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In-Game Purchase and Video Game Longevity: Case Study of CS2

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Abstrak

Penelitian ini menyelidiki dampak *Real Money Trading* (RMT) terhadap berkelangsungan *Video Game*, menggunakan *game* Counter-Strike 2 sebagai studi kasus. Waralaba *video game* yang memiliki 1 juta pemain setiap hari di Steam dengan versi terbarunya Counter-Strike 2. Model *Game Longevity* yang dimodifikasi, menggabungkan *Real Money Trade* (RMT), *Purchasing Decision* (PD), *Customer Satisfaction* (CS), dan *Game Longevity* (GL) digunakan. Metode campuran analisis kuantitatif dan kualitatif dilakukan terhadap 410 responden dan 30 orang yang diwawancarai dari seluruh dunia. Hasil menunjukkan bahwa Perdagangan Uang Riil, Keputusan Pembelian, dan Umur Panjang Game saling terkait, sementara Kepuasan Pelanggan memberikan hasil yang negatif. Kemanjuran model ini bergantung pada pengurangan peran Kepuasan Pelanggan. Temuan ini menegaskan bahwa pembelian dalam *game* meningkatkan Umur Panjangnya Game.

Kata Kunci: *Counter-Strike 2, Pembelian dalam Game, Penelitian Campuran, Perdagangan Uang Rill, Kelangsungan Game*

Abstract

This study investigates the impact of Real Money Trading (RMT) on Video Game Longevity, using Counter-Strike 2 as a case study. A video game franchise that boasts 1 million daily players on Steam with their newest installment Counter-Strike 2. A modified Game Longevity Model, incorporating Real Money Trading (RMT), Purchasing Decision (PD), Customer Satisfaction (CS), and Game Longevity (GL) was utilized. A mixed method of quantitative and qualitative analysis towards 410 respondents and 30 interviewees worldwide. Results reveal Real Money Trading, Purchasing Decisions, and Game Longevity are interlinked, while Customer Satisfaction skewed results negatively. The model's efficacy hinges on reducing Customer Satisfaction's role. Findings affirm that in-game purchase boost Game Longevity.

Keywords: *Counter-Strike 2, In-Game Purchases, Mixed Research, Real Money Trading, Video Game Longevity*

INTRODUCTION

There has been a recent push for technological advancement through the usage of Blockchain technology in the past few years. This brought on ideas and implementation of concepts such as Web 3.0, Cryptos, and NFTs. The driving force of which these technologies placed upon is secured monetary value. Real Money Trade is the term used to describe the process of which value is placed on upon the digital item. Some Video game companies introduced monetization of their games using theses concepts (King and Delfabbro, 2018). In-App purchase is a model of monetization through micropayments. Players are more likely to spend money to get more content or an advantage (Ravoniarison and Benito, 2019). The advent of online games made each player own individual game accounts. This is where, people started selling their game accounts to other people. Games soon added features such as trading and markets that made it more viable.

Valve is a video game company founded in 1996, debuting with the acclaimed game Half-Life in 1998. A couple of players modded the game and made the early concept for the game Counter-Strike in 1999. Valve acquired the IP and developers to make a full game in 2000. 12 years and a couple of sequels later, Counter-Strike: Global Offensive was released. An update a year later introduced cosmetic virtual goods in the game called skins that can gotten from playing the game or can be unboxed using the cases drop by playing the game and keys bought as an in-app purchases (Valve, 2013). This update stands as one of the most profitable ventures beyond game sales. This feature makes Valve half a million dollars every day with the spending from the players being prevalent (Zendle, 2020).

These cosmetic virtual items called skins are not just singular items, but they are affected by many different variables, such as rarity, wear value, and patterns. This made some items more valuable than others. The value of an items is never is stated by Valve themselves. The monetary value infact came from the players themselves creating a market of supply and demand (Thorhauge, 2020). The items are not only is used in game as it reaches outside the game itself with players creating markets to buy and sell. It became a tool used in gambling and betting. Since the game is targeted mostly towards teenagers and young adults, the implications made valve step in controlling more of what happens to the items outside of their platforms. Big market places were hit as their bots used in trading got banned, and gambling sites were closed down (Sanders, 2018).

The game eventually became Free to Play in 2018 creating an influx of new players. On the 22nd of March 2023, Valve announced the release of Counter-Strike 2 in Summer 2023. The game is essentially the same game but built with a new game engine called Source 2. A couple of betas later, in 27th of September the full game was released (Valve,

2023). The skins from CS: GO was brought into CS2 with a graphics update. This being the perfect scenario to gather the perspective of the players as things feels fresh.

The foundation of this research draws upon several key resources. Arkaan and Kosasih (2022), conducted quantitative research on Real Money Trade in Counter-Strike: Global Offensive and its relationship towards Purchasing Decision and Customer Satifaction. Juistenga and Bertholet (2021), performed qualitative research focusing on FIFA as a case study with focus towards brands and game longevity. McNabb (2020), book details the approach of a mixed research method. Rahman et al., (2022), provided understanding of sampling techniques. While Hulaj et al., (2020), explained the use of SPSS, AMOS, and SEM in analysing data. Finally, (Siedlecki, 2020) added depth towards research methodology. Each of these resources provides an excellent framework for this research.

Overall, this study aims to look upon the perspective of players around the concept of the in-app purchases applied in the game, the decisions they make, the satisfaction they feel, and their thoughts of the longevity of the game. Focusing a lot on the skins market and it's influences on each variable that made their opinion possible. Differentiating between a more diverse quantitative research section using Likert scale and a more individual and limited qualitative research section using Guttman Scale. Eventually, comparing the hypothesis results of each and how each compare in the model calculations.

RESEARCH METHOD

The research begins by doing reviews of published literature by academics and researchers. Afterwards, multiple research problems will be formulated. The research problem will be the questions that can be answered after a conclusion is identified. Once the research problem is set, then data gathering from a sample of the population will begin. Data gathering will be done through two different mediums. We will create Google Forms and giving them through surveys to respondents and conduct interviews using similar questions. Data gathered will be first analysed and compared to create a conclusion. Finally, the writer will write the reports containing the results.

This research aims at understanding third-party digital goods purchases. In general, third-party purchases are seen to harm the main suppliers themselves. However, that couldn't be further from the truth for a video game like CS2 without issues monetary or longevity. A video game's longevity is the variable selected to represent a game's continued success. Thus, we can confirm whether or not that real money trading of virtual goods through third parties can have a positive effect on a game's longevity.

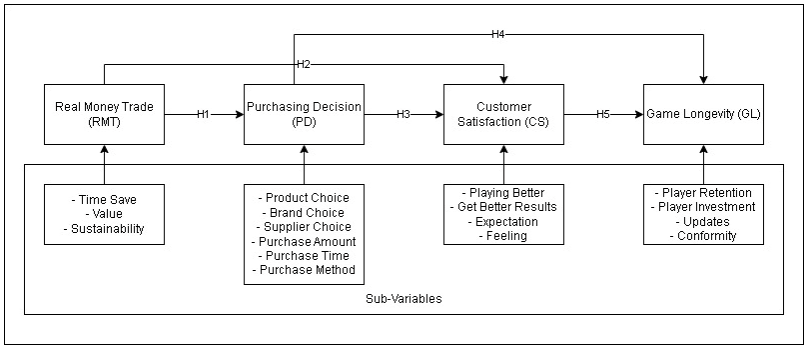

Image 1. Real Money Trade Model and its correlation to longevity

Source: (Arkaan and Kosasih, 2022)

Hypotheses are the temporary expectations of what the results could be. These are the hypotheses used in this research:

H1a: Real Money Trade (RMT) positively affects Purchasing Decisions (PD) of players.

H10: Real Money Trade (RMT) negatively affects Purchasing Decisions (PD) of players.

H2a: Real Money Trade (RMT) positively affects the Customer satisfaction (CS) of players.

H20: Real Money Trade (RMT) negatively affects the Customer satisfaction (CS) of players.

H3a: Purchasing Decision (PD) positively affects Customer satisfaction (CS).

H30: Purchasing Decision (PD) negatively affects Customer satisfaction (CS).

H4a: Purchasing Decision (PD) positively affects the Game Longevity (GL) of CS2.

H40: Real Money Trade (PD) negatively affects the Game Longevity (GL) of CS2.

H5a: Customer satisfaction (CS) positively affects the Game Longevity (GL) of CS2.

H50: Customer satisfaction (CS) negatively affects the Game Longevity (GL) of CS2.

This research is done quantitatively and qualitatively to be able to understand the Real Money Trade and connect it to Game Longevity. This research model connects the relationship between Decision, Satisfaction, and Real Money Trade (Arkaan and Kosasih, 2022). This research model integrates the variable of Longevity (Juistenga and Bertholet, 2021). The eventual goal is to confirm the relationship between Real Money Trade and Game longevity in games. This research takes CS2 as the case study of this research model.

Operational Variables are the act of keeping a set of rules regarding variables used in research. The variables will be used as factors in influencing other variables. These variables will then be defined to keep an accurate indicator of what the variables meant in particular research. There are two types of variables used in this research, which independent and dependent variables. (David, 2022) defines an independent variable as the causal element in a hypothesis and affects the dependent variable. The independent variable in this research is Real Money Trade (RMT). The dependent variables in this

research are Purchasing Decision (PD), Customer Satisfaction (CS), and Game Longevity (GL). The definition of Operational Variables is shown in the table.

Table 1. Definition of Operational Variables

Variables	Sub-Variables	Identifier	Indicator
Real Money Trade	Time Save	RMT1	I purchase digital goods using real money because it saves me time.
	Value	RMT2	I purchase digital goods using real money because it has value.
	Sustainability	RMT3	I purchase digital goods using real money because it is sustainable.
Purchasing Decisions	Product Choice	PD1	I purchase digital goods using real money because of the product.
	Brand Choice	PD2	I purchase digital goods using real money because of the brand.
	Supplier Choice	PD3	I purchase digital goods using real money because of the supplier.
	Purchase Amount	PD4	I purchase digital goods using real money because of the amount.
	Purchase Time	PD5	I purchase digital goods using real money because of the time.
	Purchase Method	PD6	I purchase digital goods using real money because of the method.
Customer Satisfaction	Performance	CS1	After purchasing digital goods, I play better.
	Results	CS2	After purchasing digital goods, I get better results.
	Expectation	CS3	After purchasing digital goods, it was to my expectations.
	Taste	CS4	After purchasing digital goods, it was to my taste.
Game Longevity	Player Retention	GL1	After purchasing digital goods, I play the game more.
	Player Investment	GL2	After purchasing digital goods, I felt more invested in the game.
	Constant Update	GL3	After purchasing digital goods, I felt happy with the updates.
	Conformity	GL4	After purchasing digital goods, I felt the game aligned with what I wanted.

Source: (Arkaan and Kosasih, 2022; Juistenga and Bertholet, 2021)

This research aims at getting data from CS2 players that have bought CS2 digital goods for real money. We conduct data gathering for the sample needed by compiling data from questionnaires and answers from interviewees that have fulfilled the criteria. The target population for this research are CS2 players that have played CSGO in the year 2023 and have bought any form of CS2 digital goods using real money.

a. Quantitative

We determine the sample size for the quantitative survey using the Slovin formula:

n = N / (1+Ne^2)

where n = sample size needed, N = population size, and e = margin of error (5%).

The target population is not exact due to a variety of factors such as inactive accounts, bots, and one-time players. However, there are a couple of statistics that will help in determining the population size. Galyonkin (2023) shows an estimated 104.820.000 plus steam accounts that own CS2 as of October 2023. Valve (2023) themselves calculated the number of active unique players in September 2023 being 31.466.851 exactly. Fedorko-Bartos and Hale (2023) has a database of 1 billion recorded CS2 skins in the inventories of 4.4 million accounts. Only (2023) shows there are 4.462.866 unique inventories. Marlamin (2023) reported there being 1.213.265 players active daily as of early October 2023.

We will be using the following formula to calculate active players with inventories:

N = (Unique Inventories/Unique Accounts) * Active Unique Players

= (4.462.866/104.820.000) * 31.466.851 = 1.339.748 (rounded)

we can calculate the following sample size using the Slovin Formula:

n = 1.339.748 / (1 + 1.339.748 x 0,05^2) = 399,8806102012614 = 400 CS2 Players.

We see that from the Slovin Formula, 400 respondents are needed for this research to be valid. We can separate the respondents using a sampling method. The sampling method is the way researchers determine the criteria of what respondent is needed (Rahman et al., 2022). We will use Clustered Disproportionate Random Sampling Method.

b. Qualitative

We will conduct 30 interviews with the population of the CS2 player base. The questions being asked are the same as the ones used in the quantitative section. The difference will be that questions will be made to target the answers of a "Yes" or "No", then followed by their overall opinions. We will also use the same sampling method as the quantitative section which is a Stratified Disproportionate Random Sampling Method.

c. Comparison

This research uses a comparative analysis method. This method is used to analyze the data from the samples to answer the questions formulated. We do this by comparing both data samples. We can do this after analyzing the relationship of variables from the hypotheses and research model stated before. This research uses the software IBM SPSS Statistics 25 and AMOS 22 as tools for analyzing both samples and comparing the results.

d. Testing

1. Outlier Testing

Outlier testing is an observation of the sample data and finding individual data that contain unique characteristics that lean towards an extreme. We can also determine false

or counterintuitive data from the ones gotten. The result we get from outlier testing is called Significance Value. We export the significance value of each data point and then show which data points are considered either too high or low in comparison to the mean. In this case, any value above 3 or below -3 are considered outliers.

2. Validity Testing

Validity testing is used to determine whether or not a survey is valid or not. A survey can be considered valid when the questions correctly measure the variables. significance value is the result of validity testing. We can consider the survey valid when the significance value is =< 0,05. However, is considered not valid when the significance value is > 0,05.

3. Reliability Testing

Reliability testing is used to determine the reliability of a question compared to the variable. We can determine the survey is reliable when the answers given by the respondents are consistent and stable. Cronbach's Alpha is the result of reliability testing. We know the results of the data are accurate if the score is high. We can consider the results reliable when the score of Cronbach's Alpha > 0,6. However, we can consider the results not reliable when the score of Cronbach's Alpha < 0,6.

e. Analysis

Analysis was carried out using a descriptive approach. The descriptive approach is to describe individuals, events, or conditions by studying them as they are in nature. The researcher does not manipulate any of the variables but rather only describes the sample and/or the variables (Siedlecki, 2020). Quantitative research is based on the Likert Scale and Qualitative research is based on the Guttman Scale. We will conduct outlier, validity, and reliability to ensure the worthiness of the data and then afterwards test both data using linear Regression tool in SPSS 25 and compiled into a table. We will use the software AMOS 22 to figure out the critical ratio and significance value using its SEM graphic functionality. Data will be gathered, edited, tabulated, and tested. Afterwards, we can analyze the confirmation factor using AMOS 22 (Hulaj et al., 2020).

The last stage of analysis is doing a hypothesis comparison. We will test the parameters of the population that provide comparative evidence using the sample size. This is also used as a test generalization (Significance of research result) in the form of comparing the variables of both samples gathered in this research. The hypothesis comparisons will be considered successful if both hypothesis test results are the same. However, if not then we will try to find where the problem lies.

RESULTS AND DISCUSSIONS

Quantitative

In the quantitative research section, we used the Clustered Disproportional Random Sampling method to gather respondents online. Using online game forums such as HLTV.org we managed to cover 410 respondents from across the world in a week. Google Form was utilized to provide the research questions. Questions such as when they started, play time, and items owned in game. variable questions were also present with the main variables Real Money Trade (RMT), Purchasing Decision (PD), Customer Satisfaction (CS) and Game Longevity (GL) with 3, 6, 4, and 4 questions respectively.

Each of these questions is answered using a 1 to 5 Likert Scale, where 1 is considered very unlikely and 5 is considered very likely. We tested the 410 respondents' data for outliers and no outliers was found. We then tested the validity of the results using SPSS which resulted in all of the sub-variables passing. Afterwards, a reliability testing was done using SPSS and resulted in all of the variables passing the reliability test without any problems. The following are the tables and images resulted from the testing.

Table 3. Quantitative Validity Testing Results. Top to Bottom: RMT, PD, CS, GL

		RMT1	**RMT 2**	**RMT 3**	**RMTALL**
RMTALL	Pearson Correlation	.792**	.872**	.839**	1
	Sig.(2-tailed)	.000	.000	.000	
		PD1	**PD2**	**PD3**	**PD4**	**PD5**	**PD6**	**PDALL**
PDALL	Pearson Correlation	.728**	.608**	.745**	.721**	.751**	.762**	1
	Sig.(2-tailed)	.000	.000	.000	.000	.000	.000	
		CS1	**CS2**	**CS3**	**CS4**	**CSALL**
CSALL	Pearson Correlation	.849**	.848**	.683**	.710**	1
	Sig.(2-tailed)	.000	.000	.000	.000	
		GL1	**GL2**	**GL3**	**GL4**	**GLALL**
GLALL	Pearson Correlation	.817**	.741**	.736**	.825**	1
	Sig.(2-tailed)	.000	.000	.000	.000	

Source: Writers Analyzed Data, 2023

Image 2. Quantitative Reliability Testing results. Left to right: RMT, PD, CS, GL

Source: Writers Analyzed Data, 2023

In the research model the relationship present are RMT – PD, RMT & PD – CS, PD & CS – GL. From the results, we divide the tests into two parts which are, a Regression test and Classic Assumption test. Regression test involve taking results of linear regression

values such as F, R Square, and t value to figure influence individually, fit of the model, and influence as a whole. Classic Assumption test involve looking at the P-Plot, Collinearity score, Scatter Plot, and Durbin-Watson value to understand randomness of data, variable independence, Difference towards future observations, and influence towards future observations. The results of the quantitative analysis are shown in the following table, including their targets, and whether pass the test or not.

Table 4. Quantitative SPSS Linear Regression Tests

SPSS Linear Regression Tests							
Type of tests	Target	RMT - PD	Pass/ Failed	RMT & PD - CS	Pass/ Failed	PD & CS - RMT	Pass/ Failed
F	F score > 30	704.414	Pass	191.176	Pass	485.278	Pass
R Square	Adjusted R square > 0.6	.631	Pass	.482	Failed	.703	Pass
t	t score significance < 0.05	.000	Pass	.013 & .000	Pass	.000 & .001	Pass
		PD = 0.994 + 0.641*RMT		CS = 0.353 + 0.128*RMT + 0.628*PD		GL = 0.160 + 0.820*PD + 0.126*CS	
Normality	Follows the line	Follows	Pass	Follows	Pass	Follows	Pass
Multicol linearity	Tolerance > 0.100 / VIF < 10	1.000 / 1.000	Pass	0.368 / 2.719	Pass	0.524 / 1.910	Pass
Heterosced asticity	No pattern in Scatterplot	No Pattern	Pass	No Pattern	Pass	No Pattern	Pass
Autocor relation	Durbin-Watson > 1.7584 & 1.7785 /1.7483 & 1.7887	2.059	Pass	1.902	Pass	2.082	Pass

Source: Writers Analyzed Data, 2023

From the tests, it shows that almost every single test pass, with the sole exception being the R Square test between RMT & PD – CS. This is a sign the relationship might not fit the model. To understand this better, we will be testing the Sequence Equation Model by using AMOS to create a graphic. Then afterwards, we can analyse and match the influence and accuracy according to the hypothesis we set up earlier. The graphic after analysing is shown in the following image.

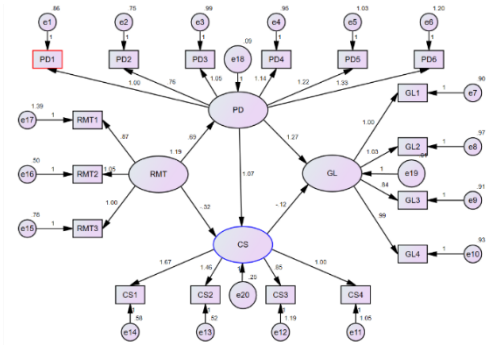

Image 3. Quantitative Sequence Equation Model (SEM)

Source: Writers Analyzed Data, 2023

A text output was also present that shows the regression weight value and P Score of individual variables towards each other. P score shows the consistency of the relationship, and the regression weight estimate shows the influence from the independent towards the dependent variable. The following is the results put forward by the analysis.

Table 5. Quantitative SEM Analysis Results

Relation	P	Target	Estimate	Results
PD ← RMT	***	*** or <0.05	.926	Reliable with a big positive influence
CS ← RMT	.046		-.471	Semi-Reliable with moderately negative influence
CS ← PD	***		1.158	Reliable with a big positive influence
GL ← PD	***		1.075	Reliable with a big positive influence
GL ← CS	.119		-.097	Unreliable with small negative influence
PD = 0.926*RMT				
CS = -0.471*RMT + 1.158*PD				
GL = 1.158*PD + -0.097*CS				

Source: Writers Analyzed Data, 2023

Qualitative

The qualitative research section uses the same variables, models, and relationship as the quantitative section to form results can be comparable in a later part. The qualitative part consists of 30 interviewees, of which all of them gathered from the in-game communication system. The data set manage to pass the outlier, validity, and reliability test without much hassle. The results of which are shown below.

Table 6. Qualitative Validity Testing Results. Top to Bottom: RMT, PD, CS, GL

		RMT1	RMT 2	RMT 3	RMTALL
RMTALL	Pearson Correlation	.827**	.920**	.903**	1
	Sig.(2-tailed)	.000	.000	.000	
		PD1	PD2	PD3	PD4	PD5	PD6	PDALL
PDALL	Pearson Correlation	.629**	.542**	.761**	.838**	.889**	.895**	1

	Sig.(2-tailed)	.000	.000	.000	.000	.000	.000	
		CS1		CS2		CS3	CS4	CSALL
CSALL	Pearson Correlation	.876**		.852**		.774**	.740**	1
	Sig.(2-tailed)	.000		.000		.000	.000	
		GL1		GL2		GL3	GL4	GLALL
GLALL	Pearson Correlation	.891**		.878**		.762**	.922**	1
	Sig.(2-tailed)	.000		.000		.000	.000	

Source: Writers Analyzed Data, 2023

Image 4. Qualitative Reliability Testing Result. Left to right: RMT, PD, CS, GL

Source: Writers Analyzed Data, 2023

We conduct Linear Regression test using this data set to form the following conclusions for the qualitative part:

Table 7. Qualitative SPSS Linear Regression Tests

SPSS Linear Regression Tests							
Type of tests	Target	RMT - PD	Pass/ Failed	RMT & PD - CS	Pass/ Failed	PD & CS - RMT	Pass/ Failed
F	F score > 30	158.150	Pass	23.753	Failed	62.566	Pass
R Square	Adjusted R square > 0.6	.844	Pass	.611	Pass	.809	Pass
t	t score significance < 0.05	.000	Pass	.413 & .070	Failed	.000 & .124	Pass & failed
		PD = 0.136 + 0.742*RMT		CS = -0.079 + 0.226*RMT + 0.638*PD		GL = 0.160 + 0.820*PD + 0.126*CS	
Normality	Follows the line	Follows	Failed	Follows	Pass	Follows	Pass
Multicollinearity	Tolerance > 0.100 / VIF < 10	1.000 / 1.000	Pass	0.150 / 6.648	Pass	0.372 / 2.691	Pass
Heteroscedasticity	No pattern in Scatterplot	No Pattern	Pass	No Pattern	Pass	No Pattern	Pass
Autocorrelation	Durbin-Watson > 1.3520 & 1.4894 /1.2837 & 1.5666	1.768	Pass	1.247	Failed	2.458	Pass

Source: Writers Analyzed Data, 2023

The test this time shows there were more failures directed at the Customer Satisfaction Variable. That mean's that the Customer Satisfaction variable might not fit this model and if placed into this model would have a negative and unreliable influence towards the results of this research. As such, the following SEM test could show the results inaccurately to results we are looking for.

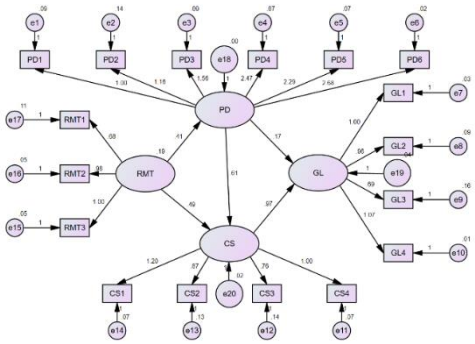

Image 5. Sequence Equation Model (SEM)

Source: Writers Analyzed Data, 2023

From the text output, we also see the inaccuracies being present and changes the models influences heavily compared to one with more numbers and accuracy.

Table 8. Qualitative SEM Analysis Results

Relation	P	Target	Estimate	Results
PD ← RMT	.003	*** or <0.05	1.044	Reliable with a big positive influence
CS ← RMT	.528		.295	Unreliable with moderately positive influence
CS ← PD	.175		.613	Unreliable with a moderately positive influence
GL ← PD	.870		.070	Very unreliable with a small positive influence
GL ← CS	.076		.823	Semi-Unreliable with a big positive influence
PD = 1.044*RMT				
CS = 0.295*RMT + 0.613*PD				
GL = 0.070*PD + 0.823*CS				

Source: Writers Analyzed Data, 2023

To remedy this problem, we removed the relationship that showed the P score being higher than expected. This created an adjusted graphic that could be more similar to the previous quantitative results.

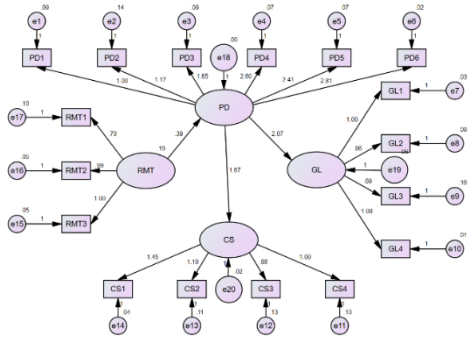

Image 6. Adjusted Qualitative Sequence Equation Model (SEM)

Source: Writers Analyzed Data, 2023

The text output of the analysis showcases a similar result to the quantitative section of which makes Customer Satisfaction the main problem towards the long-term variables of Game Longevity.

Table 9. Ajusted Qualitative SEM Analysis Results

Relation	P	Target	Estimate	Results
PD ← RMT	.005	*** or	1.033	Reliable with a big positive influence
CS ← PD	.008	<0.05	.822	Reliable with a big positive influence
GL ← PD	.015		.878	Reliable with a big positive influence
PD = 1.033*RMT				
CS = 0.822*PD				
GL = 0.878*PD				

Source: Writers Analyzed Data, 2023

Comparison and Overall Results

When comparing the results of both research method, it shows that the quantitative research method yielded more accurate results. Couple of factors plays into this including the higher number of respondents and the type of answers that have more variety in terms to Likert Scale compared to a Guttman Scale. Besides that, their seems to be connection between failing tests and Customer Satisfaction. Specifically in terms of Regression test in SPSS and P value in AMOS being higher than expected. An adjustment made to the model created a more reliable result. As such Customer Satisfaction in future observations can be removed. Finally, we confirm results of the hypothesis being:

H1a: Real Money Trade (RMT) positively affects Purchasing Decisions (PD) of players.

H20: Real Money Trade (RMT) negatively affects the Customer satisfaction (CS) of players.

H3a: Purchasing Decision (PD) positively affects Customer satisfaction (CS).

H4a: Purchasing Decision (PD) positively affects the Game Longevity (GL) of CS2.

H50: Customer satisfaction (CS) negatively affects the Game Longevity (GL) of CS2.

CONCLUSIONS

This research's main goal is to prove the usage of a Game Longevity Model adapted from a Real Money Trading model using the game Counter-Strike 2 and use quantitative and qualitative analysis to compare each result. The quantitative research gathered 410 respondents and quantitative research have 30. Using the Game Longevity model, we can conclude that Real Money Trading has a positive influence on Purchasing Decision, Customer Satisfaction has a negative influence on Game Longevity, and Purchasing Decision has a positive influence on Game Longevity. A game with a well-implemented monetization system that isn't too intrusive can help a game's longevity.

This research implies that the Game Longevity Model does work with a quantitative method research and would require a couple of adjustments for the qualitative method research. Players feel they would play more when they are not required to make the purchase. This option is prevalent in free-to-play games that require players in the lower and higher economy brackets to maintain a consistent player base. The results show that a game with only cosmetic items can work well for longevity. Future observations may use this model, but try it for other games.

This research recommends that games developed in the future don't require essential in-game purchases that target the player. Instead, providing interesting cosmetic items can increase spending with mixed of factors like rarity and tradeable items can help. However, it doesn't mean games that use essential purchases don't have longevity. Research in future observations can observe other games that implement different types of monetization to better understand the variables present towards Game Longevity.

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