook live-selling. The study used Binary Logistic Regression to predict whether an individual will purchase an item on impulse in Facebook live-selling. The dependent variable was categorized by the individual's intention towards the product, it was denoted as (0 = will not buy; 1 = will buy). The model revealed that among the factors, only sex ($\rho = 0.049$), frequency of purchase ($\rho = 0.00$), impulse buying tendency ($\rho = 0.00$), and trust propensity ($\rho = 0.035$) are significant predictor variables in the model, which were only internal factors. Overall, the model helps broaden our understanding of how the latest marketing strategy (live selling) affects the impulse buying behavior of consumers. Limitations and implications are further discussed in the study.

Keywords
Impulse Buying, Online shopping, Facebook Live online-selling, Binary Logistic Regression, and E-commerce

1. Introduction
Social commerce (s-commerce) is a new type of e-commerce. It continues to engage more customers since social media accelerates consumer-to-consumer information to develop social interactions on e-commerce platforms (Shirazi et al. 2022). The widespread proliferation of live streaming has boosted its fusion with marketing campaigns and driven a boom in e-commerce economies (Lu et al. 2021). It has recently been implemented into social media platforms and social business applications. Sellers can use real video to promote their products and engage with potential buyers through the live-streaming shopping feature, where customers can give their opinion and give feedback in real-time. Live streaming is particularly effective at introducing and selling products like clothes and cosmetics.

According to Statista (2021), there were nearly 76 million Facebook users in the Philippines, making it the most popular live-streaming platform. Fenol (2021) pointed out that the Philippines' big business firms have even turned to live online selling to showcase their flagship products, such as top-of-the-line hardware and phones. Fenol (2021) also stated that the most common users of Facebook live selling in the Philippines are small-scale businesses in the fashion industry.

Due to the Covid-19 pandemic, purchasing online has become more convenient and safer for consumers. Most consumers who do not usually engage in online shopping have no choice but to opt for shopping online. During the imposed lockdown in March 2020, physical stores and establishments were closed mandatorily, and social distancing was essential. Necessities and groceries were bought through the internet to avoid contracting the virus. The trend for online shopping and consumer behaviors changed due to the pandemic. Due to the imposed lockdowns, the use of online shopping and the risk of going outside has increased, leading to impulsive buying behavior (Goel et al. 2022). Impulse buying is defined as the unplanned and sudden purchases that are initiated on the spot. It is unreflective and unintended (Goel et al. 2022). The characteristics that constitute impulse buying behavior are consumer exposure to internal and external stimuli, lack of planning before purchase, and spontaneous decision-making.

Morgan and Trinh (2020) stated that financial literacy will have a positive and significant relation to savings behavior. The previously stated study by Morgan and Trinh (2020) shows the effect of the prevention of impulse buying, allowing for more responsible spending and frequent saving. Unnecessary purchases can also lead to debt, as a response to mandatory payments being delayed. The stress amounting from these accumulative debts from impulsive buying behavior would impair a person majorly in a cognitive aspect. This affects anxiety levels and present bias, which resulted in psychological and decision-making impairments This further justifies the predictive model's purpose of providing intrinsic information about its user, information that could prevent these negative effects.

1.1 Objectives

Live selling allows consumers to experience the concept of "seeing is believing" by providing a digital face-to-face shopping experience and real-time interaction. The purpose of this study is to assess which internal and external factors influence the impulse buying behavior of the consumer during a Facebook Online Live Selling session. Also, this study developed a Binary Logistic Model to predict the probability that the individual will purchase on impulse based on internal and external factors.

2. Literature Review

2.1 Live Streaming Commerce

E-commerce nature is to embrace technological advancements and innovative business models to make customers' purchasing decisions easier, enrich their shopping experience, and materialize future purchases (Hu et al. 2017). When compared to traditional e-commerce, live streaming commerce offers significant benefits and allows viewers (consumers) to make smart decisions (Gao et al. 2021), w: [i] Streamers use real-time visual depictions of products paired with their gestures to give accurate and thorough product information (Zhang et al. 2022); [ii] Streamers reveal their identities, offer personalized services, and assist consumers (Sun et al. 2019) and based on simple cues or heuristic inferences in the environment, viewers can evaluate the streamers' trustworthiness and attractiveness (Sun et al. 2019); [iii] "Viewers get rich information by observing other co-viewers and can use others' bullet-screen comments and response actions as their shopping references" (Gao et al. 2021). However, Gao et al. (2021) stated that the investigation of live streaming commerce is still at an early stage, and the theoretical approaches and research results are sporadic and scant. For example, the stimulus-organism-response (S-O-R) paradigm, the perspective of information technology (IT) affordance, and the perspective of 'match-up' are applied to investigate consumer behavior in live streaming commerce.

Lo et al. (2022) stated that live streaming commerce has become a new avenue in which impulsivity has been practiced. Live streaming has been able to garner billions in revenue, which has led to it being welcomed into the global spotlight as a source of profitability. It has given the ability for anyone to be able to show their own content that is as interactive, informative, and immersive even from a remote location. As live streaming becomes a new industry, there is still too little information that would fully quantify the success of the industry at its current early stages.

According to Zhang et al. (2022), with the advancement of information technology, live streaming has become widely recognized as a new economic strategy that integrates specialized activities with videos for its unique content presentation and high-level involvement. Because of the highly social engagement enabled by virtual face-to-face technology, live streaming commerce, as a subset of live streaming, significantly extends traditional e-commerce (Xu et al. 2020). It shows products to customers through real-time video live streaming, effectively narrowing the gap between them and the products. Although live streaming commerce has advanced significantly in recent years, some critical challenges remain unresolved, one of which is trust. Traditional e-commerce cannot connect with sellers in real-time to get dynamic product information, which increases transaction risk and hinders trust-building. On the contrary, live streaming commerce providing real-time visual communication can precisely address the problems of information opacity in traditional e-commerce (Zhang et al. 2022).

2.2 Emergency of Online Live Streaming Commerce

Instagram affects the buying likelihood due to the platform enjoyment while using it and that would make the consumers skip the evaluation phase of their decision, which leads to impulse buying. Instagram acts as a stimulus for impulse purchases. Researchers found that the influence of Instagram on impulsive buying purchases to be a stimulus to trigger purchases such as promotional advertisements. Lastly, Instagram also allows retailers to sell products directly to followers and it became a significant stimulator for impulse purchases (Djafarova and Bowes 2021). Instagram was also found to be a key stimulus and it was found that respondents act upon it, therefore triggering these impulsive fashion purchases. The next factor is the BGC or Brand-generated Instagram content. BGC can be defined as the initiated marketing communication shared to pages to gain popularity (Djafarova and Bowes 2021). These brand contents published on Instagram accounts were also found to generate new needs that will eventually lead to purchasing items from the brands.

2.3 Impulse Buying in Live Streaming Commerce

Lo et al. (2022) aimed to unravel the critical determinants that influence impulsive buying behavior in live streaming consumers. Factors such as impulse buying urge, impulse buying tendency, affective reactions, cognitive reactions, parasocial interaction, social contagion, vicarious experience, scarcity interaction, and price perception were considered when defining impulsive buying behavior in live streaming commerce through a cognitive-affective processing system (Lo et al. 2022). Impulse buying tendency, in its general sense, is the moderator between an organism's reactions and impulse buying urges as well as between impulse buying urge and impulse buying behavior (Zafar et al. 2021). High levels of impulse buying tendency entail traits such as weak cognitive planning, low conscientiousness, high action orientation, and weak affective autonomy (Lo et al. 2022).

Affective reactions are the emotions such as arousal, pleasure, and dominance which can influence impulse buying urge as impulse buying is a hedonic concept rooted in emotions. This explains why an affective reaction like gratification from impulse buying behavior can affect impulse buying urge (Lo et al. 2022). Cognitive reactions are the mental processes which are evoked by receiving stimuli with the usefulness of information first assessed before attitudes are created. Perceived usefulness can then be related to affective reactions which then translates into impulse buying urge (Lo et al. 2022). Parasocial interaction was developed as the idea behind the relationship between the viewers and the anchor in mass media. These are the digital interactions between the viewers and the anchors that are bound together by a reciprocity constituted by mutual awareness, adjustment, and attention (Lo et al. 2022). Social Contagion is the phenomenon in which humans adapt sentiments and actions of other humans as a response to primitive emotional contagion. It applies to livestreaming commerce as it is a communal experience, one of which enables viewers to influence each other during sessions (Lo et al. 2022). Scarcity Interaction is the utilization of limited stocks for timed promotions to entice the viewers with a sense of competition as to who will get the limited product first, hence, increasing its value. Price Perception is the monetary value of the product (Lo et al. 2022). Interactivity, being a dominant feature of a live webcast, gives the customers a sense of the host's temperance, mental aura, and body language. The live stream allows customers to interact in real-time and this creates the atmosphere that all customers are present at the same time, therefore, giving the viewers a strong sense of immediacy. The virtual experience was found to have a positive correlation with the customer's virtual experience. A stronger sense of immediacy is developed when there is a higher virtual experience (Tong 2017).

3. Methods

The study mainly focuses on live-streaming commerce platforms in the Philippines such as Facebook Live. To do this a statistical tool, Logistic Regression will be utilized. Logistic regression is a statistical tool that measures the relationship between the categorical target variable and one or more independent variables. Binary logistic regression refers to the logistic regression that results in only two outcomes (binary) (Frost 2022). The variables in this study have been thoroughly defined in the process of literature review and variables were based from the Conceptual framework. The buying impulsiveness of the consumer during live online selling is the dependent variable. The independent variables consisted of the internal stimuli and the live-streaming website features, which were variables that influence the impulsiveness of a consumer in an online live-shopping setup. Also, the dependent variable whether the consumer is likely to impulse buy or not was coded as (0,1) in the Binary Logistic Regression. This process works by putting a mathematical model as required in the Binary Logistic Regression and this would predict whether the consumer would impulse buy or not.

3.1 Flowchart of the Methodology

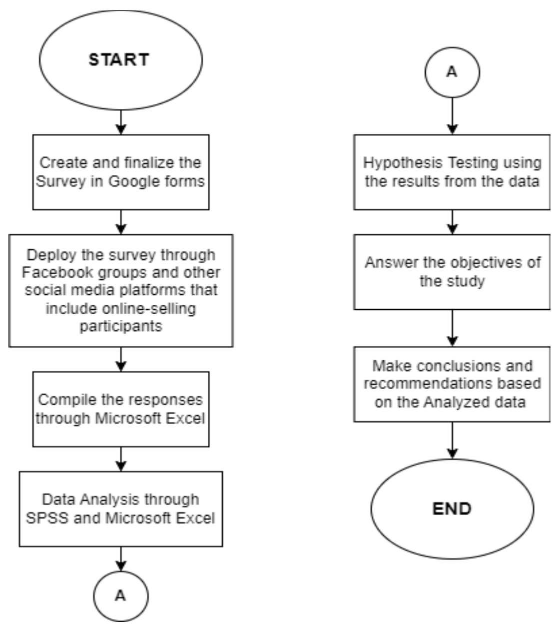

Figure 1. Flowchart of Methodology

Figure 1 shows the methodology flowchart, representing the steps in which the data gathering process was done. The flowcharts also show how the data gathered was processed to come up with conclusions and recommendations based on the analyzed data.

3.2 Definition of Variable and Description of Relationship

Table 1 summarized the variables used in the study and its corresponding definitions in relevance to the study. It consists of 11 factors including demographics, internal, and external variables.

Table 1. Definition of Variable and Description of Relationship

Variable	**Definition of Variable & Description of Relationship**	**Reference**
Sex	Sex influences the behavior when shopping online.	Molinillo et al. (2021)
Monthly Income	Socio-Economic Status may impact their impulse buying tendency.	
Source of Income	Consumer's source of income might affect their purchasing intention	
Occupation	Individual's occupation may affect purchasing intention because of their affordability.	
Frequency of Buying	Consumers' perceived value has an important power to predict repurchase intention.	Molinillo et al. (2021)
Consumer's Mood	Indicates likelihood of unplanned purchases.	Febrilia and Warokka (2021)
Impulse Buying Tendency	Impulse buying was influenced by individual's their impulse buying tendency	Febrilia and Warokka (2021)
Trust Propensity	Trust inclination influenced the consumer's impulse buying.	Kimiagari and Malafe (2021)
Parasocial Interaction	It possessed the capacity to affect consumer's impulse buying.	Lo et al. (2022)
Price Perception	It was learned that monetary value of a product has an impact on impulse buying	Lo et al. (2021)
Vicarious Experience	It was learned that visual experience has an impact on impulse buying	Lo et al. (2022) Lu and Chen (2021)

4. Data Collection

4.1 Subjects and Study Site

Respondents of the study are buyers in online live selling. Filipinos are prolific users of social media according to the International Trade Administration and shows that 72.5 million are on Facebook making it the best platform to do online live selling. The emergence of e-commerce and social media live selling has been very evident since the COVID pandemic. And e-commerce industry's usage increased and started to trust online platforms as an alternative to brick and mortar stores. Participants of the study were customers who buy online, specifically from Facebook live selling.

Data was collected online by survey questionnaire dissemination. It was targeted at our niche respondents; the demographics were observed through past live selling sessions. All factors were measured using Likert scale. A total of 386 respondents were involved in the study.

4.2 Statistical Analysis

To assess the impact of one or more predictor variables of the outcomes Binary Logistic regression can be used (Fawad 2021). Additionally, the researchers used Binary Logistic Regression to create a predictive model that would forecast the probability that a consumer will buy or will not buy in live online selling in relevance to the independent variables' relationship to the dependent variable.

5. Results and Discussion

5.1 Factor Measurement Model Testing

The method used to gauge the adequacy of the questionnaire used was Cronbach's Alpha. It is a measuring instrument which evaluates a set of items of internal consistency, in the case of the questionnaire is the questions under the same internal or external factor. Cronbach's alpha states that the range of acceptability is 0.70 onwards, with above 0.80 being better and more than 0.90 being best (Moran 2021). Utilizing Cronbach's alpha, resulted in values ranging from 0.701 to 0.849 which indicates internal reliability for all questions under each factor.

5.2 Hypothesis Testing

The hypothesis testing revealed that there were only four factors of internal, external, and demographic origin that have a relationship with impulse buying impulsiveness of the consumer during a live e-commerce session. They are namely sex, frequency of buying, trust propensity, and impulse buying tendency. All adhering to $p<0.05$ with sex at 0.0295439, frequency of buying at 0.0000002, IBT at 0.0000006, and trust propensity at 0.0484499. Complete results of the variable in the study and its corresponding significance level are presented in Table 2.

Table 2. Summary of Hypothesis Testing

Hypothesized Path	B	Standard Error	Sig.
$H_1: Sex \rightarrow IB$	.605	.278	.0295439
$H_2: Monthly\ Income \rightarrow IB$	-.174	.124	.1620983
$H_3: Source\ of\ Income \rightarrow IB$	.188	.119	.1157261
$H_4: Occupation \rightarrow IB$	.210	.246	.3937763
$H_5: Frequency\ of\ Buying \rightarrow IB$	1.131	.218	.0000002
$H_6: CM \rightarrow IB$	-.095	.182	.6004715
$H_7: IBT \rightarrow IB$	1.045	.209	.0000006
$H_8: TP \rightarrow IB$	.249	.126	.0484499
$H_9: PI \rightarrow IB$	.143	.216	.5079258
$H_{10}: VE \rightarrow IB$	.167	.158	.2924737
$H_{11}: PP \rightarrow IB$	.269	.230	.2419278

5.3 Binary Logistic Regression Assumption Evaluation

Binary Logistic Regression distinguishes itself from linear regression by having its dependent variable be dichotomous in nature, that there are no outliers by having there be no continuous predictors beyond +/- 3.29 when converted to z scores, there must also be no multicollinearity among predictor variables (Statistic Solutions 2021). The dependent variable in the case of the study, is "will buy" and "won't buy". There are also no outliers as there are no continuous predictors, only ordinal and nominal. Multicollinearity diagnostics were executed and Table 3 showed that no tolerance level reached below 0.25 nor did any Variance Inflation Factors reach above 4.00, which according to Corporate Finance Institute if the variables exceeded then multicollinearity issues would exist.

Table 3. Multicollinearity Diagnostics

	Collinearity Statistics	
	Tolerance	**VIF**
Sex	.932	1.073
Monthly Income	.561	1.784
Source of Income	.424	2.357
Occupation	.467	2.142
Frequency of Buying	.820	1.220
CM	.554	1.807
IBT	.549	1.821
TP	.889	1.124
PI	.521	1.919
VE	.627	1.595
PP	.559	1.788

5.4 Binary Logistic Regression Fit Test

According to Wuensch and Poteat (2021), Block 0 is the model in which no explanatory variables entered and is the former model. Block 1 is the new model with the explanatory variables entered. The Omnibus Tests of Model Coefficients, shown in table 4, was utilized to evaluate the model, resulting in a ρ<0.001 specifically at 0.000 showing that the model is more accurate when the variables are added.

Table 4. Omnibus Tests of Model Coefficients

	Chi-square	**df**	**Sig.**
Step	140.295	4	.000
Block	140.295	4	.000
Model	140.295	4	.000

The Hosmer and Lemeshow Test was also utilized, as shown in table 5, it delivered the same results of model fit at which the significance value is ρ>0.05 at 0.584. The classification table for the new model (block 1) shows how effectively predicted "Won't buy" at 67.6.1% and "Will buy" at 82.5% are by the model, with an overall correct prediction percentage of 75.6%.

Table 5. Hosmer and Leeshawn Test

	Chi-square	**df**	**Sig.**
Step 1	5.624	7	.584

5.5 Binary Logistic Regression Model and Predictive Model

Present in Table 6 are the results of the variables in the equation which includes only the four significant factors found in the study. The Beta or B value corresponds to what constitutes an increment that would have an effect of the value in Exponential B or Exp(B). A negative B means that with every answer of "strongly agree" then chances increase by the value in the Exp(B) towards the non-focus group of "Won't buy". A positive B means that for every answer of "strongly agree", then chances increase by the value in the Exp(B) towards the focus group of "Will buy". All significant factors found, all had Exp(B) values of more than one which shows a prediction capability towards "Will buy".

Table 6. Results of Binary Logistic Regression Model

Variables in the Equation						
	B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**
Sex	.515	.262	3.884	1	.049	1.674
Frequency of Buying	1.242	.208	35.622	1	.000	3.461
IBT	1.091	.174	39.315	1	.000	2.978
TP	.254	.120	4.454	1	.035	1.289
Constant	-6.570	.781	70.683	1	.000	.001

The model below follows the denotation for sex, frequency of buying, IBT and TP as X1, X2, X3 & X4. According to Minitab (2022), the regression coefficients (B) in the model represent what direction (negative or positive) and by how much (multiplier) the independent variables individually affect the binary dependent variable of “Will buy” or “Won’t buy”. Aligned with the mentioned logical pattern, the model was generated below using SPSS. Plugging in values next to their respective regression coefficients, then we get the value of p̂, which is the percentage probability that the consumer will buy on impulse in a Facebook live e-commerce session.

$$\hat{p} = \frac{e^{\beta 0+\beta 1x1+\beta 2x2+\beta 3x3+\beta 4x4}}{1+e^{\beta 0+\beta 1x1+\beta 2x2+\beta 3x3+\beta 4x4}}$$

$$\hat{p} = \frac{e^{-6.57+0.52x1+1.24x2+1.09x3+0.25x4}}{1+e^{-6.57+0.52x1+1.24x2+1.09x3+0.25x4}}$$

5.6 Proposed Improvements

The resulting predictive model could function as an identifier for respondents, for the purpose of profiling themselves of their inherent qualities covered in the study. As per the model’s binary results, it could help in gauging the likelihood of the outcome if the respondent is exposed to Facebook live streaming e-commerce. Such awareness could give the respondents a more objective view of themselves as they are about to participate in Facebook live-selling. When the results are properly interpreted by the user or a third party, the information could provide an objective view. An objective view could lead to better internal understanding and therefore better decision-making. Better decision-making in financial, psychological, emotional, mental, and even physical. The results would help identify if the user is susceptible to the aspects within himself and of the live-streaming session itself. It is recommended to take reassessment upon discovering the tendencies revealed by the binary results.

5.7 Validation

One of the factors that was found to be significant in the study is the consumer’s sex. Studies have shown differences in how females’ behavior on the internet shows that they are at higher risk of online buying behavior since they are likely to use retail therapy. Retail therapy is defined as the use of shopping to alleviate negative emotions, which may lead to compulsive buying, and women are likely to use retail therapy to appease their negative emotions (Zheng et al. 2020). Additionally, the study found that perceived stress is a predictor for online buying behavior, which suggests that women have higher levels of perceived stress and may be at a higher risk of compulsive buying behavior (Zheng et al. 2020). In the hypothesis of the said study, one of their variables is negative coping. It showed that self-esteem buffered a relationship between perceived stress and online compulsive buying with the indirect effect of negative coping. The first pattern of consumer behavior has to do with the frequency of purchases, which was found to be another significant factor in the study. According to Farías (2019), consumers get more familiar with a product, and the more frequently they make purchases. Customers might think that the more they purchase items, the more they will become knowledgeable about the prices. Hence, leading to impulsive buying tendencies. According to Febrilia and Warokka (2021), the more significant the tendency of the consumers to shop impulsively, the more likely the consumers will purchase products unexpectedly at certain online stores. Consumers who tend to not have the control within themselves to make planned purchases are most likely to become impulsive buyers. They have a strong urge or feeling to buy products online and they would be happy if they could make it happen. Lastly, trust propensity was found to be another significant factor in the study. Consistent with Kimiagari and Malafe (2021) study, trust propensity had a direct effect on online impulse buying behavior. According to Assarut and Wongkitrungrueng (2020), consumers' views of online trust play a role in giving accurate information and meeting expectations. Consumers in both offline and online setup must have faith in a number of different entities: the business, the product, the market/channel (physical, Internet), and the agent (seller, salesperson, online platform). This study demonstrated how trust propensity in live streaming contributes to a consumers' impulse buying decisions.

6. Conclusion

While the market for Live-selling grows, companies have been using live-streaming as a new economic strategy that integrates specialized activities with videos for its unique content presentation and high-level involvement (Zhang et al. 2022). Live streaming has been able to garner billions in revenue, leading it to be welcomed into the global spotlight as a source of profitability. Live streaming enables anyone to have access to information, interact with hosts live, and show their content from a remote location.

In this study, various factors were considered relating to the impulse buying behavior of consumers in an online live selling set up. By using descriptive statistics, the proponents found out that only four factors significantly affect the impulse buying behavior of the consumers. This result is consistent with prior studies on how sex, purchase frequency, impulse buying tendency, and trust propensity correlates to online impulse buying. The Binary Logistic Regression Model was used to predict whether the consumers will purchase on impulse or not based on the significant factors found in the study. The model may be very beneficial to consumers who want to limit their unnecessary online purchases.

The study enriches our understanding of the rising development of selling in a social commerce context. However, the study revealed that there is no significant relationship between the live streaming features and the impulsive buying behavior of consumers. Further study is needed to effectively grasp and utilize the live streaming features in the Philippines since it is a relatively new instrument that is still under development. This study can further explore the different factors that could be involved in the use of other live-streaming platforms aside from Facebook.

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Biographies

Kian Justin O. Angeles is a 4th year student in University of Santo Tomas – Manila, taking up Bachelor of Science in Industrial Engineering specializing in Operations Research and Analytics Track. He served as a Corporate Associate in Operations Research Society of the Philippines – UST Chapter under the Community Development team. Currently, he is an Executive Associate for Team Academics in UST Industrial Engineering Circle. Additionally, he took his OJT/Internship in Core Enabler Business Process Solutions.

Karl G. Espina is a senior industrial engineering student at the University of Santo Tomas. Specializing in Operations Research and Data Analytics. He has become a part of a dean's list in multiple semesters. He has served as a member of the Industrial Engineering Circle and is currently an executive associate under team Publicity. His other university organizations were the Thomasian Film Society, serving as a writer and as a research department head, and the UST UNESCO Club as a youth ambassador. He had undergone work experience as he was accepted as an intern at the university's Industry, Government, Academe, and Alumni Relations Program (IGAARP), where he managed the relations of the students and companies and helped organize the engineering job fair.

Bianca DP. Lipata is a senior at the University of Santo Tomas where she is taking up BS in Industrial Engineering major in Operations Research and Data Analytics as she is interested to explore more about scientific processes and data analytics. She has joined several student organizations which makes her learn the value of collaboration, communication, and time management. During the summer of 2022, she was accepted as a Supply Chain Operations Support Intern at Meralco Industrial Engineering Services Corporation (MIESCOR). Her knowledge in Engineering, Procurement, and Construction (EPC) widened as she was assigned to sourcing, accreditation, band-coding, quotation, and evaluation of the vendors and suppliers.

Jan Cedrick V. Sta. Cruz is currently a 4th year student, taking up BS Industrial Engineering at the University of Santo Tomas. He was a consistent honor student in high school and a dean's lister in the second and third year of college. He has undergone his internship at Polyfoam-RGC International Corporation in June 2022. His experience in the internship broadened his views and knowledge towards improving the plant's efficiency and effectiveness. His work experience in the internship includes time and motion study, plant capacity planning, and process improvement.

Carlos Ignacio P. Lugay, Jr. is an Associate Professor in the Department of Industrial Engineering at the University of Santo Tomas. He started his career at the University in November 1992 and earned his BSIE degree at the University in 1992. He earned his MS IE Degree in 1999 in the University of the Philippines-Diliman. He also earned his Ph.D. in Commerce degree in the University of Santo Tomas in 2015 as he taught and held his academic and administrative positions. He specialized in the areas of Ergonomics and Operations Management and published and presented papers in local and internal conferences/symposia. He is a Professional Industrial Engineer and an ASEAN Engineer.