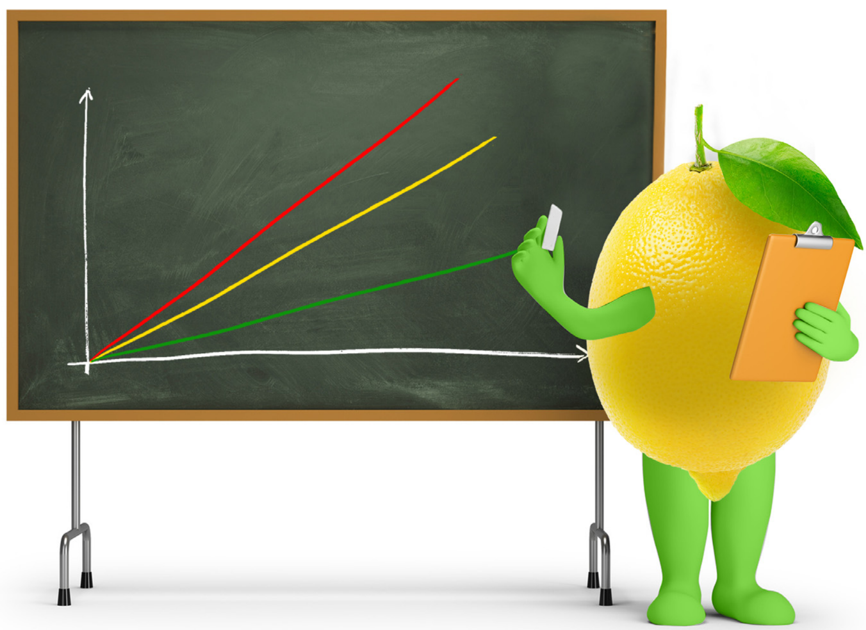

ASSESSING A MODERATING EFFECT AND THE GLOBAL FIT OF A PLS MODEL ON ONLINE TRADING

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ASSESSING A MODERATING EFFECT AND THE GLOBAL FIT OF A PLS MODEL ON ONLINE TRADING

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Summary

This paper proposes a PLS Model for the study of Online Trading. Traditional investing has experienced a revolution due to the rise of e-trading services that enable investors to use Internet conduct secure trading. On the hand, model results show that there is a positive, direct and statistically significant relationship between personal outcome expectations, perceived relative advantage, shared vision and economy-based trust with the quality of knowledge. On the other hand, trading frequency and portfolio performance has also this relationship. After including the investor's income and financial wealth (IFW) as moderating effect, the PLS model was enhanced, and we found that the interaction term is negative and statistically significant, so, higher IFW levels entail a weaker relationship between trading frequency and portfolio performance and vice-versa. Finally, with regard to the goodness of overall model fit measures, they showed that the model is fit for SRMR and dG measures, so it is likely that the model is true.

Keywords: PLS-SEM, Moderating Effect, Goodness of Fit Measures, Online trading, e-Business, e-Commerce

Introduction

The use of online trading has increased the number of both brokerage houses and investment services companies because online trading allows many brokers to cut costs further, and part of the savings can be passed on to customers in the form of lower commissions. Online financial trading websites offer retail investors the ability to trade products in different financial markets without the physical presence of a broker. Direct individual investor participation in financial markets via Internet is not a recent phenomenon; it started in the second half of the 90s and quickly expanded in the last decade. With a few clicks, investors today can buy or sell stocks through online trading accounts with the same ease as they search on the Internet or play computer games, thus, they obtain instant order execution, lowest spreads, flexible starting capital and fast deposits. Investors' online access has grown dramatically in the past years. With many brokerage firms now offering on-line trading services, investors have direct access to options, futures, foreign currencies, stocks, and bonds on many financial markets (García-Machado et al., 2009). Two factors are contributing to the enormous growth of online investing. First, the Internet gives ready access to raw data. Second, investment services firms can offer transactions at lower prices than traditional methods by eliminating the need for brokers or financial advisers. Internet is a powerful resource in that is allows investing directly online. Further, online trading is well established and highly developed in the European financial market.

According to Roca et al. (2009 and 2010), we define online trading as the act of placing buy/sell orders for financial securities and/or currencies with the use of a brokerage's Internet-based proprietary trading platforms. An online trading site is a brokerage house that allows online investors to buy and sell stocks and obtain investment information from its website. The penetration of e-trading accounts is growing to a fast pace among European investors. E-Trading is a growing practice around the world. However, before investors use the Internet for online investing, they should have an overall understanding of the potential risks that are inherent to investing.

In this research, our primary objective is to examine the influence of personal outcome expectations, perceived relative advantage, share vision, and Economy-based Trust on the quality knowledge, as well as, its influence on trading frequency, and subsequently, on the investor's portfolio performance. In addition, a second objective is to assess the goodness of overall model fit. In the end, we extend the model including different moderator variables to study possible changes in the strength or even the direction of the relationship between the constructs trading frequency and portfolio performance.

Conceptual framework

García-Machado et al. (2009) empirically examined an extension of the Technology Acceptance Model (TAM) in online financial trading context. This research evaluated the impact of perceived trust and perceived risk on e-investors' intention to use online dealers' and stockbrokers' services. A partial least-squares structural modelling approach was used to evaluate the explanatory power and causal links of the model. Findings indicated that perceived risk is an important barrier in the use of online trading systems. In contrast, perceived trust is crucial for enhancing the use of these systems. This research showed that online dealers and stockbrokers should pay more attention to the importance of trust as a means of creating the adequate climate for conducting securities transactions. Trust can be considered the main mechanism for increasing e-investors' intentions to invest using online trading systems by reducing perceived risk and by improving investment intentions. Some limitations may affect these results. First, the different dimensions of trust — benevolence, integrity and ability — were not incorporated in our model. The influence of these dimensions on other constructs should be carefully studied in future research. Second, there is still a need to find additional variables that can improve a higher R^2, for example familiarity, loyalty or information quality among others.

Afterwards, Roca et al. (2009) carried out a study where they focused their attention on examining the influence of personal innovativeness, perceived security and perceived privacy on the TAM1 constructs. Specifically, this work was to confirm the influence of these constructs jointly with perceived usefulness and perceived ease of use on behavioural intention to use online trading services. Therefore, they empirically tested the link between trust, security, privacy, usefulness, ease of use and behavioural intention in the online trading context (Roca et al., 2010).

Finally, Roca et al. (2013), investigated the role of virtual communities as support in financial investments decisions. In this study, they focused on the effects of outcome expectations, relative personal advantages, shared vision and the Economy-based Trust in the quality of knowledge, trading frequency and profitability, in the context of online trading. Their analysis showed that, in case of online trading, the confidence that the information originated from the virtual community will have positive economic consequences, and it was the most influential reason so that the knowledge generated in the virtual community itself was perceived as quality.

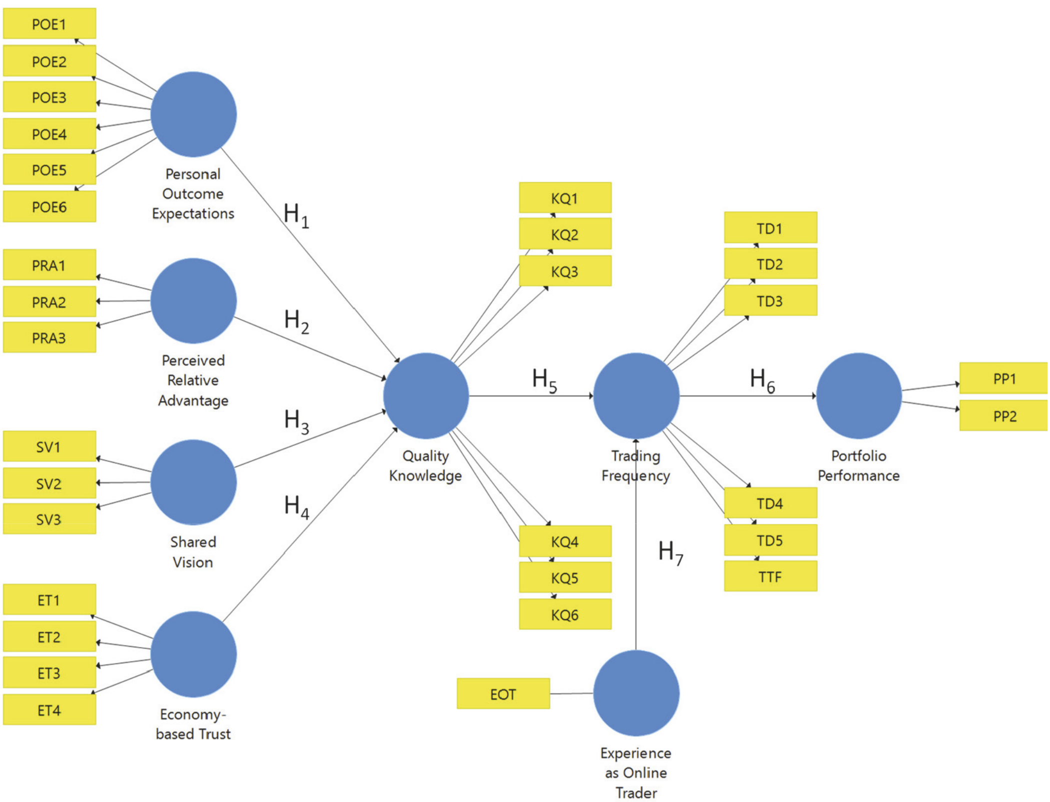
In conclusion, despite the results achieved and the usefulness of their implications, these studies have some limitations that suggest and open the way to future areas of research.

Proposed model and research hypothesis

The previous theoretical review enable us to propose the conceptual model shown in Figure 1. This is based on incorporating the Experience as Online Trader (EOT) as a single-item construct and to analyse the moderating effect of two moderator variable: Income and Financial Wealth (IFW), and emotional attitudes (EA). As shown in Figure 1, the proposed model posits that the exogenous latent variables affects directly the endogenous latent variable Quality Knowledge (QK), which in turn, jointly with the independent variable Experience as Online Trader (EOT), affect the target constructs of interest: Trading Frequency (TF) and Portfolio Performance (PP). We consider four independent variables as source of Quality Knowledge: Personal Outcome Expectations (POE), Perceived Relative Advantage (PRA), Shared Vision (SV), and Economy-based Trust (ET).

In summary, the research model has two main conceptual/theoretical components: (1) the target constructs of interest — namely, QK, TF and PP (dependent variables) — and (2) the five dimensions POE, PRA, SV, ET and EOT (independent variables), which represent key determinants of the target constructs.

Figure 1. **Model proposed**



Source: Own research.

Personal Outcome Expectations (POE)

According to the Social Cognitive Theory (Bandura, 1997), individuals are more likely to perform an activity or behaviour if they expect that the result provides them favourable consequences. Several studies carried out in the IS area provide support for this affirmation. Compeau and Higgins (1995), showed that POE have a significant effect on the predisposition to use computers. Another study found that POEs are significantly related to the commitment of end-users to the organization's computer structure (Stone and Henry, 2003). Some studies (Andrews, 2002, Zhang and Hiltz, 2003) indicated that people are willing to share their knowledge in virtual communities (online communities, social networks, etc.) with the expectation of enriching their own, seeking support, making friends, etc. Butler et al. (2002) suggested that the main reason for people to share their knowledge is the expectation of being seen as experts or specialists in a specific topic. Therefore, we establish the following hypothesis:

H1. Personal outcome expectations have a positive influence on quality knowledge.

Perceived Relative Advantage (PRA)

Perceived relative advantages, unlike personal outcome expectations, have a less social and more focused component on the practical and/or economic consequences derived from knowledge sharing in virtual communities. Chen and Hung (2010) showed that depending on the perceived relative advantages, the behaviour of individuals when sharing their knowledge is different. Therefore, we state the following hypothesis:

H2. Perceived relative advantages have a positive effect on quality knowledge.

Shared Vision (SV)

When the members of a virtual community have a common goal and share their interests, they have a shared vision that helps them to appreciate in greater measure the results that are derived from knowledge sharing. Tsai and Ghoshal (1998) pointing out that "A shared vision embodies the collective goals and aspirations of the members of an organization" (p.467). These researchers indicate that a shared vision can be understood as "a bonding mechanism that helps different parts of an organization to integrate or to combine resources" (p.467). The concept of shared vision is used to refer to shared values and goals and mutual understanding that originate in a cooperative relationship (Morgan and Hunt, 1994, Parsons, 2002). Li (2005) showed that shared vision influences the transfer of knowledge that occurs in organizations. Chiu, Hsu and Wang (2006) showed that shared vision affected positively the quality of shared knowledge. Therefore, we establish the last hypothesis:

H3. Shared vision has a direct and positive influence on quality knowledge.

Economy-based Trust (ET)

These consequences result from the economic benefit or the fear of suffering an economic sanction due to an abuse of trust (Panteli and Sockalingam, 2005). Hsu et al. (2007) showed that the economic dimension of trust helps the members of a virtual community to rely more on the information that is shared in that community. From our point of view, in the field of online trading, the Economy-based Trust have an impact on the quality of knowledge generated in the virtual community. Therefore, we state the following hypothesis:

H4. Economy-based Trust have a positive effect on quality knowledge.

Quality Knowledge (QK)

In the present work, the quality of knowledge is defined as that knowledge that is useful and innovative for a specific objective. In the case of online trading, the members of a virtual community want to acquire quality knowledge since they will use it to establish their financial investment strategies, that is, it becomes a key element to obtain positive results of their financial behaviour. To the extent that a member of a virtual community perceives that the quality of this knowledge is increasing, that is, he/she perceives it as more useful, he/she will be more predisposed to increase the frequency of negotiation. Finally, a higher quality, useful and practical knowledge will allow the members of this type of communities to obtain greater profitability of their financial investments. So:

H5. There is a positive relationship between quality knowledge and trading frequency.

H6. Trading frequency has a positive effect on portfolio performance.

Experience as Online Trader (EOT)

Franzosi and Pellizzoni (2004) found out that the trading frequency of cash instruments and the probability of trading derivatives are positively related to the perceived autonomy and to the financial sophistication of online investors (synthetic indicator calculated as a mix of actual knowledge and experience). In other interesting research for the Italian Stock Exchange, Alemanni and Franzosi (2006) found that Italian online traders demonstrate a quite extended experience, despite the fact that Italy remained for a long time an emerging market for financial services provided by Internet. On average, they have been trading financial products via Internet for 5 years. In Germany, investors experience (not only with Internet) is equal to 7 and half years at the survey time as described by Glaser (2003) and Glasser and Weber (2005) or Dorn and Huberman (2005). In Spain, García-Machado et al. (2013) carried out a survey to study the traits and characteristics of Spanish high frequency online retail investors, which allow them to analyse their socio-demographic characteristics, portfolio choices, investment strategies, trading patterns and performances and their similarities and differences with online traders from other countries. Therefore, in our opinion, greater experience as online investor, greater trading frequency, so:

H7. Experience as online trader has a positive and significative influence on trading frequency.

Methodology

The proposed model for assessing a moderating effect and the global fit of a PLS Model on trading online is framed with respect to latent constructs as given in the diagrammatic design in Figure 1. The inclusion of constructs and its relationships in the model is based in previous knowledge and relevant researches and studies which were previously cited.

In this study, we used the SmartPLS 3 software (v. 3.2.6) developed by Ringle et al. (2015) and subject to subscription and authorization of its authors. Since SmartPLS is an estimation model and SEM analysis, the estimation process used in two steps evaluating the outer model and the inner model (Hair et al., 2014). This sequence ensures that we have adequate indicators of constructs before attempting to reach conclusions concerning the relationships included in the inner model (Roldán and Sánchez-Franco, 2012).

Sample

Data were obtained from a survey made to the members of the Investment Strategies forum (http://www.estrategiasdeinversion.com). It is a platform specialized in offering the necessary contents so that the investor can optimize the result of his/her investments. The survey was published on the Investment Strategies website and members of the forum were invited to participate on it. A total of 260 responses were received, after debugging the incomplete ones, were valid a total of 243 (response rate of 93,46%). Respondents were 211 men and 32women.

Measurement scales

Items included in the questionnaire have been adapted from previous studies, therefore, their validity and consistency have been previously established. All items were measured with a 7-point Likert scale from 1 = strongly disagree to 7 = strongly agree, where 4 is interpreted as a point of indifference.

Items for Personal Outcome Expectations were measured by adapting those of Bock and Kim (2002), Coleman (1998) and Hendriks (1999). The scale of Perceived Relative Advantage was adapted from the articles by Chen and Hung (2010). The elements for the Shared Vision were adapted from Nahapiet and Ghoshal (1998) and Tsai and Ghoshal (1998). The items of the Economy-based Trust were adapted from the work of Ratnasingam (2005), Gefen, Karahanna and Straub (2003) and Hsu et. al (2007). The Quality Knowledge items were evaluated with questions adapted from DeLone and McLean (2003) and Chiu, Hsu and Wang (2006). These selected indicators and latent variables or constructs are showed in Table 1.

Different from those constructs, Experience as Online Trader is operationalized by a single item that is related to one question in the survey indicating the number of transaction per year. Conversely, Trading Frequency and Portfolio Performance are measured by multiple items.

Table 1. **Indicators for common factor models (reflective measurement model constructs)**

Personal Outcome Expectations (POE)	
POE1	Sharing my knowledge will help me to make friends with other members in the virtual community.
POE2	Sharing my knowledge will give me a feeling of happiness.
POE3	Sharing my knowledge can build up my reputation in the virtual community.
POE4	Sharing my knowledge will give me a sense of accomplishment.
POE5	Sharing my knowledge will strengthen the tie between other members in the virtual community and me.
POE6	Sharing my knowledge will enable me to gain better cooperation from the outstanding members in the virtual community.
Perceived Relative Advantage (PRA)	
PRA1	Sharing knowledge with members in this virtual community will increase my solving-problem capability.
PRA2	Sharing knowledge with members in this virtual community will rapidly absorb and react to new information regarding the area.
PRA3	Sharing knowledge with members in this virtual community will be effective in my job and improve my performance.
Shared Vision (SV)	
SV1	Members in the community share the vision of helping others solve their professional problems.
SV2	Members in the virtual community share the same goal of learning from each other.
SV3	Members in the virtual community share the same value that helping others is pleasant.
Economy-based Trust (ET)	
ET1	By joining this online community, I will save time in getting information.
ET2	By joining this online community, I will save costs in getting information.
ET3	I can get specific information from this online community.
ET4	The information I get from this online community will help me improve my capabilities.
Quality Knowledge (QK)	
QK1	The knowledge shared by members in the virtual community is relevant to the topics.
QK2	The knowledge shared by members in the virtual community is easy to understand.
QK3	The knowledge shared by members in the virtual community is accurate.
QK4	Wiedza, którą dzielą się członkowie tej społeczności wirtualnej jest całościowa.
QK5	Wiedza, którą dzielą się członkowie tej społeczności wirtualnej jest wiarygodna.
QK6	Wiedza, którą dzielą się członkowie tej społeczności wirtualnej jest aktualna.

Experience as Online Trader (EOT)

Point out your experience as online trader (EOT):

Without experience	0	3 years	2	5 years	4
1–2 years	1	4 years	3	6 years	5
More than	6				

Trading Frequency (TF)

Point out your trading frequency with Blue Chips (TD1):

More than 10 times a day	9	1–2 times a day	6	Once every 2 weeks	3
6–10 times a day	8	Once every 2 or 3 days	5	Once a month	2
3–5 times a day	7	Once a week	4	Less than once a month	1

We asked the same question for trading frequency with other country's shares (TD2), foreign shares (TD3), futures and options (TD4) and securitised derivatives (TD5). We also asked about the trading frequency in general and portfolio performance.

Total Trading Frequency (TTF)

Point out the total number of transactions per year:

None	0	At least one a month	2	One per week	4
At least one per year	1	At least one every two weeks	3	Almost every day	5

Portfolio Performance (PP)

1. Point out the returns obtained with your portfolio (PP1):

More than 30,00%	6	Between –5,00 and 5,00%	3
Between 15,00 and 30,00%	5	Between –5,00% and –15,00%	2
Between 5,00 and15,00%	4	Less than –15,00%	1

2. Point out the returns you expect to obtain with your portfolio (PP2):

More than 30,00%	6	Between –5,00 and 5,00%	3
Between 15,00 and 30,00%	5	Between –5,00 and –15,00%	2
Between 5,00 and 15,00%	4	Less than –15,00%	1

Components and data analysis

We use our data set with 243 observations for our empirical Online Trading PLS Model analyses. Following Cohen's (1992, p. 158) recommendations for multiple OLS regression analysis, we would need 158 observations to detect R^2 values around 0.10, assuming a significance level of 1%, and a statistical power of 80%. In addition, following Nitzl's (2016, p. 26) recommendations, we would need 114 observations to detect a medium effect size of 0.15, assuming the same significance level and statistical power. Because our sample size in this study was 244, there appears to be no problem with respect to the necessary sample size.

All indicators and data are compute in an Excel work file, and then translated into CSV format to run SmartPLS software in order to apply the SEM-PLS path modeling, goodness-of-fit measures and testing measurement and structural models.

Results

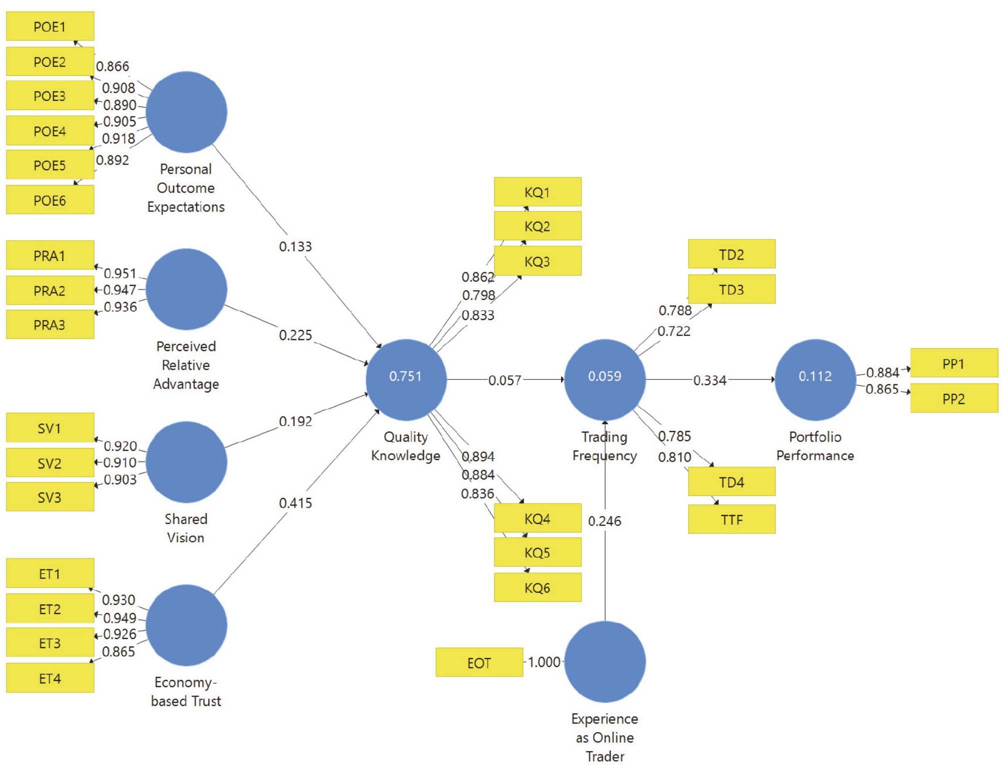
Validity Assessment of Reflective Measurement Models

The goal of reflective measurement model assessment is to ensure the reliability and validity of the construct measures and therefore provide support for the suitability of their inclusion in the path model (Hair et al., 2017). The measurement model for constructs with reflective measures is assessed by looking at: indicator reliability, composite reliability, convergent validity (AVE2) and discriminate validity (Fornell-Larcker and HTMT[3] criterions).

First of all, we need to check if the PLS algorithm converged (i.e. the stop criterion of the algorithm was reached before the maximum number of iterations). This number should be lower than the maximum number of iterations (e.g. 300) that we defined in the PLS-SEM algorithm parameter settings. In our model, the algorithm converged after iteration 9.

As rule of thumb for evaluating reflective measurement models (Hair, et al., 2017) the indicator's outer loadings should be higher than 0.708. Indicators with outer loadings between 0.40 and 0.70 should be considered for removal only if the deletion leads to an increase in composite reliability and AVE above the suggested threshold value. After running the PLS algorithm, we notice that 2 indicators of the 31 did not reach the level of acceptance indicator reliability and they were initially drawn. So, we decide to improve our initial path model deleting and changing some indicators as it is showed in Figure 2. Now, the algorithm converged again after iteration 9, thus it found a quick and stable solution.

Figure 2. **Online trading PLS-SEM Path Model**



Source: Opracowanie własne.

Tabele 2, 3 i 4 pokazują wyniki oceny modelu pomiaru refleksyjnego względem rzetelności i trafności prowadzonych działań.

Table 2. **Construct Reliability and Validity**

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Economy-based Trust	0,9374	0,9380	0,9554	0,8428
Experience as Online Trader	1,0000	1,0000	1,0000	1,0000
Perceived Relative Advantage	0,9398	0,9408	0,9614	0,8926
Personal Outcome Expectations	0,9511	0,9521	0,9609	0,8038
Portfolio Performance	0,6929	0,6954	0,8667	0,7648
Quality Knowledge	0,9241	0,9262	0,9407	0,7258
Shared Vision	0,8975	0,9013	0,9360	0,8297
Trading Frequency	0,7891	0,8252	0,8590	0,6041

Table 3. **Discriminant Validity: Fornell-Larcker Criterion**

	ET	EOT	PRA	POE	PP	QK	SV	TF
Economy-based Trust	0,9180							
Experience as Online Trader	–0,1465	1,0000						
Perceived Relative Advantage	0,8083	–0,1086	0,9448					
Personal Outcome Expectations	0,6625	–0,0659	0,7470	0,8966				
Portfolio Performance	0,0068	0,2632	0,0280	0,0984	0,8745			
Quality Knowledge	0,8168	–0,1664	0,8001	0,6978	0,0134	0,8519		
Shared Vision	0,6881	–0,1546	0,7320	0,6362	–0,0877	0,7268	0,9109	
Trading Frequency	–0,0081	0,2362	0,1018	0,1307	0,3344	0,0161	0,0283	0,7772

Table 4. **Discriminant Validity: Heterotrait-Monotrait Ratio (HTMT)**

	ET	EOT	PRA	POE	PP	QK	SV	TF
Economy-based Trust								
Experience as Online Trader	0,1513							
Perceived Relative Advantage	0,8608	0,1126						
Personal Outcome Expectations	0,6998	0,0669	0,7889					
Portfolio Performance	0,0856	0,3143	0,0937	0,1486				
Quality Knowledge	0,8748	0,1729	0,8561	0,7423	0,0904			
Shared Vision	0,7503	0,1625	0,7945	0,6856	0,1091	0,7940		
Trading Frequency	0,0862	0,2393	0,1265	0,1611	0,4352	0,1139	0,0698	

Assessment of the Structural Model

Once we have confirmed that the construct measures are reliable and valid, the next step is addresses the assessment of the structural model results. The structural model represents the relationships between constructs or latent variables that were hypothesized in the research model (Duarte, et al., 2010). Since the primary objective of PLS is prediction, the goodness of a theoretical model is established by the strength of each structural path and the combined predictiveness (R^2) of its exogenous constructs (Chin, 1998). Thus, the key criteria for assessing the structural model in PLS-SEM are the significance of the path coefficients, the level of the R^2, values, the f^2 effect size, the predictive relevance (Q^2) and the q^2 effect size (Hair et al., 2017). But, before assessing the structural model results, we need to analyse collinearity issues among constructs. Table 5 shows the tolerance (VIF[4]) values for this analyses. As can be seen, all VIF values are clearly below the threshold of 5 (tolerance higher than 0.20). Therefore, collinearity among the predictor constructs is not an issue in our structural model.

Table 5. **Collinearity Assessment for Inner model: VIF values**

	ET	EOT	PRA	POE	PP	QK	SV	TF
Economy-based Trust						3 0972		
Experience as Online Trader								1,0285
Perceived Relative Advantage						41307		
Personal Outcome Expectations						2 3819		
Portfolio Performance								
Quality Knowledge								1,0285
Shared Vision						233529		
Trading Frequency					1,0000			

Continuing with our assessment of the structural model, we examine the R^2 values of the endogenous latent variables. This coefficient is a commonly used measure to the model predictive accuracy. The coefficient represents the exogenous latent variable's combined effects on the endogenous latent variable. Because the coefficient is the squared correlation of actual and predicted values, it also represents the amount of variance in the endogenous constructs explained by all of the exogenous constructs linked to it (Hair et al., 2017). Falk and Miller (1992) suggest that the variance explained, or R^2s for endogenous variables should be greater than 0.1. As SEM-PLS aims maximize R^2 values of the endogenous latent variables in the path model, the objective is high R^2 values. While the exact interpretation of R^2 value level depends of the particular model and research discipline, in general, R^2 values of 0.75, 0.50 or 0.25 for the endogenous constructs can be described as respectively substantial, moderate, and weak. The variance explained for each dependent construct is showed in Table 6.

Table 6. **Variance Explained**

	R Square	**R Square Adjusted**
Portfolio Performance	0,1119	0,1082
Quality Knowledge	0,7512	0,7470
Trading Frequency	0,0590	0,0511

As can be seen, two of them meet Falk and Miller's (1992) rule of 0.1. Following Hair et al. (2017) rules, the R^2 value of the final dependent construct Quality Knowledge (0.751) can be considered substantial, whereas Portfolio Performance (0.111) and Trading Frequency can be considerate rather weak.

After computing the path estimates in the structural model, a bootstrap analysis was performed to assess the statistical significance of the path coefficients. Table 7 displays the path coefficients, the *t*-values and their significance levels, *p*-values, and the confidence intervals.

From the initial set of paths, five were revealed as significant at 0,99, one significant at 0,95, and only one is no significant, as shown in table 7. After examining the significance of relationships, it is important to assess the relevance of significant relationships, because they may be significant, but their size me be so small that they do not warrant managerial attention. As in an OLS regression, these path coefficients represent the estimated change in the endogenous construct for a unit change in the exogenous construct. If the path coefficient is statistically significant, its value indicates the extent to which the exogenous construct is associated with the endogenous construct.

Table 7. **Significance Testing Results of the Structural Model Path Coefficients**

Path	Path Coefficients	*t* Values	*p* Values	Standard Error	95% Confidence Intervals (a)		Significance (*p* <0,05)?
					Lower bound	Upper bound	
Economy-based Trust → Quality Knowledge	0,4148	5,9217	0,0000	0,0700	0,3025	0,5284	***
Experience as Online Trader → Trading Frequency	0,2457	3,9815	0,0000	0,0617	0,1331	0,3357	***
Perceived Relative Advantage → Quality Knowledge	0,2250	2,9432	0,0016	0,0764	0,0983	0,3489	***
Personal Outcome Expectations → Quality Knowledge	0,1326	22282	0,0130	0,0595	0,0319	0,2278	**
Quality Knowledge → Trading Frequency	0,0570	0,8618	0,1944	0,0661	-0,0523	0,1631	NS
Shared Vision → Quality Knowledge	0,1924	3 0267	0,0012	0,0636	0,0846	0,2942	***
Trading Frequency → Portfolio Performance	0,3344	5 9372	0,0000	0,0563	0,2295	0,4160	***

Note: NS = not significant. * p <0,10, ** p <0,05, *** p <0,01; (based on $t_{(55)}$, one tail test).
(a) Bootstrap confidence intervals for 5% probability of error (α = 0,05).

The goal of PLS-SEM is to identify not only significant path coefficients in the structural model but significant and relevant effects (Hair et al., 2017). Researchers are often interested in evaluating not only one construct's direct effect on another but also its indirect effects via one or more mediating constructs. The sum of direct and indirect effects is referred to as the total effect. Table 8 shows the corresponding results for the total effects.

Table 8. Significance Testing Results of the Total Effects

Path	Path Coefficients	*t* Values	*p* Values	Standard Error	95% Confidence Intervals (a)		Significance (p <0,05)?
					Lower bound	Upper bound	
Economy-based Trust → Portfolio Performance	0,0079	0,8151	0,2075	0,0097	–0,0072	0,0242	NS
Economy-based Trust → Quality Knowledge	0,4148	5,9217	0,0000	0,0700	0,3025	0,5284	***
Economy-based Trust → Trading Frequency	0,0236	0,8359	0,2016	0,0283	–0,0213	0,0710	NS
Experience as Online Trader→ Portfolio Performance	0,0822	3,0245	0,0013	0,0272	0,0387	0,1269	***
Experience as Online Trader → Trading Frequency	0,2457	3,9815	0,0000	0,0617	0,1331	0,3357	***
Perceived Relative Advantage → Portfolio Performance	0,0043	0,7810	0,2174	0,0055	–0,0026	0,0156	NS
Perceived Relative Advantage → Quality Knowledge	0,2250	2,9432	0,0016	0,0764	0,0983	0,3489	***
Perceived Relative Advantage → Trading Frequency	0,0128	0,7830	0,2168	0,0164	–0,0071	0,0473	NS
Personal Outcome Expectations → Portfolio Performance	0,0025	0,7191	0,2361	0,0035	–0,0013	0,0107	NS
Personal Outcome Expectations → Quality Knowledge	0,1326	22282	0,0130	0,0595	0,0319	0,2278	**
Personal Outcome Expectations → Trading Frequency	0,0076	0,7447	0,2282	0,0101	–0,0040	0,0301	NS
Quality Knowledge → Portfolio Performance	0,0191	0,8441	0,1993	0,0226	–0,0176	0,0563	NS
Quality Knowledge → Trading Frequency	0,0570	0,8618	0,1944	0,0661	–0,0523	0,1631	NS
Shared Vision → Portfolio Performance	0,0037	0,7842	0,2165	0,0047	–0,0024	0,0132	NS
Shared Vision → Quality Knowledge	0,1924	3,0267	0,0012	0,0636	0,0846	0,2942	***
Shared Vision → Trading Frequency	0,0110	0,8001	0,2119	0,0137	–0,0069	0,0390	NS
Trading Frequency → Portfolio Performance	0,3344	5,9372	0,0000	0,0563	0,2295	0,4160	***

Note: NS = not significant. * p <0,10, ** p <0,05, *** p <0,01; (based on $t_{(55)}$, one tail test).
(a) Bootstrap confidence intervals for 5% probability of error (α = 0,05).

Finally, Another test applied in PLS models is the Stone-Geisser test (Q^2 values). This test can be used joined to the R^2 values (predictive accuracy) as an additional assessment of model fit in PLS Analysis. (Geisser, 1975; Stone, 1974). According to Chin (1998), the Q^2 represents a measure of how well observed values are reconstructed by the model and its parameter estimates. Models with Q^2 greater than zero are considered to have predictive relevance. Models with higher positive Q^2 values are considered to have more predictive relevance. Table 9 provides the Q^2 values of all endogenous constructs. All Q^2 values for endogenous constructs are above zero (with a very high value for Quality Knowledge), thus providing support for the model's relevance regarding the endogenous latent variables.

Table 9. **Results of Q^2 values**

	SSO	SSE	Q^2 (= 1-SSE/SSO)
Economy-based Trust	972,0000	972,0000	
Experience as Online Trader	243,0000	243,0000	
Perceived Relative Advantage	729,0000	729,0000	
Personal Outcome Expectations	1,458,0000	1,458,0000	
Portfolio Performance	486,0000	448,9803	0,0762
Quality Knowledge	1,458,0000	720,8523	0,5056
Shared Vision	729,0000	729,0000	
Trading Frequency	972,0000	948,5356	0,0241

Hypothesis testing

Our results confirmed six of the relationships established in the research model (Table 10). It can be see a clear influence of Economy-based Trust on Quality Knowledge and Trading Frequency on Portfolio Performance. Another important relationship is the influence of Experience as Online Trader on Trading Frequency. However, we must reject the hypothesis H5 because is not getting and adequate size and significant level.

Table 10. Hypothesis testing

Hypothesis	Suggested effect	Path Coefficients	t-Values (bootstrap)	Accepted?
H1: Personal Outcome Expectations → Quality Knowledge	(+)	0,1326 *	2,2282	Yes
H2: Perceived Relative Advantage → Quality Knowledge	(+)	0,2250 **	2,9432	Yes
H3: Shared Vision → Quality Knowledge	(+)	0,1924 **	3 0267	Yes
H4: Economy-based Trust → Quality Knowledge	(+)	0,4148 ***	5,9217	Yes
H5: Quality Knowledge → Trading Frequency	(+)	0,0570 NS	0,8618	No
H6: Trading Frequency → Portfolio Performance	(+)	0,3344 ***	5 9372	Yes
H7: Experience as Online Trader → Trading Frequency	(+)	0,2457 ***	3,9815	Yes

*** $t_{(0001;\ 4999)}$ = 3,106644601
** $t_{(0,01;\ 4999)}$ = 2,333843952
* $t_{(0,05;\ 4999)}$ = 1,64791345

Assessment of the goodness of overall model fit

After running the PLS Bootstrapping using SmartPLS, we can provide the following overall goodness of fit measures to our Online trading PLS Model, as it is shown in Table 11.

The estimated model is the model as graphically specified. The saturated model has the same measurement model as the estimated model, but does not restrict the relationships between constructs. For instance, in the saturated model all constructs are correlated. The SRMR quantifies how strongly the empirical correlation matrix differs from the implied correlation matrix, therefore the lower the SRMR, the better the fit of the theoretical model (Henseler, 2017). The SRMR original value is lower than the threshold of 0.08 suggested by Hu and Bentler (1999) and much lower of 0.10 proposed by Ringle (2016), so the model fits very well for SRMR. The model also fits for dG, but it is unfit for d_{ULS}.

Table 11. **Goodness of overall model fit measures**

	Original Sample (O)	**95%**	**99%**
SRMR[5]			
Saturated Model	0,0554	0,0409	0,0441
Estimated Model	**0,0625**	**0,0516**	**0,0571**
d_{ULS}[6]			
Saturated Model	1,3343	0,7288	0,8467
Estimated Model	**1,7017**	**1 1571**	**1,4207**
D_G[7]			
Saturated Model	1,2294	1,2325	1,3287
Estimated Model	**1,2658**	**1,2830**	**1 344**

Modeling a moderating effect

To illustrate the estimation of a moderating effect, we first need to extend the original model by including the moderator variable. We focus on the relationship between Trading Frequency and Portfolio Performance. Specifically, we introduce Income and Financial Wealth (IFW) as moderator variable that can be assumed to negatively influence the relationship between Trading Frequency and Portfolio Performance. That is, for higher-income and financial wealth investors, there may be little or no relationship between the two variables. But for lower-income and financial wealth investors, there may be a strong relationship between them. We measures Income and Financial Wealth (IFW) reflectively using two indicators, each measured as follows:

Income and Financial Wealth (IFW)

1. Point out the level of monthly net incomes of your household (in euros) (IFW1):

Less than 1 000,00	1	Between 2 500,00 and 5 000,0	3	More than 7 500,00	5
Between 1 000,00 and 2 500,00	2	Between 5 000,00 and 7 500,00	4		

2. 2.Point out the level of financial wealth of your household (in euros) (IFW2):

Less than 25 000,00	1	Between 45 000,00 and 55 000,00	3	More than 75 000,00	5
Between 25 000,00 and 45 000,00	2	Between 55 000,00 and 75 000,00	4		

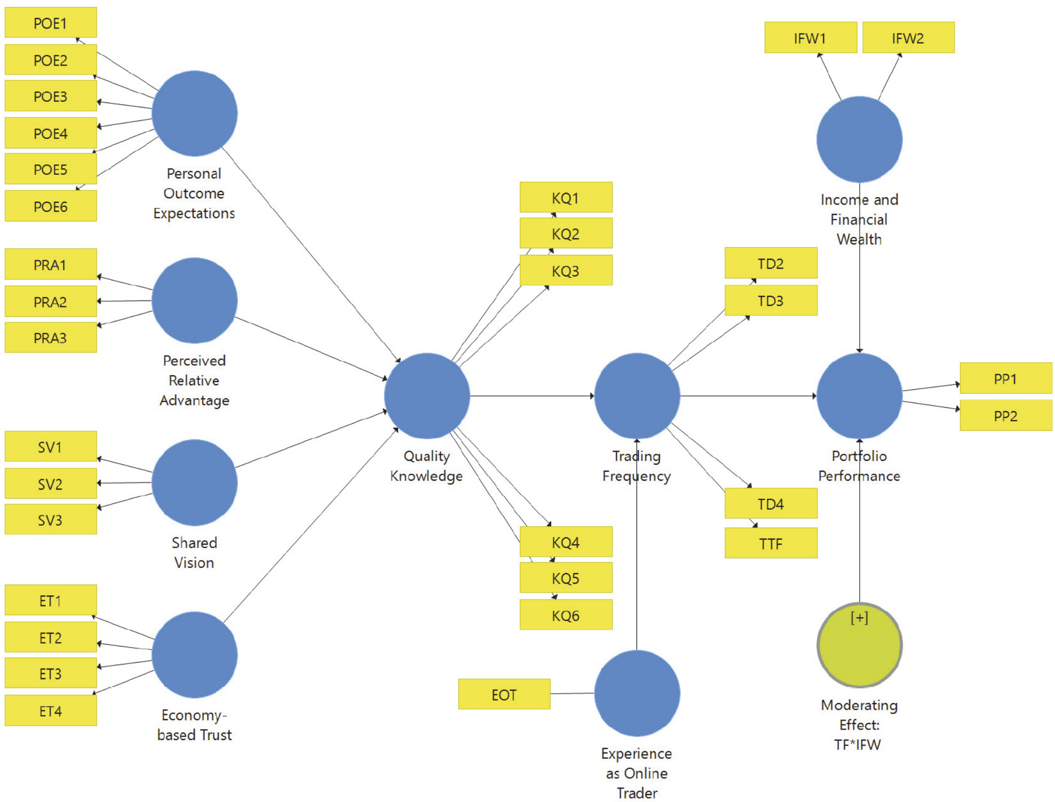
In the next step, we need to create the interaction term. The SmartPLS 3 software offers an option to automatically include an interaction term based on the product indicator, orthogonalizing, or two stage approach. Following Hair et al. (2017) recommendations, we choose the two stage approach as most appropriate as it is the most versatile and it also works when de exogenous construct and/or the moderator are measured formatively (see Figure 3).

We can now proceed with the analysis by running the PLS-SEM algorithm (see Figure 4).

The evaluation of the moderator variable's measurement model shows that the constructs measures are reliable and valid. Due to the inclusion of additional constructs in the path model (i.e., IFW and the interaction term), the measurement properties of all other constructs in the path model will change (even though changes will likely be marginal). Reanalysing all measurement models provides support for the measure´s reliability and validity.

Our next concern is with the size of the moderating effect. As can be seen in Figure 4, the interaction term has a negative effect on Portfolio Performance (–0,121), whereas the simple effect of Trading Frequency on Portfolio Performance is 0,319. Jointly, these results suggest that this

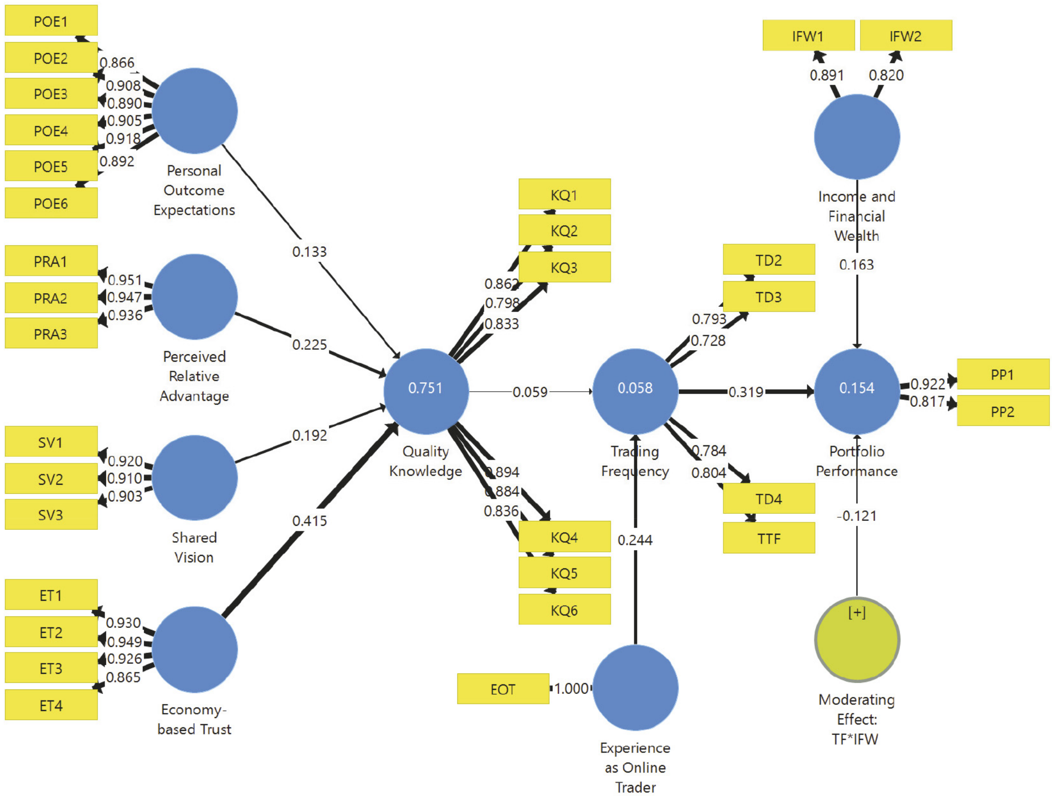
Figure 3. **Online trading PLS-SEM Model with moderating effect**



Source: Own research.

relationship is 0,319 for an average level of Income and Financial Wealth. For higher levels of Income and Financial Wealth (e.g., IFW is increased by one standard deviation unit), the relationship between Trading Frequency and Portfolio Performance decreases by the size of the interaction term (i.e., 0,319 — 0,121 = 0,198). On the contrary, for lower levels of Income and Financial Wealth (e.g., IFW is decreased by one standard deviation point), the relationship between Trading Frequency and Portfolio Performance becomes 0,319 + 0,121 = 0,440. Figure 5 shows the simple slope plot to a better understanding of the moderator analysis.

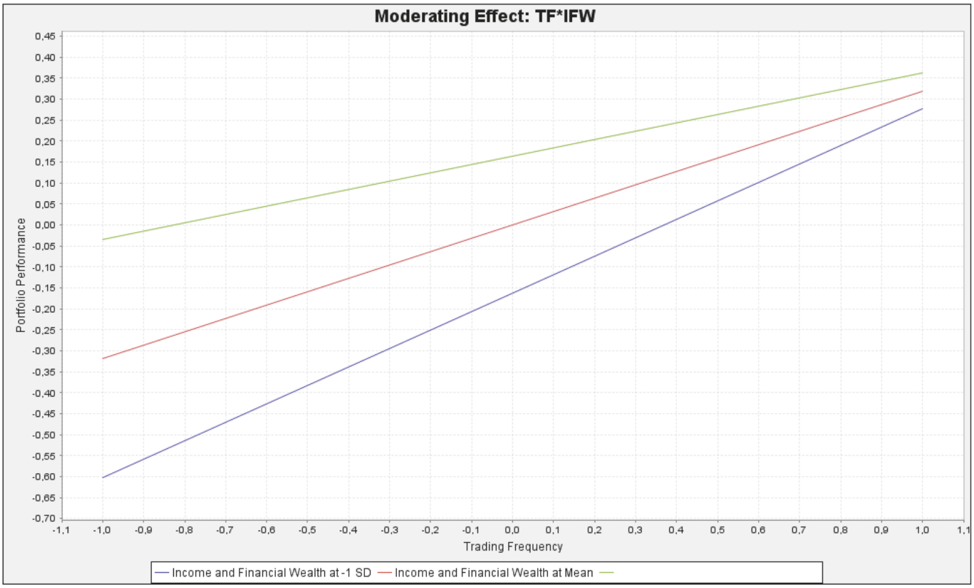
Figure 4. **Moderator analysis results**



Source: Own research.

As can we see, the relationship between Trading Frequency and Portfolio Performance is positive for all three lines as indicated by their positive slope. Hence, higher levels of Trading Frequency, higher levels of Portfolio Performance. In addition, we can analyse the moderating effect's slope in greater detail. The upper line (in green), which represents a high level of the moderator constructor IFW, has a flatter slope while the lower line (in blue), which represents a low level of the moderator construct IFW, has a steeper slope. This makes sense since the interaction effect in negative. Hence, the simple slope plot supports our previous discussion on the negative interaction term: higher IFW levels entail a weaker relationship between Trading Frequency and Portfolio Performance and vice-versa.

Figure 5. **Simple Slope Plot Analysis**



Source: Own research.

Next, we assess whether the interaction term is significant. For this purpose, we run the bootstrapping procedure included in SmartPLS 3 software. The analysis yields a p-value of 0,046 for the path linking the interaction term and Portfolio Performance. Similarly, the 95% bias-corrected bootstrap confidence interval of the interaction term´s effect is [–0,243, –0,007]. As the confidence interval does not include zero, we conclude that the effect is significant.

Finally, last step addresses in the moderator's f^2. effect size. The interaction term´s f^2 effect size has a value of 0,017, and, according to Kenny (2016), the value indicates a medium effect.

Conclusions and implications

This research proposes a theoretical model for the study of an Online Trading PLS Model. It has been analysed through a path diagram PLS-

SEM algorithm. Initially, 31 indicators were used and a sample size of 260 observations (211 men and 32 women). After debugging them, the sample included 243 observations with 29 indicators. Initially, the theoretical model, based on searching in the literature for variables related to outcome expectations, relative personal advantages, shared vision, economy-based trust, quality of knowledge, experience as online trader, trading frequency and portfolio performance, in the context of online trading, was framed regarding eight constructs.

From the analysis, we were able to show that several factors contribute to the quality knowledge, trading frequency, and portfolio performance in the context of online trading, especially those related to the economy-based trust and the experience as online trader. The findings of this study are supported by the literature, and the estimation model validates 3 of the 7 relationships hypothesized in our conceptual model at the 0,01 significance level, 2 of 7 at 0,05 and 1 of 7 at 0,10. Only one hypothesis was not verified.

With a statistical power of 80%, the R^2 for the final model proposed was 0,112, and the algorithm converged after iteration 9, which is found as a quick and stable solution. We think it can be considered very satisfactory, taking into account its complexity in defining and measuring some latent variables as quality knowledge. The four latent constructs explain 75,1% of the variance of the endogenous construct Quality Knowledge. Trading Frequency explains 11,2% of the variance of Portfolio Performance.

After including the moderating effect, the PLS model was enhanced, and the algorithm converged surprisingly after iteration 2. In this case, Trading Frequency and Income and Financial Wealth also jointly explain now 15,4% of the variance of Portfolio Performanc (R^2 = 0,154).

With regard to the goodness of overall model fit measures, results showed that the model was unfit for d_{ULS}, and fit for d_G discrepancies and it is below the threshold value for SRMR given by Ringle (2016) or even less than 0,08, in a more conservative version (Hu and Bentler, 1999), so, according to Dijkstra and Henseler (2015), it is likely that the model is true.

Despite the results we have achieved and the usefulness of their implications, this study has limitations that suggest future areas of research. As we pointed, due to the complexity of the process of quality knowledge and trading frequency and its influence on portfolio performance, it is assumed that not all the factors and relations were included, which could be seen as a limitation. Another limit may be the number of indicators in some latent variables (e.g. the single-item construct Experience as Online Trader). Moreover, we have completed all stages following a systematic procedure for applying PLS-SEM modeling. But in our next research it might be completed by including formative indicators and other latent variables and their measurement. We will also take into account higher-order and hierarchical components.

Finally, in future studies it would be interesting because this type of analysis will provide important and reliable information to the online trading investors to conduct securities transactions and make better decisions. Economy-based trust can be considered the main mechanism for increasing e-investors' intentions to invest using online trading systems.

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[1] Technology Acceptance Model (Davis, 1989 and Davis et al., 1989).
[2] Average Variance Extracted.
[3] Heterotrait-monotrait ratio.
[4] Variance Inflation Factor.
[5] Standardized Root Mean Square Residual.
[6] Euclidean Discrepancy.
[7] Geodesic Discrepancy.

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