NOVA IMS Information Management School

MGI

Mestrado em Gestão de Informação
Master Program in Information Management

The Impact of E-trading and retail investor behaviour.

Diogo Miguel Pedro Esteves

Dissertation

presented as partial requirement for obtaining the master's degree Program in Information Management

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

The impact of e-trading and the behaviour of retail Investor

By

Diogo Miguel Pedro Esteves

Dissertation presented as partial requirement for obtaining the master's degree in Information Management, with a specialization in Information Systems and Technologies Management

Advisor: Mijail Naranjo Zolotov

November, 2022

ACKNOWLEDGEMENTS

Acknowledging the help of others must not be forgotten and I must follow this rule as one of the principles that I walk upon. My enormous thank you to all who, directly or indirectly, have contributed to one of the most important steps of my life.

I would like to start by thanking to Professor Mijail Naranjo-Zolotov, for accepting in being my supervisor, for the assistance and time provided during the process of this dissertation.

To all the professors I came across throughout my academic life, for sharing all their knowledge support even on personal matters.

A special thanks to my work colleagues, Catarina and Debora. Such a demanding phase of my life, to thank for all the flexibility that allowed me to successfully complete this master's degree. Extending my gratitude to Serafim who, never failed me with this friendship and unconditional support.

The warmest thanks go to my family, for their love, support and for always believing in me. Especially to my parents, for prioritizing my education and dedicating themselves to giving me the best so that I could succeed in any path I decided to follow.

Finally, to Me. Nothing is possible if we don’t believe in yourselves, if we don’t do it for us no one will do it, believing is the first step between us and our goal.

A deep thank you.

ABSTRACT

Human behaviour is always a complicated subject of study but is one of the most wanted in many related areas, such as finance. Behavioural finance studies have been booming over the last years once scientists and organizations try to understand the causes and effects that lead to a particular action. This is in line with the general information on areas related to finance (e.g. Investments, personal finance, decision and control, among others. With this rapid spread of information, social interaction is more than ever an exciting topic to consider once the financial decision can help us predict behaviour. During the pandemic, many people worldwide were in lockdown, which drew their attention to finance investments. Cases like the Game stock and Reddit users show that retail investors can move prices up and down the market enough to create a loss for great corporations and financial institutions. This type of social behaviour shows how important it is to understand what drives human behaviour in finance to avoid a crash in the market system. This study uses the validation and expansion of the technology acceptance model (TAM) on social interaction in trading and investment applications and tries to predict if people are being influenced when or to use this kind of application. To achieve this mark, we collected 233 responses using Qualtrics and then indicated that social interaction significantly affects user behavioural finance.

KEYWORDS

Financial Market; Social interaction; Trading and Investing; Behaviour; Finance applications

LIST OF ACRONYMS AND ABBREVIATIONS

TAM - Technology Acceptance Model

Securities - Financial product with value that can be traded

Stocks - Type of security that gives stockholders a share of ownership in a company

NOVA IMS – Nova Information Management School.

Retail investor – Person who does not do Investing or Trading as part of his daily job.

NASDAQ - National Association of Securities Dealers Automated Quotations

ECN – Electronic communication network

CME – Chicago Mercantile Exchange

Globex - Electronic trading system providing global connectivity

VIF – Variance inflation factor

ÍNDICE

INDEX TABLE OF FIGURES

INTRODUCTION

Over the last decade the pace on developing new technologies have been increasing like never seen, and one of the effects directs or indirect is on how information is being shared and consumed. Every day we are fill with advertising in any aspects that the main purpose to influence our behaviour to a certain extent. As technology advances and information spreads across the globe, more acknowledgement that human behaviour becomes even more essential to bring to the discussion table. In recent years there has been an explosion of studies related to human behaviour and its role in society. This importance was more visible during the Covid-19 pandemic, as the world suffered from isolation on many countries, which had an impact on how society interact with each other. This kind of standard about social interactions and human behaviour, seems to be shaping how we see and deal with people, it seems that a new era is here to stay.

Human behaviour has always been a subject of study due to thematic complexity, not only for a predictable purpose but also to better understand human society interactions in ancient times. Social interaction has many definitions, as example the one use on the American Psychological Association website that describes as "*any process that involves reciprocal stimulation or response between two or more individuals*". Social interaction can be categorized in two parts: One-sided and Two-sided interactions (*Effects of Social Interaction in Financial Markets*, n.d.). One sided, is when this interaction is indirect e.g., reading a book, website or watching television. Two-sided or social group interaction is considered direct e.g., a class, a lecture or talking with others. Interaction in society is how people learn, and this interaction is leading to impact our decisions day by day, also applied to financial decisions.

Investing, cryptocurrencies, bonds, and stocks are concepts growing from the financial world into our daily lives. You might be hearing these concepts for the first time, but those concepts are not new. If we analyse deeper and investigate the books of history, negotiations like spices, textiles and precious metals were among the most traded goods in ancient times. Nowadays, trading and investing are mainly associated with economic concepts involving buying and selling goods and services, with compensation paid by a buyer to a seller or exchanging goods or services between parties. We can also say, "In financial markets, trading refers to the buying and selling securities, such as the purchase of stock"(HAYES, 2022).

Trading securities are now more connected with our daily lives due to the expansion of information around the world and have arrived at the normal consumer, the Retail investor. We can find everything there is about to know on the internet. YouTube for example has a huge number of tutorials and information shared, that just by the total numbers of users that can produce and consume information worldwide, last data says that in the end of 2021 there were about 2.24 billion users (Degenhard, 2021)

Online videos are one of the multiple ways to provide advertising to trading and investing platforms. However, we can also find that information in radio ads, billboards, and pop-ups in TV ads...the list is long, but we want to point out that the more information we consume, the greater the chance of sharing the same information. In its simplest form, sharing is taking the information from A and delivering it to B. This sharing of information can directly or indirectly influence both sides. Sharing as a society can lead to a bigger influence on our actions or what we call "social influence". Generally speaking, social influence comes when information that we have (or believe) is still uncertain and is "in the middle between our perception and reason (our senses and views, which we routinely trust)" (Spears, 2021b).

The current research proposes that this easy access to the market through these trading and investing applications have more exposure to social interactions and consequence influence on users' behaviours meaning choices. Therefore, this research analyses whether social interaction strongly influences user behaviour using quantitative data from survey analysis.

Alternatively, this study aims to contribute to the exitance literature and further understand on human behaviour in a social environment and the impact on the decisions on financial applications such as trading and investing. The results could further support the understanding of how retail investors are being influenced in their financial decision. It could also support on data to algorithms and safe policies to prevent unexpected and aggressive market movements due to social engagement.

LITERATURE REVIEW

Researchers concluded long ago that social connections and interactions change and shape economic variables that affects financial decisions directly and indirectly influenced by beliefs and behaviours, as (Spears, 2021) mentioned in his paper. Behavioural finance is the study of the influence of psychology on the behaviour of financial practitioners and the subsequent effect on markets (Sewell, 2007). Daniel Kahneman refers in his paper "Prospect Theory: An Analysis of Decision under Risk" that there are many factors influencing the decisions, which primarily will depend on the understanding of the event, not only influenced by ambiguity and vagueness but primarily by significant biases. This is the reflection that all what we perceive as an effect on our way of thinking.

THE HISTORY OF TRADING

How did we get here and mix the social influence with online trading and investing? It all begins when a company called "Instinet" created the first electronic communication network or ECN. Until 1969 it was not possible to buy or sell stocks after the closing of the market. This was the first step to an industrialization of electronic trade. NASDAQ (National Association of Securities Dealers Automated Quotations) was the first electronic stock market created in the 70's. However, still far away from what we know as "electronic trading". For example, on that time, prices were only updated once per day, that when looking at today if you open on Bloomberg channel you will see the price updating in a window of 30s or less.

The Black Monday crash in 1987 was other mark in the impulsion of the electronic trading. Back in the days Brokers-dealers were allowed to delay trading to try to balance the market. On that day the market open with a huge, never seen, selling orders across the day. Since the market was so one side the broker and dealers stop answering the phone and place the orders to their clients which lead to a crash. Later, during the years 96 up to the year 1999, online trading increased as the internet was wildly commercialized, which allowed small traders to have access to similar conditions as professional brokers, the meaning of "day trader" was born. Other of bookmarks of electronic trading is CME Globex, the online platform, that enable to all customers to trade directly in the system which gave the freedom of trading over the telephone

Even though the stock market was accessible to the investors across the internet this type of new technologic, was mainly use by professionals and big companies due to the complexity and the amount of cash or collateral that needed to be invested. As we follow through the financial history, the use of trading using online applications is not new, and it was already in placed but only due to our technologic, rapid evolution and a better internet accessible coverage that number was growing. Covid by the other hand boost that growth. The fact that many countries adopt a lockdown culture to stop the spread of COVID-19 lead to a huge surge in trading and investing stock on mobile phones and online access up to 45% in May 2020 compared to 24% May 2019 the impressive that most of the users did have more than 30 years (Rukhaiyar, 2020). Not only on the field of stocks but also the new electronic assets such as Bitcoin and his electronic coins made the contribution for people that never had entering in the market became part of the group of the retail's investors. Online trading was an incentive to the thousands of people that had their income cut and saw the opportunity to have an extra income, or simple the ones that had extra money and with the desire to spend, in both cases the variables such the free time and social contact trigger people to use these services.

TECHNOLOGIES AND E- TRADING

It would not be possible to relate all these variables if we would not have into account the technologic factor. The fact that nowadays we are surround by technologic that produce a large amount of information due to the globalization of the internet. A brief look from the *DataReportal* report from Jan2022 is reported that 4.95 billion of people have internet access, which is a big key factor for a globalization of the information and give us a brief look at the mount information we can get on the XXI century.

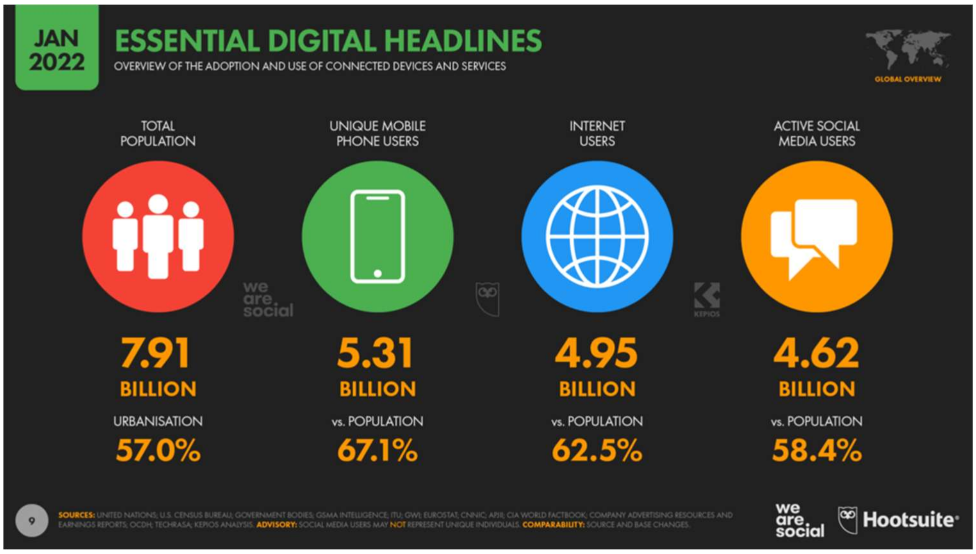

Figure 1 Digital overview of 202. Source: *Global Digital Overview January 2022 DataReportal*

This massive access generates a large of information not filtered which is becoming more and more difficult to process what is a valid or not information. This gap of not accurate information can influence the behaviour and by consequence their actions of the users who are consumed by. The impact will depend on the information provided and how we use, which can lead to many discussions, therefore, let's just concentrate on the information that retail investors have available and consume.

The retail investor is a non-professional investor or person who does not use investing as a career (*Retail Investors Definition | Nasdaq*, n.d.). By default, they have more limitations than corporate investors, not only on monetization but also on information available for decisions. Perceived value, perceived usefulness and perceived compatibility were crucial factors that led people to download a particular application (Tang et al., 2020). The introduction of online trading stocks and investments was a big win for retail investors. One of the most popular trading applications is *Robinhood*, the first mobile application to apply the model of no-commission brokerage and last year, was still the best choice among others to start investors by some online financial magazines and blogs (appendix 1)

Today *Robinhood* is still relevant in the world of trading apps even though its active users have declined since this year compared to last year, accordingly to CNBC. Trading apps and online platform are associated with gambling, as a paralleled some authors suggests, as these platforms and applications have high risk as it allows the borrowing of capital for easy access; although some platforms have knowledge test, those are easily manipulated to get the higher score.

RETAIL VS INSTITUTIONAL INVESTORS BEHAVIOR

Studies are targeting retail investors as big movements over the years are becoming more frequent. Examples of small investors and people with less economic power are making moves on the market due to the easier accessibility provided by online brokerage applications. If we try to establish a relationship between both, individual investors are less sophisticated because of the imitated attention, memory, time, profession, and infrastructure.

Some theories(Lai, 2019)believe that people behave rationally, and such behaviours can be predicted using" Behavioural finance". Yeh and Li, stated eight stages where the psychological can influence the market: suspicion, hope, optimism, euphoria, overconfidence, ambivalence, pessimism, and fear. Depending on the stage, we can have different type of return. Other difference is the availability to keep the position, retail investors tend to keep the losing positions to long and sell winning positions too soon. Some studies suggest that extrovert have more intention to do a short-term investment whereas a more neurotic and risk aversion tend to avoid those instruments. On the other hand, institutional investors, exhibit pieces of confidence, optimism, hight emotional intelligence and flexibility.

Other's authors point the gambler fallacy Bias as one of the factors that influence the strategic of the investors, assuming that the market is reacting in a way, and it is not. We would assume that the 100% independent have full knowledge and with all the information possible, however social interaction as we notice on the flow above is part of this change.

FINANCIAL BEHAVIOR

The human brain has the need to understand everything that is not predictable. In this quest for knowledge, some financial corporations, such as Barclays and Russell investments (appendix 1), have tried to apply the cycle of the investor model for risk assessment. In 2021, Barclays published the cycle to provide a notion of the emotion of the investor

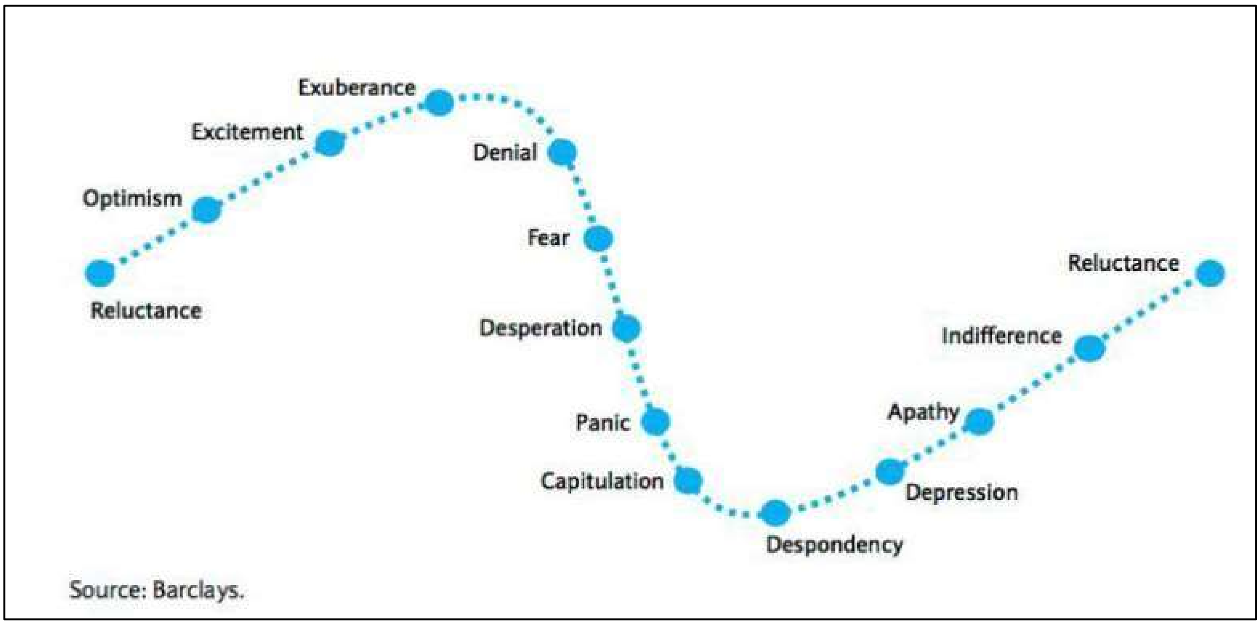

Figure 2 - Emotion of the investor, Source: Barclays

The following are the descriptions of the stages:

The first stage starts from almost zero point on believing until the maximum emotion, such as euphoria or exuberance. In this stage, the individual investor will start to gain confidence as expectations are fulfilled, and the user gets more returns as time passes until he reaches the top. At this point, overconfidence is one of the key emotions, big returns, and less risk perceptions. The user is taken to a point where we feel he understands how the market operates, and I can tell by personal experience that this is a fact. However, less risk aversion is not free of risk, and it is only our perception of the risk that is shaped by our emotions; as a matter of fact, at this point, we have high returns but also have the same amount of financial risk.

On the second stage, his when the reality starts not to comply with our perception. Ours decisions starts not match what expected, so we turn to the media, advises and support to understand what action the investor can take in order to back on the positive line of the investment. Normally on this stage users gets anxiously and act defensively, as he starts to consume more information about the market, not necessary from professionals or reliable.

As Losses starts to bigger than the gains, investor lose the confidence and act in desperation starting to withdraw from the market securities to protect investors assets. Doubt on whether to invest or stop is one of the feelings of the third stage.

As these feelings become deeper investors gradually become too volatile to act and make new investors with the fear of lose all. Investors starts looking at the retrospective trying to analyse what they miss and if they should start making new investments. However, this recall brings the memories of loss, fear and uncertain, which makes the investor not miss some opportunities for investing, as he is contaminate by the feelings. In this stage is when there is greater opportunity to invest since this is the point of maximin financial opportunities. As more positive news arrive about the market users will gradually reach to point zero again.

FRAMEWORK

In order to understand user behaviour linked with technological adoption and align with this study we have used Acceptance Model or TAM (Davis, Bagozzi, & Warshaw, 1989) as the original starting point. According with TAM model, a person's attitude toward new technology is determined by two perceived variables: Usefulness and Ease of Use. Since both are related with what a person & user perceives, the TAM model uses Perceived usefulness (PU) and Perceived Ease of Use (PEU or PEOU)

Perceived usefulness (PU) is defined here as "the degree to which a person believes that using a particular system would enhance his or her job performance". (Davis, 1989). Perceived Ease of Use (PEOU) on the other hand refers to "the degree to which a person believes that using a particular system would be free of effort"(Davis, 1989), Which goes in line with the word "ease" and his definition "something does not involve difficulty or effort"

Later developments by Venkatesh and Davis extended the methodologic and call it TAM2, now with the social interaction and cognitive processes ad part of the balance weight. An Individual's subjective norm helps motivate him/her to perform a certain behaviour even if he/she does not favour of the behaviour, but because other referents feel that he/she Should perform it hence the individual complies with those norms, therefore having a direct impact. We use the TAM2version in this study.

HYPOTHESES

The (*Icek Ajzen: Homepage*, n.d.) social norms have an influence on the user intentions perception for a determined behaviour. Using this information and using our model TAM2, where says subjective norms influence the intention to use based on perceived usefulness, we formulate the hypothesis below:

H1.1: Users “Subjective Norm” on using trading/investing applications has positive influence on “perceived usefulness.”

Previous studies have found a correlation between choosing an eco-friendly backpack instead of a luxury when private from social status and visibility to others. Others develop the visibility to understand behaviour which led us to the below hypothesis:

H1.2: Users “Visibility” on using trading/investing applications has a positive influence on “perceived usefulness”.

Collective action often depends on the social ties of the member of an organization or in a group and is common to see this type of actions emerge in a group.

H1.4: Users “Critical Mass” on using trading/investing applications has a positive influence on “perceived usefulness”

Image is the “degreed to which use of an innovation is perceived to enhance one's image or status in one's social system"(Moore & Benbasat, 1991). Is by far the most unquestionably factor for a person adopts and innovations as part of the desire to achieve social status. Is also link to the with the perception of one image of their position in the social structure (Moore & Benbasat, 1991). Since the goal of this study is to reach conclusions on whether the investing applications user are high expose to social interaction image could not be left behind and we formulate the below hypothesis:

H1.3: Users’ “image” on using trading/investing applications has positive influence on “perceived usefulness.”

Perceived ease of use refers to the degree to which an individual believes that using a particular system is free of effort(What Is Perceived Ease of Use (PEOU) | IGI Global, n.d.). This variable is link with the user intention once the easer it gets to operate more is the change for the person become the use.

Perceived ease of use was used in this study to refer to the degree to which a person& user feel that using investing and trading applications will have a positive effect of buy and selling securities

H2: Users' "perceived ease of use" of trading/investing applications has positive influence on their "perceived usefulness."

H3: Users' "perceived ease of use" of trading/investing applications has positive influence on their "intention to use".

An individual's perceived Usefulness is described as a person's tendency to use an application and to believe that this perception will help him do a better work. It was further explained that it was due to social influence would positively deepen the image on the value of an innovation and the image would then positively influence perceived usefulness(Mei & Boon Aun, n.d.)

H4: Users' "perceived usefulness" of trading/investing applications has positive influence on their attitude about "intention to use"."

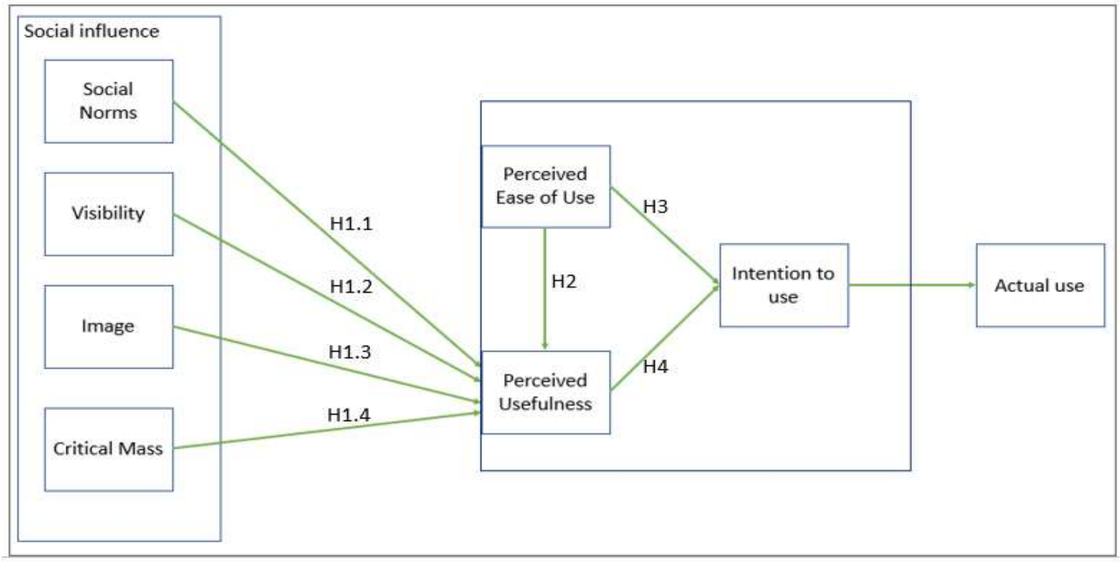

Figure 3 - TAM2 modify and hypotheses

METHODOLOGY

DATA COLLECTION

In order to obtain measurable data, it was used a survey “Qualtrics”. The following table shows the questions for the participants using the Likert Scale: (1) Strongly disagree; (2) Disagree; (3) Neither agree nor disagree; (4) Agree; (5) Strongly agree. We also export from Qualtrics in numeric version, so we could use in analytic software to understand our data.

Since the purpose of this study is to understand the social interaction influence on trading and investing decisions, the only parameter we use on this study to collect data was “user must have more than 18 years old”, this is in line with the fact that for gambling, trading or investing the user/ participant need to have more than 18 years old.

Table 1 - Questions from survey

Name	Item
Image	People in my organization (or at school) who use trading and investing applications are more desirable than those who do not.
	Doing online trading/investing are a status symbol in my organization (or at school).
	People in my organization (or at school) who use trading and investing applications have a high profile.
Intention	I have an intention to buy/sell Stocks on trading and investing applications
	If I have an opportunity, I will buy/sell Stocks on trading and investing applications.
	I think trading and investing applications are an acceptable place to buy/sell stock
	I intended to keep to buy/sell Stocks in trading and investing applications
Critical mass	Of the people I am in contact with regularly, many use this trading/investing application
	Of the people I network with, many use this online social network.
	The people I am in contact with that use this trading and investing applications will continue to use it in the future.
	Many people I know use this trading/investing application.
	Of the people I am in contact with using this online social network, many use it frequently.
Perceived Ease Of Use	I can easily visit online trading and investing applications
	I can visit online Trading and investing applications whenever necessary.
	I can quickly find favourite stocks lists in trading and investing applications.
	Payment is easy, when I buy/sell stocks through trading and investing applications.
	The process of buy/sell stocks through trading and investing applications smoothly.
Perceive Usefulness	Using trading and investing applications would increase my productivity in buy and selling stocks.
	Using trading and investing applications would improve my performance in buy and selling stocks
	Using trading and investing applications would enhance my effectiveness in buy and selling stocks

	I would find trading and investing application useful in buying and selling stocks
Social norms	People who influence my behaviour think that I should use trading/investing applications
	People who are important to me think that I should use trading/investing applications
	People whose opinions I value prefer me to use trading/investing applications
Visibility	On the Internet, I see a lot of commercials about trading and investment
	trading/investing applications are very commonly used by people from my age
	It is easy for me to observe others using online trading and investing applications

RESULTS AND DISCUTIONS

In other to understand our data collected from the surveys, this study analyses the data using partial least squares structural equation modelling (PLS–SEM) model type in SmartPLS version 4. PLS-SEM is used for exploratory analyses, as it aims to explain the variance of the dependent variable(J. F. Hair et al., 2014) It has been widely applied in management and information systems and some areas of finance and behaviour. Due the complexity of the subject and the variables in study PLS-SEM is the chosen for analysis the relations of this research model that is proposed as an estimate model combining related theories and empirical studies.

DEMOGRAPHIC INFORMATION

The following table 1 resumes the information of the first part demographic information. Most of the participances were male around 65% following by female around 35% leaving only 0.5% to 3rd Gender. Data also shows us more than 50% were in the ages between 18 -35 years, and the remaining above 36 years old around 25%. Most of the respondents are employed full time more than 90% which show us strong unbalance, on the other hand the income gap is the one of the more balances since there is no group outstanding, on the middle we have incomes between 20k and 49,999K 36.2% and 50k and 74.999. A total of 232 response were collected and validated for this study, during a period of one and half months.

Characteristic	Frequency	Percentage
Gender		
Man	150	64.7%
Woman	81	34.9%
Non-Binary / 3rd Genre	1	0.4%
Age		
18-25	36	15.5%
26-35	139	59.9%
36-45	21	9.1%
46-65	33	14.2%
65+	3	1.3%
Employment status		
Full time	220	94.8%
Half of the time	3	1.3%
Student	7	3.0%
Other	1	0.4%
Unemployed	1	0.4%
Income		
Less than 20,000	22	9.5%
20,000 - 49,999	84	36.2%
50,000 - 74,999	79	34.1%
75,000 - 99,999	32	13.8%
100,000 +	15	6.5%

DATA ANALYSIS

Reliability Analysis

Reliability analysis allows you to study the properties of measurement scales and the items that compose the scales.(*Reliability Analysis Statistics - IBM Documentation*, n.d.). In summary is a measure of trustworthiness or stability and allow us to observe which items are related with each other.

Our model is composed by reflective indicators, in the graphic arrows point out. Before we start the quality assessment, we test our model using the criteria of variance inflation factor (VIF) which looks at a random variable and looks for common method biases, having above 3.3 points that relation is positive (Kock, 2017). Upon adding a random variable on the model and run It again, our values were lower than 3.3, having a maximum value of 2.875 (Table 2), therefore our model is considered free of common method bias. On the measurement of quality model, we follow the approach of the (J. Hair et al., 2017). We are looking for internal consistency, construct reliability and discriminant validity.

Composite reliability (CR) and the Cronbach's alpha (CA) of most variables were above 0.7, only Visibility had a value of 0.709, which is still above 0.7, overall, we can consider this numbers a good internal consistency. The average variance (AVE) that assesses the convergent validity and the outer loadings are expected to be above 0.5. However, the values that we get are not ideal. Visibility, Perceive Usefulness and Perceived ease of use have values below 0.5 (0.451; 0.434; 0.479 respectively). Fornell suggest an AVE above 0.5, however (Lam, 2012) goes further on the analysis by (Fornell & Larcker, 1981)on the condition if CR is more than 0.6 the model is still valid once most of the variables have more than 0.5 recommended by Fornell and Larcker.

Table 2 - Measurement Model

Name	Abbreviations	Mean	Standard deviation	Loading	CA	CR	AVE
Image	IMG_1	2.914	1.261	0.99	0.922	0.949	0.803
	IMG_2	2.867	1.295	0.977			
	IMG_3	2.876	1.252	0.689			
Intention	INT_1	3.712	0.917	0.847	0.805	0.822	0.52
	INT_2	3.691	0.898	0.662			
	INT_3	3.73	0.926	0.623			
	INT_4	3.661	0.994	0.732			

Critical mass	M_1	3.785	0.906	0.757	0.889	0.89	0.615
	M_2	3.88	0.942	0.815			
	M_3	3.837	0.893	0.736			
	M_4	3.944	0.787	0.784			
	M_5	3.88	0.905	0.826			
Perceived ease of use	PEOU_1	4.047	0.695	0.703	0.821	0.825	0.479
	PEOU_2	4.094	0.764	0.629			
	PEOU_3	4.03	0.69	0.648			
	PEOU_4	3.88	0.766	0.779			
	PEOU_5	3.974	0.764	0.693			
Perceive Usefulness	PU_1	4.004	0.618	0.626	0.754	0.756	0.434
	PU_2	3.97	0.799	0.665			
	PU_3	3.996	0.625	0.628			
	PU_4	4.077	0.707	0.714			
Social norms	SN_1	3.721	0.919	0.921	0.872	0.881	0.698
	SN_2	3.781	1.01	0.821			
	SN_3	3.785	0.952	0.757			
Visibility	VS_1	4.056	0.765	0.647	0.709	0.712	0.451
	VS_2	3.979	0.794	0.661			
	VS_3	3.897	0.863	0.704			

Note: SD - Standard Deviation, CA - Cronbach's Alpha, CR - Composite Reliability, AVE - Average Variance Extracted

This result shows that the discriminant validity theory concepts are also applied on the practical since they don't reveal to be related with each other.

For analysis of the discriminant validity the method of Heterotrait-Monotrait Ratio (HTMT) and Fornell-Larcker criteria were used. The Heterotrait-Monotrait Ratio of the correlations measure the similarity between latent variables. The measure should be less than 1.00 (Henseler et al., 2015). On the following table the results we can see that all the variables are less than 1, which is confirms our part 1 of discriminant validity since there is no strong evidence of correlation.

Variables	1	2	3	4	5	6	7
Image							
Intention	0.105						
Critical Mass	0.245	0.636					
Perceived ease of use	0.174	0.617	0.827				
Perceived usefulness	0.281	0.565	0.764	0.861			
Social Norms	0.187	0.538	0.822	0.653	0.718		
Visibility	0.201	0.542	0.880	0.875	0.789	0.735	

Figure 4 Heterotrait-Monorait ratio

For the second part of our model discriminant validity, we use Fornell-Larcker criterion which is an analysis to compare the value of the AVE square root with the construct correlation value showing the highest value in any column or row compared to the highest correlation value of any other construct (Sarstedt et al., 2017). On the following table our values were not what we were expecting, as PEOU, PU and VS have higher values than its correlation. Although since our model was validated on the HMTM, we further analyse our residuals to understand how correlated the variables were.

Variables	1	2	3	4	5	6	7
Image	**0.896**						
Intention	0.065	**0.721**					
Critical Mass (M)	0.250	0.640	**0.784**				
Perceived ease of use (PEOU)	0.165	0.622	0.829	**0.692**			
Perceived usefulness (PU)	0.286	0.558	0.765	0.860	**0.659**		
Social Norms (SN)	0.191	0.546	0.816	0.658	0.720	**0.836**	
Visibility (VS)	0.206	0.541	0.881	0.874	0.790	0.732	**0.671**

Figure 5 -Fornell-Larcker discriminant validity

Analysing the correlations between the variables on the residuals we noted that most of the correlations were below 0.2 which indicates very low or no correlations, however there was some variables that were above 0.2 that brings our attention. On table 5, Table 6 we had values above 0.2 until 0.23, which is not the ideal. With his examination we can determine this model is adequate and have discriminant validity except for the two scales of measurement (namely: PEOU_1 with M_4 and PU_4 with M_5).

STRUCTURAL MODEL

To test the model structural, we used the bootstrapping technic with 5000 subsample to run the algorithm. This technique allows us to see the validation of our hypotheses using the p-value criteria. Since all of our hypotheses would have a positive effect on the next variable, to prove there is an influence on the behaviour, we expect the relations between variables were positive. However, looking at the Table 3 six of our hypotheses were validated (H1.1, H1.2, H1.3, H2, H3, H4) and one was rejected (H1.4).

To support our data, we need to look at the coefficient of determination (R^2). This method helps to understand how good is our model to predict the outcome where the numbers can go from 0 to 1, being 0 the lower point where our model does not predict the outcome and 1 the maximum leading to a perfect prediction Coefficient of Determination (R2) | Calculation & Interpretation, n.d.)

On the below table – R Square data suggests that both variables have R-square strong to be predictable, however “intention”

Table 3 - R - Squere

Item	R-square
Intention	0.389
Perceive Usefulness	0.802

Reliability analysis allows you to study the properties of measurement scales and the items that compose the scales.(*Reliability Analysis Statistics - IBM Documentation*, n.d.). In summary is a measure of trustworthiness or stability and allow us to observe which items are related with each other

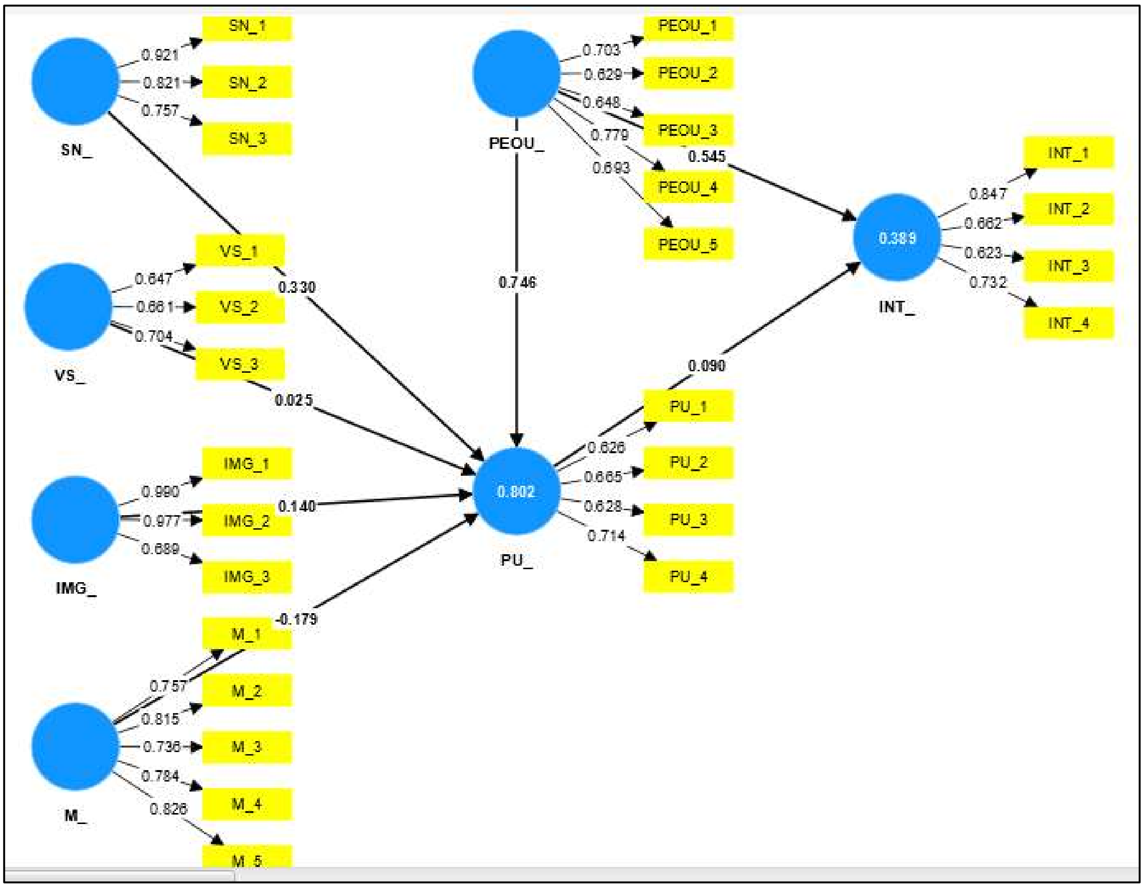

Figure 6 - Structural model

DISCUSSION

The current study investigates a complex topic on the present day's financial decisions and social interactions using trading and investment applications. The researcher gathers qualitative data from 233 users in an online questionnaire with users around the world and examined seven hypotheses through structural equation modelling.

The data, upon analysis, during this questionary (*N =233*) were in line with the theories we use as the background as social interaction influences users' decisions. Six hypotheses were validated, and one rejected Critical Mass). Critical Mass presupposes that a group of people can influence user behaviour. In our study, this correlation has a slightly negative effect which is different from other studies. The result could indicate that our study needed to have a number of replies to validate these hypotheses (*N = 233*)

Theoretical implications

There are many studies about financial applications as well as users' behaviour in a social environment. However, in recent years, especially post-COVID, the booming studies related to each other are being brought to light. In this scenario, this study is a contribution and can support future studies on the above effects.

The results of H1.1, H1.2 and H1.3 indicate that Social Norms, Visibility and Image, have a positive effect on user perception usefulness to use trading and applications investments. These findings suggest that what users find helpful is hight impacted by external forces and are more likely to use that kind of application if there is an external stimulus such as peers, ads, or perceptiveness from how others use the same tools to leverage their lives (status or financial) (Hirshleifer, 2015)

It needs to be mentioned that in H1.4, critical mass did not positively influence user perception, meaning that in this study group of users does not have a relevant influence on user behavior and, therefore, no influence. However, as already mentioned, this can be a limitation of our study, as critical mass presupposes a significant number of people, and further studies should be conducted to determine how many should be necessary to have a positive correlation.

The second part of our study is on user awareness of how easy it is to use the applications. Our data shows that the more the user perceives less effort to use applications more probability has to use(Dolan, 2015; Power, 2019).

Table 4 - Resultes

Hypotheses	Path	Original sample (O)	P values	Supported or rejected
H1.1	SN -> PU_	0.33	0.000	Supported
H1.2	VS_ -> PU_	0.021	0.000	Supported
H1.3	IMG_ -> PU_	0.138	0.000	Supported
H1.4	M_ -> PU_	-0.177	0.000	Rejected
H2	PEOU_ -> PU_	0.748	0.000	Supported
H3	PEOU_ -> INT_	0.545	0.972	Supported
H4	PU_ -> INT_	0.09	0.995	Supported

Practical implications

This study has implications for policymakers and further developments in this field. Human behavior is one of the most things to predict in all external and internal interactions. However, it should continue us to understand our actions in complex filed such as finance. Policymakers should use all that is available to create security for the financial market when understanding what moves retail investors to take a particular decision. Since external factors play a crucial part in investor decisions, it is expected that more investment should be made to educate the investor in a way to be less influenced by external forces. (*The Effect of Higher Education on Graduates' Attitudes: Secondary Analysis of the British Social Attitudes Survey*, 2015).

The findings on this paper could encourage users on self-education to be more protected from the investor emotion cycle. This paper focus on trading in investment applications, however the finding of this study can provide information that can be used on other applications where social interaction may have a significant role on the user final decision

CONCLUSION

The results and data are in line with the previous research where studies were conducted about social interaction and the relation with householding market (Bailey et al., 2018). This model applies one extension of the Technologic acceptance model 2. The results suggests that Critical Mass does not have a positive effect on the perceive usefulness on using applications to buy or sell securities, which means that by the definition of critical mass we don’t need an elevated number of people to propose a change on the individual behaviour. However, the main focus of this study was indeed target once our data suggests that indeed individuals’ behaviour can be influence by social interaction.

LIMITATIONS AND FUTURE RESEARCH

Even though this study provides some data about social interaction on the investor behaviour there are some limitations we need to point out to be address in future studies. We acknowledge that the time of this study is only a small representation sample. The collection of the respondents was random but base on the availability of the research, which means, this is a sample and does not represent the whole population or retails investors. Although we did not provide any restriction on the max age, most of our participants were on Gen Z and millennials, which could interfere on the data, as some saying the older, we get less influence from others on our decisions we get. Futures studies should apply and even number to the respondents to compare if same results are applied.

Questionnaires are always an estimation and subject to errors, since these respondents might not have fully accurate and therefore have affected the data provided This study provides support to the data available on the marker about social interaction and investment decisions.

There is some data available on the market about the circle of the investor that trying to explain the emotions of the investor (*The Cycle of Investor Emotions | Barclays Smart Investor*, n.d.) since we are now on a contraction and a period of savings, people are not so willing to invest, therefore less available to accept changes, being said futures studies should also evaluate period of abundance.

These limitations should be considered in future studies, and research models should be adjusted accordingly.

BIBLIOGRAPHICAL REFERENCES

Bailey, M., Cao, R., Kuchler, T., & Stroebel, J. (2018). The economic effects of social networks: Evidence from the housing market. *Journal of Political Economy*, *126*(6), 2224–2276. https://doi.org/10.1086/700073

Coefficient of Determination (R^2) | Calculation & Interpretation. (n.d.). Retrieved November 22, 2022, from https://www.scribbr.com/statistics/coefficient-of-determination/

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339. https://doi.org/10.2307/249008

Degenhard, J. (2021, July 20). *Youtube users in the World 2025 | Statista*. https://www.statista.com/forecasts/1144088/youtube-users-in-the-world#statisticContainer

Dolan, R. M. (2015). *SOCIAL MEDIA ENGAGEMENT BEHAVIOUR: A USES AND GRATIFICATIONS PERSPECTIVE*.

Effects of Social Interaction in Financial Markets. (n.d.).

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312

Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, *26*(2), 106–121. https://doi.org/10.1108/EBR-10-2013-0128/FULL/PDF

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management and Data Systems*, *117*(3), 442–458. https://doi.org/10.1108/IMDS-04-2016-0130/FULL/PDF

HAYES, A. (2022, September 15). *Trade Definition in Finance: Benefits and How It Works*. https://www.investopedia.com/terms/t/trade.asp

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/S11747-014-0403-8/FIGURES/8

Hirshleifer, D. (2015). Behavioral Finance. *Https://Doi.Org/10.1146/Annurev-Financial-092214-043752*, *7*, 133–159. https://doi.org/10.1146/ANNUREV-FINANCIAL-092214-043752

Icek Ajzen: Homepage. (n.d.). Retrieved November 21, 2022, from https://people.umass.edu/aizen/index.html

Kock, N. (2017). Common method bias: A full collinearity assessmentmethod for PLS-SEM. *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications*, 245–257. https://doi.org/10.1007/978-3-319-64069-3_11/COVER

Lai, C. P. (2019). Personality Traits and Stock Investment of Individuals. *Sustainability 2019, Vol. 11, Page 5474*, *11*(19), 5474. https://doi.org/10.3390/SU11195474

Lam, L. W. (2012). Impact of competitiveness on salespeople's commitment and performance. *Journal of Business Research*, *65*(9), 1328–1334. https://doi.org/10.1016/J.JBUSRES.2011.10.026

Mei, Y. C., & Boon Aun, N. (n.d.). *Factors Influencing Consumers' Perceived Usefulness of M-Wallet in Klang Valley, Malaysia*. Retrieved November 21, 2022, from http://buscompress.com/journal-home.html

Moore, G. C., & Benbasat, I. (1991). *Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation*.

Power, J. (2019, February). *The Influence of Task Difficulty on Engagement, Performance and Self-Efficacy*. https://www.researchgate.net/publication/330849025_The_Influence_of_Task_Difficulty_on_Engagement_Performance_and_Self-Efficacy

Reliability Analysis Statistics - IBM Documentation. (n.d.). Retrieved November 20, 2022, from https://www.ibm.com/docs/en/spss-statistics/25.0.0?topic=analysis-reliability-statistics

Retail investors Definition | Nasdaq. (n.d.). Retrieved June 14, 2022, from https://www.nasdaq.com/glossary/r/retail-investors

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial Least Squares Structural Equation Modeling. *Handbook of Market Research*, 1–40. https://doi.org/10.1007/978-3-319-05542-8_15-1

Sewell, M. (2007). Behavioural Finance. *London: University Collegge London*. https://www.academia.edu/2813323/Behavioural_Finance

Tang, J., Zhang, B., & Akram, U. (2020). User willingness to purchase applications on mobile intelligent devices: evidence from app store. *Asia Pacific Journal of Marketing and Logistics*, *32*(8), 1629–1649. https://doi.org/10.1108/APJML-06-2019-0411

The cycle of investor emotions | Barclays Smart Investor. (n.d.). Retrieved November 23, 2022, from https://www.barclays.co.uk/smart-investor/news-and-research/investing-for-beginners/understanding-the-cycle-of-investor-emotions/

The effect of Higher Education on graduates' attitudes: Secondary Analysis of the British Social Attitudes Survey. (2015).

What is Perceived Ease of Use (PEOU) | IGI Global. (n.d.). Retrieved November 21, 2022, from https://www.igi-global.com/dictionary/perceived-ease-of-use-peou/22284

ANNEXES

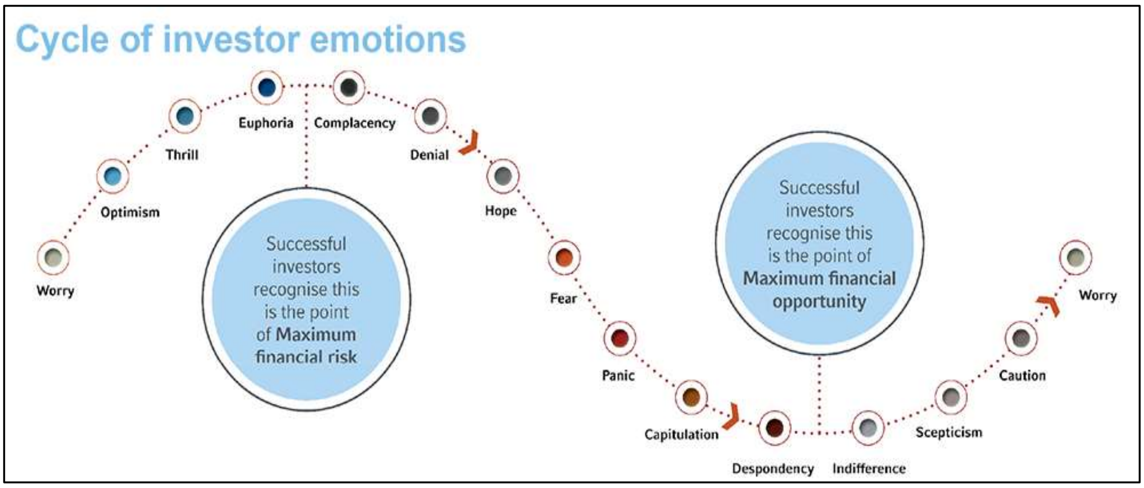

Figure 7 - Investor emotions. Source: Russel Investment

Table 5 - Collinearity VIF

	IMG_	INT_	M_	PEOU_	PU_	Random	SN_	VS_
IMG_						1.104		
INT_						1.321		
M_						2.875		
PEOU_						2.593		
PU_						1.980		
Random								
SN_						1.313		
VS_						2.260		

Table 6 - Bootstrapping - 5 000 subsample

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
IMG_ -> PU_	0.140	n/a	n/a	0.000	0.000
M_ -> PU_	-0.179	n/a	n/a	0.000	0.000
PEOU_ -> INT_	0.545	0.724	3.223	0.169	0.866
PEOU_ -> PU_	0.746	n/a	n/a	0.000	0.000
PU_ -> INT_	0.090	-0.087	3.227	0.028	0.978
SN_ -> PU_	0.330	n/a	n/a	0.000	0.000
VS_ -> PU_	0.025	n/a	n/a	0.000	0.000

Table 7 - Residuals correlation PEOU and CM

	M_1	M_2	M_3	M_4	M_5
PEOU_1	-0.030	-0.208	0.039	0.244	-0.036
PEOU_2	-0.177	0.114	-0.194	0.009	0.231
PEOU_3	-0.005	0.093	0.059	-0.044	-0.064
PEOU_4	0.179	-0.058	0.006	-0.156	0.063
PEOU_5	0.066	0.079	0.126	-0.037	-0.139

Table 8 - Residuals correlation PU and CM

	M_1	M_2	M_3	M_4	M_5
PU_1	0.208	-0.093	0.048	0.053	-0.126
PU_2	-0.030	0.095	-0.058	0.031	-0.012
PU_3	-0.058	0.035	0.103	0.003	-0.054
PU_4	-0.077	-0.011	-0.058	-0.053	0.217

Table 9- Residuals correlation PU and PEOU

	PEOU_1	PEOU_2	PEOU_3	PEOU_4	PEOU_5
PU_1	0.134	-0.097	-0.097	0.052	0.041
PU_2	-0.012	0.129	-0.091	-0.018	0.039
PU_3	0.035	-0.032	0.085	-0.033	0.015
PU_4	-0.126	0.094	0.158	0.032	-0.081

Table 10 - Residuals correlation VS and CM

	M_1	M_2	M_3	M_4	M_5
VS_1	0.027	0.105	-0.131	0.126	-0.121
VS_2	-0.030	0.097	0.075	-0.141	0.069
VS_3	0.088	-0.178	0.155	-0.021	0.071

Table 11 - Residuals correlation VS and PEOU

	PEOU_1	PEOU_2	PEOU_3	PEOU_4	PEOU_5
VS_1	0.033	0.079	0.103	-0.090	-0.048
VS_2	0.082	0.018	-0.012	-0.107	0.099
VS_3	-0.032	-0.039	-0.062	0.217	-0.016

Table 12 - Residuals correlation VS and PU

	PU_1	PU_2	PU_3	PU_4
VS_1	0.045	0.006	-0.025	0.039
VS_2	-0.018	0.060	0.013	0.009
VS_3	0.013	0.001	0.042	0.026

Table 13 - Residuals correlation VS and CM

	SN_1	SN_2	SN_3
VS_1	0.077	-0.076	0.053
VS_2	-0.086	0.098	0.007
VS_3	0.026	0.011	0.018