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A novel artificial autonomous system for supporting investment decisions using a Big Five model approach

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ABSTRACT

This paper presents the design of an artificial autonomous system (called AAS) for the stock market domain that considers an approximation from the Big Five model, which proposes that the personality of an individual belongs to one of five different personality profiles: openness, conscientiousness, extraversion, agreeableness, and neuroticism. Several studies have explored investment and financial issues while considering the Big Five model, usually by analyzing data obtained from surveys applied to real people. However, to the best of our knowledge, there are no proposals that suggest the design of an AAS for supporting investment decisions that use the Big Five model as the central approach. The main objective of this proposal is to design an AAS for making investment decisions, where the decisions are adjusted to market conditions through the use of a policy function that adapts over time. This policy function adjusts the consumption level and investment portfolio composition required by the investment profile, considering both the market conditions and the Big Five model profile associated with the AAS. The effectiveness of the investment process is measured by observing the variations in the accumulated wealth and utility. The utility is measured through an abstract representation of the well-being or satisfaction of the investor (i.e., the AAS). AAS—Extraversion obtained the highest accumulated wealth, while AAS—Agreeableness obtained the highest level of utility, showing that the accumulated wealth is only one factor influencing the investor's well-being.

1. Introduction

In economic science, it is important to understand how individuals make decisions in the field of investment and how wealth generation mechanisms can maintain a consistent state with respect to people's standards of living. Among the models that have tried to explain the economic behavior of investors are those of Aiyagari (1994), Huggett (1993), and Krusell et al. (2011), which explored the processes of saving and consumption as important mechanisms of the distribution of wealth during the life cycle of an investor. Therefore, knowing the psychological causes that promote or influence investment decisions are relevant in understanding the heterogeneity that underlies the investment processes of individuals. Understanding the heterogeneity of investor behavior promotes a paradigm shift in observing the investment process.

Regarding the stock market domain, a policy function represents a mechanism for guiding an investment process along time, such as in terms of consumption level and the configuration of an investment portfolio. Depending on each decision maker, it is possible to define a unique policy function to be used during an extensive investment time or to modify the policy function according to the market conditions. The literature shows that for defining the policy function, a rational perspective is usually considered (Abdul-Salam and Phimister, 2019; Espino et al., 2018; Gala et al., 2019; Gordon and Guerron-Quintana, 2018; Guthrie, 2020; Mitra and Roy, 2017). In finance and stock markets, a rational perspective is typically considered both in the research literature (Alhnaity and Abbod, 2020; Altan et al., 2019; Altan and Karasu, 2019; Kia et al., 2020) and implementation and use of technology devoted to supporting investment decision processes ("MetaTrader 5", 2020; "XStation 5", 2020). Usually, each investment decision is carefully evaluated according to the profitability obtained (Fulkerson and Riley, 2019; Jiang et al., 2019; Kazak and Pohlmeier, 2019; Mo et al., 2019). However, gradually, the affective dimension has been incorporated into new research proposals for investment decision environments (Cabrera-Paniagua et al., 2015, 2014; Cabrera et al., 2019, 2018) in terms of artificial emotions used as decision criteria within decision-making models.

For several decades in the past century, the body of knowledge related to human behavior was associated with the identification of personality traits. This converged into the Big Five model (Digman,

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1990; Goldberg, 1992, 1990), which proposes that the personality of an individual belongs to one of five different personality profiles: openness, conscientiousness, extraversion, agreeableness, and neuroticism. According to these personality profiles, each person has a tendency to experience different reactions to the same situation. Therefore, sensations, feelings, reasoning, and decision-making are conditioned by a person's personality type. This applies to all areas and domains, including investment scenarios.

Several studies have explored investment and financial issues while considering the Big Five model (Tauni et al., 2020; Tharp et al., 2020; Thomas et al., 2020), usually by analyzing data obtained from surveys applied to real people. However, to the best of our knowledge, there are no proposals that suggest the design of an artificial autonomous system (AAS) for supporting investment decisions that use the Big Five model as the central approach. An AAS is endowed with an investment decision engine that makes decisions considering an investment profile, which, in turn, is defined both by technical parameters and one of the personality profiles of the Big Five model. The central objective is to have an AAS for making investment decisions, where the decisions are adjusted to market conditions through the use of a policy function that adapts over time. This policy function adjusts the consumption level and investment portfolio composition required by the investment profile, considering both the market conditions and the Big Five model profile associated with the AAS. In this proposal, the effectiveness of the investment process is measured by observing the variations in the accumulated wealth and utility. The utility level is measured through an abstract representation of the well-being or satisfaction of the investor (i.e., the AAS).

The novelty of the present research lies in the following: (1) it designs a general architecture of an AAS while considering an approximation from the Big Five model; (2) it designs an algorithm for investment decision-making processes to be used by the AAS; (3) it defines an experimental scenario based on official data from the New York Stock Exchange (NYSE) Composite Index; and (4) it analyses promising results obtained from an experimental scenario.

The remainder of this paper is organized as follows: Section 2 presents the related literature; Section 3 explains the theoretical background of the Big Five model and economic decision models; Section 4 shows the AAS design; Section 5 includes the scenario description and experimental results; Section 6 contains a discussion of the obtained results; and Section 7 presents the conclusions of this work and relevant areas for future research.

2. Related work

A study on investor profiles and investment decisions (Dincer et al., 2016) affirmed that investors' perceptions on portfolio investments rely strongly on the performance and risk of individual stocks. The authors proposed the use of a fuzzy-hybrid analytic model for improving the results obtained by each investment decision. The factors considered to obtain an investor's perception for industry selection were as follows: the investment intention of market makers; consistency of returns; international investors' demand; clarity of the information; regulations; management capability of the firms; extent of industry competition; and the innovation capability and profitability of the firms. A study by Geronikolaou and Papachristou (2016) showed that as competition increases, investors become more willing to finance risky projects that may otherwise be infeasible; in other words, the risk tolerance of investors is variable and adapts to market conditions. Frydman and Camerer (2016) indicated that some investors make investments in local stocks (i.e., in their home countries) without any consideration for risk diversification. This is called home bias and is based on psychological mechanisms that are not precisely known. Bakar and Yi (2016) conducted a study related to the impact of psychological factors on investors' decision-making in the Malaysian stock market by distributing 200 questionnaires to investors aged 18–60. Their results showed that overconfidence, conservatism, and availability bias have significant impacts on an investor's decision-making. In addition, the investor's gender has an influence on the psychological factors associated with each investor profile. Tsai (2017) explored whether an investor's optimism or pessimism could spread to other investors and affirmed that the diffusion of pessimistic sentiment is significant and that bad news can easily induce a rapid diffusion of pessimistic investor sentiment. Hoffmann and Shefrin (2014) found that individual investors who use technical analysis and trade options frequently make poor portfolio decisions, obtaining poor results due to the selection of more concentrated portfolios. Other studies associated with investment decisions have explored the behavior of investors when they use the Internet, social networks, and electronic platforms by analyzing the sentiments related to stock markets (Derakhshan and Beigy, 2019; Ruan et al., 2018); by studying how influential investors can influence other investors using post messages on stock forums (Ackert et al., 2016); and by analyzing the investors' sentiment toward stocks while considering different times of the day (Drerup, 2015).

Several studies have also explored how the affective dimension influences decision-making processes and human behavior, addressing issues such as seeking health information using online systems (Myrick, 2017); investment decisions in energy efficiency (Busic-Sontic et al., 2017); purchase decisions on e-commerce systems (Cabrera et al., 2015; Richard and Chebat, 2016); and risky choices made by bank customers and financial professionals (Lucarelli et al., 2015). Affective dimensions represent the relevant aspects within personality traits. In the same sense, the Big Five model has been considered in several studies of personality traits and affective issues for exploring the relationships between personality, sports participation, and athletic success (Steca et al., 2018); for exploring the relationship between the Big Five model and social networks (Choi et al., 2017; Eşkisu et al., 2017); for examining the association between the Big Five model and Internet addiction (Kayiş et al., 2016; Zhou et al., 2017); for exploring the relationship between the Big Five model and pro-environmental tourist behavior (Kvasova, 2015); and for studying the relationship between the Big Five model and a range of entrepreneurial outcomes (e.g., changing organizational practices) (Leutner et al., 2014).

Considering an association between the Big Five model and stock markets, Tauni et al. (2017) studied the impact of the frequency of information acquisition on the frequency of stock trading, examining whether the Big Five personality traits of investors influenced the association between information acquisition and stock trading behavior. Phung and Khuong (2016) explored the effects of the Big Five traits and moods on the investment performance of individual investors trading on the Vietnam stock market. Tauni et al. (2015) conducted a study that considered 333 individual investors in Chinese futures markets, following the Big Five personality framework presented by Digman (1990). The results obtained showed that information acquisition is directly proportional to trading frequency. Moreover, the conscientiousness and extraversion dimensions strengthen the positive relationship of information acquisition and trading frequency. However, the authors did not mention a relation between information acquisition and the effectiveness of the investment decisions. Zhang et al. (2014) examined the impact of the Big Five traits and gender on overtrading in a unilateral trend stock market, using a personality questionnaire. Oehler et al. (2018) applied a personality test on 364 business students (undergraduates) and analyzed their behavior in the stock market. The authors only evaluated extraversion and neuroticism. The experimental market scenario considered 15 periods, each one minute. Santos et al. (2011) proposed the Big Five model for incorporating affective characteristics into an agent-based group decision-making. The experimental scenario considered an ad hoc experimental scenario without data sets, where a group of participants attempted to select the best renewable power source for a certain location. Mayfield et al. (2008) examined several psychological antecedents to both short-term and long-term investment intentions using the Big Five model. The methodology for evaluating the investment intentions was implemented by surveying over 197 undergraduate business students; subsequently, structural equation modeling was used on short-term and long-term investment intentions.

Business literature in the stock market domain usually promotes a rational approach for decision-making, as seen in the large body of literature on technical analysis (Farias Nazário et al., 2017; Lin et al., 2018; Lin, 2018). Commercial applications available on the market also assume that investment decisions require only technical parameters and no other type of variables (such as the confidence level of a human investor as an affective variable). Furthermore, each investment decision should be based on human instructions; in other words, the commercial platform cannot sell or buy stocks without prior instruction from an investor. Therefore, commercial platforms do not display real autonomous behavior. Commercial platforms available in market include "Binary Bot" (2020), "IB WebTrader" (2020), "MetaTrader 5" (2020), and "SureTrader Activeweb" (2020), among others. However, the field of neuroscience research has provided evidence that human decision-making corresponds to a unified rational–emotional process (Bechara, 2004; Damasio, 1994). In the field of applying artificial systems to decision-making processes, we have presented a proposal of an autonomous affective decision-making system for supporting investment decisions (Cabrera-Paniagua et al., 2015), an extended version of the aforementioned proposal with an additional stabilization mechanism for controlling emotional fluctuations during investment processes (Cabrera et al., 2018), and another proposal that suggested a resilience mechanism for supporting investment decision-making processes performed by artificial autonomous systems (Cabrera et al., 2019). It is important to mention that in all of these, each investment decision is made by the autonomous system while considering technical and emotional criteria, all within a unique decision layer.

This literature review shows that the studies and analyzes related to the applications of the Big Five model are typically based on the use of surveys or the measurement of decision processes with real people; they did not use the Big Five model to design an AAS devoted to making decisions on stock markets. Thus, the current work presents a new development in this field, where decision-making is adjusted to market conditions through the use of a policy function that adapts over time, considering both the market conditions and the Big Five model profile associated with an AAS. Moreover, the performance will be measured considering both the rational/objective perspective (i.e., the accumulated wealth) and the affective/subjective perspective (i.e., the utility level).

3. Theoretical background

3.1. The Big Five model

In the 20th century, several proposals that described personality structures and personality trait models were presented, which converged in the beginning of the 1990's into the Big Five model (Digman, 1990; Goldberg, 1992, 1990; McCrae and John, 1992). The Big Five model is also commonly referred to as the OCEAN (openness, conscientiousness, extraversion, agreeableness, and neuroticism) model:

– Openness is characterized by the presence of curiosity, imagination, and creativity. The individual by nature seeks a life with new experiences.
– Conscientiousness is based on the self-control of the individual and the ability to plan and execute tasks aimed at achieving specific goals. The individual stands out for being responsible and reliable.
– Extraversion characterizes the individual by high sociability. A tendency to feel positive emotions, such as joy and satisfaction, is observed. The individual is assertive and optimistic.
– Agreeableness is focused on interpersonal relationships. The individual is generous, helpful, altruistic, and trusting of others.
– Neuroticism is associated with emotional instability. There is a bias tendency oriented toward maintaining a negative perception about situations. The individual has a low tolerance for stressful situations and is nervous and insecure.

For measuring personality traits and other individual differences, the International Personality Item Pool ("International Personality Item Pool", 2020) has more than 3000 items and over 250 different scales derived from them. Some scales proposed to measure the Big Five are available in Donnellan et al. (2006) and Johnson (2014). To determine the personality traits of a person, it is necessary that they answer a questionnaire, which usually requires a few minutes, depending on the length of the questionnaire. Online questionnaires that automatically determine the Big Five personality traits profile of a person are available in "Interactive IPIP Big-Five Factor Markers" (2020), "Psychometric Tests: Open Psychometric Test Resource" (2020), and "The Big Five Inventory" (2020).

3.2. Economic decision model and personality traits

An economic model corresponds to a theoretical representation of agents and their behaviors, which interact in a certain economy using logical and mathematical tools. There are several economic models that define the behavior of agents. Stigler (1950) reviewed the utility function as applied to the economy, where the utility function represented an approach of well-being related to an economic agent. It is generally accepted in the literature that the price is not the only factor that affects purchase decisions. Cabrera et al. (2015) conducted an extensive review on the factors that influence purchase decisions and found that psychological factors (such as personality traits) play a fundamental role. The adequate characterization of psychological factors in economic models is a complex task. The mentioned problems were characterized by Benartzi and Thaler (1995), who explained the behavior of individuals using two psychological concepts of decision-making. The first concept is "loss aversion", which refers to the tendency of individuals to be more sensitive to the reduction of welfare levels as they grow (Kahneman et al., 1990; Tversky and Kahneman, 1992). The second is "mental accounting", which refers to individual and heuristic methods for evaluating financial results.

3.3. Utility function

It is commonly believed that financial managers seek to optimize a model based on wealth weighted by the level of risk, which is usually expressed as the volatility indicator of a financial asset (Merton, 2014; Merton and Muralidhar, 2017; Muralidhar et al., 2013). For the purposes of this research, an investor seeks to maximize their benefits and wellness over time through investment in financial assets. The level of consumption is an important factor that influences the investor utility, and the investment represents a way to generate wealth or ensure future consumption. Considering an economic perspective, the preferences of an investor in an economy are represented by a utility function, which is measured through an abstract representation of the well-being or satisfaction of the investor. Thus, investors usually face the following optimization problem:

$$\max_{c_t,\gamma_t} E_0 \left\{ \sum_{t=0}^{\infty} \beta^t \frac{\left(\frac{c_t}{\gamma_t}\right)^{1-\sigma} - 1}{1-\sigma} \right\} \tag{1}$$

Subjected to:

$$c_t + q_a a_{t+1} = a_t + y_t \tag{2}$$

$$\gamma_t = 1 + \theta a_{t+1}^2 \tag{3}$$

$$c_t \geq 0, q_a \geq 0, a_{t+1} \geq 0 \tag{4}$$

where,

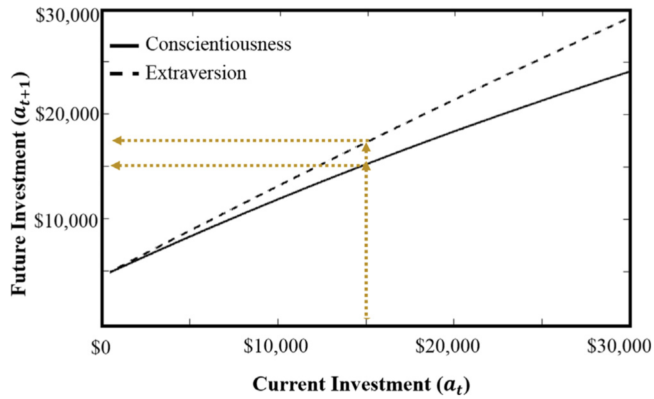

Fig. 1. Policy function example.

- E_0 corresponds to the expected value of the utility function at t=0.
- c_t represents the consumption in period t.
- γ_t corresponds to the relation between the investment volume (represented by the quantity of investment assets) and the risk level associated with these investment assets. A higher value of gamma indicates that there is a major volume of investment as well as a major level of risk. Conversely, a lower value of gamma indicates that there is a lower volume of investment as well as a lower level of risk.
- β corresponds to the intertemporal subjective discount factor that represents the degree of impatience of an investor. A minor value of beta indicates that investors seek or prefer to obtain returns in the short term, while a higher value of beta indicates that investor is willing to obtain returns in the long term.
- σ represents the level of risk aversion, which does not depend on the investment volume.
- q_a corresponds to the price of the asset a traded in the financial market.
- a_t corresponds to the investment amount made on asset a in period t.
- θ corresponds to a constant that represents the degree of "anxiety" that an investor has when maintaining a specific level of investment within his portfolio.

From the optimization process performed by Eq. (1), a policy function is derived. Period by period, the policy function guides the investment process, both in terms of the consumption level and the conformation of the investment portfolio. Thus, the consumption level and investment portfolio are adjusted according to market conditions and the investment profile. Fig. 1 contains examples of policy functions for a conscientiousness investment profile and an extraversion investment profile. The abscissa axis corresponds to the investor's current investment status, while the ordinate axis corresponds to the next investment decision that the investor will make given the current investment status.

It can be observed that, given an investment equivalent status of $15,000 in the current period, the conscientiousness investment profile will maintain the same investment level for the following period, while the extraversion investment profile will modify its investment to $17,500. Therefore, considering equal market conditions but different personality profiles, each investor makes different decisions related to their investment. In this case, the extraversion investment profile takes a riskier investment position for the following period than the conscientiousness investment profile since the former increases the amount of investment in assets that are subject to market fluctuations.

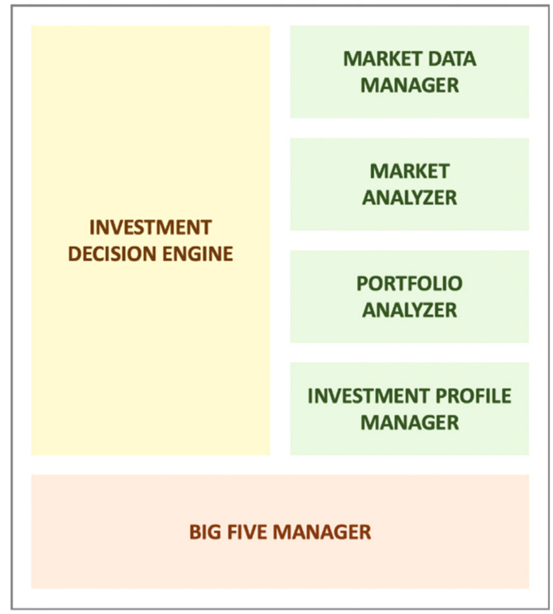

Fig. 2. AAS general architecture.

4. Artificial autonomous system design

4.1. General architecture

Fig. 2 shows the general architecture of an AAS that will be applied to the stock market domain. Its components are explained below.

The "Big Five Manager" registers and manages the personality profile associated with the AAS, following the Big Five model. Then, the personality profile is used to define the investment profile.

The "Investment Profile Manager" defines the investment profile to be used by the AAS. To accomplish this task, it considers both the personality profile and technical parameters (such as the investment capital and the investment horizon).

The "Market Data Manager" is devoted to getting updated time series from the markets. In addition, this component can obtain global data that does not correspond precisely to the investment data but rather references the data to support decision-making in the investment domain (such as the country risk level, growth expectative, and unemployment rates).

The "Market Analyzer" analyzes the market structure, calculates and examines several stock market indicators (such as profitability and risk), and analyzes general indicators of the global scope (such as interest rates, GDP, and country risk).

The "Portfolio Analyzer" analyzes the investment portfolio associated with the AAS by obtaining and examining specific portfolio indicators such as the profitability, risk, accumulated wealth, and utility level.

The "Decision Engine" makes the investment decision period by period (until the investment horizon is reached) according to the policy function (which is derived from Eq. (1)). For this purpose, it determines a profitability estimation for the next period, analyzes the standard deviation of the market time series, determines the price asset (that corresponds to an estimated of future gains), and finally defines the policy function.

4.2. Investment decision-making processes using AAS

Algorithm 1 shows a sequence of an investment decision-making process performed by the AAS. The algorithm begins with the Big Five personality profile setting. Then, the technical parameters are defined (such as the amount of investment capital and investment horizon). Both the personality profile and the technical parameters are considered in the definition of the investment profile. Then, the time series on the market are obtained with a specific time horizon, and an initial investment portfolio is defined.

For each of the investment periods (as long as the final investment horizon is not reached), the updated time series on the market are obtained, allowing the calculation of profitability and market risk. Then, the profitability and risk of the investment portfolio are obtained. Similarly, the accumulated wealth and level of perceived utility are calculated using the observed results. All results derived from the investment portfolio are recorded.

Regarding the investment evaluation for the following period, the future profitability and risk of the current investment portfolio are estimated and the "price asset" is determined, which corresponds to an estimate of future earnings. These are all considered in the definition of the policy function, which guides the investment decision of the AAS.

Algorithm 1 Investment decision-making process

Begin
set {*BFP*} **in** {*Personality Profile*}
set {*IC*; *IH*} **in** {*Technical Parameters*}
invProfile = **set** InvProfile (*Personality Profile, Technical Parameters*)
marketTimeSeries = Get updated Market Data()
invPortfolio = set Initial Inv Portfolio (invProfile, marketTimeSeries)
For each investment period:
  /* *Investment results are obtained* */
  marketTimeSeries = Get updated Market Data()
  marketProfitability = calculate Market Profitability (marketTimeSeries)
  marketRisk = calculate Market Risk (marketTimeSeries)
  invPortfolioProfit = calculate Portfolio Profitability (invPortfolio, marketProfitability)
  invPortfolioRisk = calculate Portfolio Risk (invPortfolio, marketRisk)
  wealth = calculate Wealth (invPortfolio, marketProfitability)
  utility = calculate Utility (invPortfolio, marketProfitability, marketRisk)
  Add (*profitability*, *risk*, *wealth*, *utility*) **in** {*investment Results*}
  /* *Investment decision for the next investment period is defined* */
  exp_Profitability = estimate Profitability (*invPortfolio*)
  exp_Risk = estimate Risk (*invPortfolio*)
  priceAsset = 1 / (1+ exp_Profitability • 52)
  policyFunction = define Policy Function (*invProfile, exp_Risk, priceAsset, IC*)
  invPortfolio = set Investment Portfolio (*invPortfolio*, policyFunction)
End For
End Algorithm 1

5. Test scenario and results

5.1. General context

The experimental scenario used official data from the NYSE Composite Index from January 1 2010 to December 31 2018 ("New York Stock Exchange", 2020), assuming that there were no transaction costs. The NYSE Composite Index represents a weighted average of more than 2000 stocks traded in the market. Using this data, the simulation parameters of an ARMA model were estimated (see Table 1). The ARMA model defined the simulated time series of the NYSE Composite Index, allowing the generation of different trajectories for observing the behavior of each investment profile.

Table 1
ARMA model parameters.

Constant	L.ar	L2.ar	L.ma	L2.ma	Std. deviation	N° simulations
0.000407	0.12317	0.74401	−0.17968	−0.73667	0.00941	500

Table 2
Parameter values for investment profiles.

Parameters	O	C	E	A	N	Neutral
β	0.983	0.965	0.991	0.986	0.951	0.97
σ	1.961	1.980	1.799	1.996	2.049	1.8
θ	0.0594	0.0693	0.0193	0.0547	0.0403	0.05

The best ARMA model approach, defined through the Akaike criterion (Akaike, 1998), corresponds to an ARMA model (2.2) with the following parameters: "Constant" represents the value of the intercept of the model; the parameters "L.ar" and "L2.ar" correspond to the autoregressive part of Order 1 and Order 2, respectively; the parameters "L.ma" and "L2.ma" correspond to the factors of the moving average component of Order 1 and Order 2, respectively; and the "Std. Deviation" parameter corresponds to the standard deviation of the random element of the stochastic process.

The experimental scenario considered the implementation of the AAS general architecture presented in Fig. 2 and the use of different artificial investor profiles according to a specific Big Five model profile. Each artificial investor profile used Algorithm 1 for performing its investment decision-making processes.

At the beginning of each experimental scenario, each artificial investor configures an initial investment portfolio, which can be modified according to the investment strategies over time. They each receive market results on a weekly basis. All artificial investors used the sliding window concept for calculating both the expected return and expected volatility, using the last 52 weeks from a specific period. The expected return is calculated as the average return of the 52 weeks, while the observed volatility corresponds to the standard deviation of the 52 weeks. Thus, according to each experimental configuration, it is possible to maintain the current investment portfolio or apply changes. It is important to mention that the experimental scenario is oriented to evaluate variations in both the accumulated wealth and observed utility for each investment profile.

5.2. Parameters of the investment profiles

Table 2 shows a set of parameters whose values can represent the economic behavior of investors according to each dimension of the Big Five model. In the case of the σ and θ parameters, a parameterization derived from CFC (consideration of future consequence) was used (Thelken and de Jong, 2017), which corresponds to a model that attempts to determine how conscious an individual is about the future effects of their current decisions. On the other hand, in the case of β, a parameterization derived from the proposal of Adams and Nettle (2009) was considered. The authors defined a numeric relationship between the different personality profiles of the Big Five model using an inverse value of the β parameter.

In Table 2, column "O" corresponds to the artificial investor with an openness profile; column "C" corresponds to the artificial investor with a conscientiousness profile; column "E" corresponds to the artificial investor with an extraversion profile; column "A" corresponds to the artificial investor with an agreeableness profile; column "N" corresponds to the artificial investor with neuroticism profile; and column "Neutral" represents the average investor in the economy.

Regarding the β parameter, a value tending to one is associated with an investor who values both present satisfaction and future satisfaction equally. Meanwhile, a β value tending to zero indicates that the investor values current consumption more than future consumption. Thus, it can be observed that the extraversion profile strongly values future satisfaction. The σ parameter represents the level of risk aversion measured as the degree of curvature of the utility function. A higher value of σ is associated with a low degree of curvature, implying that the utility derived from the consumption level is low. Conversely, a low value of σ is associated with a high degree of curvature, implying that the utility derived from the consumption level is high. Therefore, the neuroticism profile has a high value, which implies that when observing the conditions for modifying their investment portfolio, the artificial investor tends to maintain its current configuration. The θ parameter represents the degree of "anxiety" derived from the level of investment. When the θ value is major, an investor has a major degree of "anxiety" when maintaining a level of risky stocks within its portfolio. According to Table 2, the artificial investor with a conscientiousness profile has high risk aversion, whereas the artificial investor with an extraversion profile has low risk aversion.

5.3. Experimental results

Table 3 shows experimental results summarized from 500 independent simulations carried out according to the ARMA model. The "Investment Profile" column represents each possible configuration of the experimental scenario, i.e., the five possible configurations of the Big Five model for the AAS and an additional configuration called AI—neutral, which represents an artificial investor with no dominant characteristics that can be interpreted as a representative agent of the economy. The columns labeled "[USD]" are associated with the wealth, while the columns labeled "[UT]" are associated with the utility.

Regarding the wealth, the columns are initial wealth (at the beginning of 2011), final wealth (at the end of 2018), maximum wealth, minimum wealth, and wealth standard deviation. Meanwhile, regarding the utility, the columns are initial utility (at the beginning of 2011), final utility (at the end of 2018), maximum utility, minimum utility, and utility standard deviation.

Fig. 3 graphically shows the average value of the accumulated wealth and its variability for each of the personality profiles associated with the artificial investors. The size of each box represents the degree of dispersion of the data between the 25th and 75th percentiles, obtained from the 500 simulations. The internal horizontal line within each box corresponds to its mean value, and the external segmented vertical lines of each box represent the data whose values are lower than the 25th percentile or higher than the 75th percentile. Similarly, Fig. 4 graphically shows the mean value of the utility and its variability for each of the personality profiles associated with the artificial investors.

On average, AAS—Extraversion (US$22,663) obtained the highest final accumulated wealth, followed by AAS—Agreeableness (US$19,516). AAS—Conscientiousness (US$17,393) obtained the lowest final accumulated wealth, followed by AAS—Openness (US$18,778). AAS—Extraversion (US$1,788) obtained the highest standard deviation associated with the accumulated wealth, followed by AAS—Neuroticism (US$1,602). AAS—Conscientiousness (US$1,376) obtained the lowest standard deviation associated with the accumulated wealth, followed by AAS—Openness (US$1468).

Meanwhile, AAS—Agreeableness (5,815) obtained the highest final utility, followed by AAS—Extraversion (5,680). AAS—Neuroticism (1,662) obtained the lowest final utility, followed by AAS—Conscientiousness (1,936). AAS—Agreeableness (1,259) obtained the highest standard deviation associated with the utility, followed by AAS—Extraversion (1,199). AAS—Neuroticism (0,374) obtained the lowest standard deviation associated with the utility, followed by AAS—Conscientiousness (0,419).

6. Discussion

The investment results obtained by each investment profile should be observed first. Both AAS—Extraversion and AAS—Agreeableness presented the best overall accumulated wealth because the proportion of risky stocks was higher than those selected by the other investment profiles. The reasons for this are in line with the modern portfolio theory (Markowitz, 1952), in which a higher reward (measured as a higher profitability) comes with a higher market risk. The above was observed in AAS—Extraversion and AAS—Agreeableness, both of which presented the highest standard deviations in the simulated process. Meanwhile, the accumulated wealth of both AAS—Conscientiousness and AAS—Openness presented the worst overall results during the evaluation period. This is likely because the portfolio defined by these investment profiles had a lower level of risky stocks than those chosen by the other investment profiles in a period when the financial stocks presented a positive performance.

AAS—Extraversion obtained the highest level of utility, which is consistent with the financial results obtained by taking a risky position in the financial market. This resulted in major capacity at the consumption level and, therefore, in obtaining a higher level of utility. Meanwhile, AAS—Neuroticism presented a lower level of utility mainly because of its tendency to take less risky positions and, therefore, to maintain a lower consumption capacity given its financial results in the evaluation period.

The general results showed that the AAS—Agreeableness and AAS—Extraversion investment profiles presented a major standard deviation regarding utility because the combination of the parameters that defined the behavior of these investment profiles provided greater sensitivity to external situations, which influenced the computation of their utilities. This led to major satisfaction in the face of favorable market events as well as major discontent in adverse situations or financial crises. Meanwhile, the AAS—Conscientiousness and AAS—Neuroticism investment profiles presented less variability because the combination of the parameters that defined their behavior provided a lower degree of sensitivity, driving a trend toward stability in their investment strategies.

The results showed that, in general, following the investment profiles of AAS—Extraversion or AAS—Agreeableness facilitated the attainment of better results of accumulated wealth and that following the investment profiles of AAS—Openness, AAS—Agreeableness, and AAS—Extraversion facilitated the attainment of better results of utility as compared to a neutral investment strategy, i.e., AI—neutral. Although AAS—Extraversion presented better results in accumulated wealth, its performance in the perceived utility was not the best because market variations have a greater impact on the variation of perceived utility.

In scenarios with higher volatility, AAS—Extraversion had a lower sensitivity to the amount of risky stocks within the portfolio due to the configuration of its parameters. This caused AAS—Extraversion to take higher levels of risk and increase its invested amount, causing greater fluctuations in the investment results. Greater fluctuations in financial results may have caused a lower level of utility for AAS—Extraversion. Meanwhile, AAS—Agreeableness obtained better results in high volatility scenarios by taking a more conservative position, considering the perceived utility as a metric.

The general AAS architecture distinguishes between three key aspects of the decision-making process in the stock market domain: the management of the personality profile associated with the decision maker; the evaluation of market data by considering an investment profile derived from both a personality profile and technical investment parameters; and the availability of an investment decision-making engine.

The proposed general architecture suggests the incorporation of personality profiles based on the Big Five model. This is supported by the fact that in the field of psychology, it is a reference model

Table 3
Experimental results.

Investment profile	Wealth (Initial) [USD]	Wealth (Final) [USD]	Wealth (Max) [USD]	Wealth (Min) [USD]	Wealth (Std. Dev.) [USD]	Utility (Initial) [UT]	Utility (Final) [UT]	Utility (Max) [UT]	Utility (Min) [UT]	Utility (St. Dev.) [UT]
AAS—Openness	10,000	18,778	23,128	15,416	1468	0	4.481	6.720	1.993	0.983
AAS—Conscientiousness	10,000	17,393	21,500	14,273	1376	0	1.936	2.898	0.898	0.419
AAS—Extraversion	10,000	22,663	27,970	18,565	1788	0	5.680	8.318	2.484	1.199
AAS—Agreeableness	10,000	19,516	23,954	16,081	1499	0	5.815	8.679	2.606	1.259
AAS—Neuroticism	10,000	19,089	23,778	15,395	1602	0	1.662	2.495	0.719	0.374
AI—neutral	10,000	19,416	23,919	15,869	1531	0	2.831	4.242	1.242	0.623

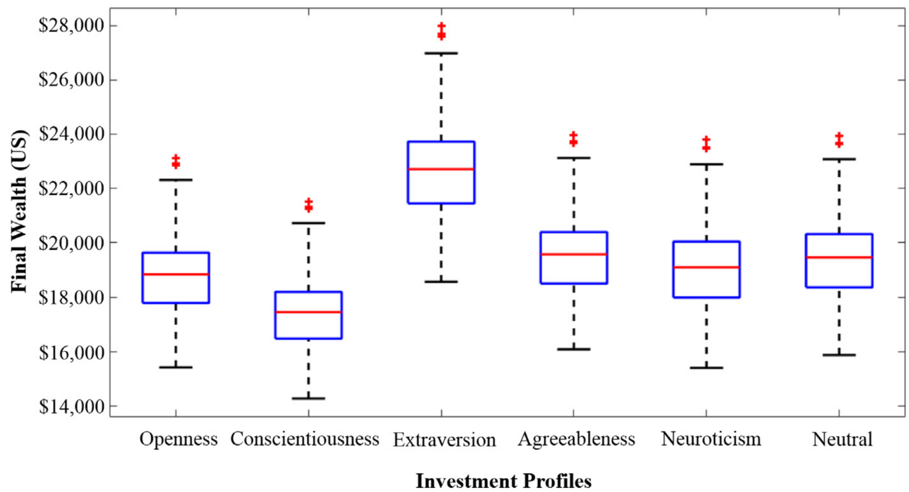

Fig. 3. Average values of the final accumulated wealth obtained from 500 independent simulations.

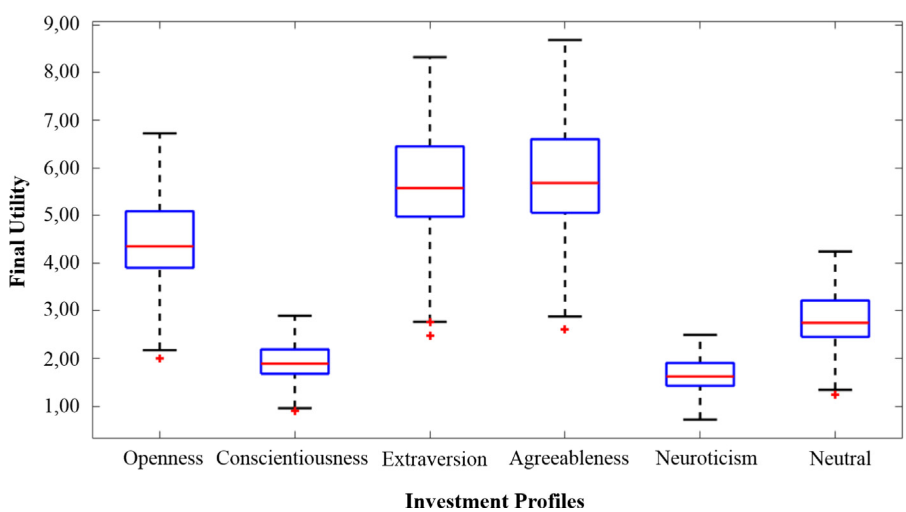

Fig. 4. Average values of the utility obtained from 500 independent simulations.

that is widely studied and analyzed as an approach to explain and understand human behavior. A specialization is observed in each of the components that make up the general architecture. The "Market Analyzer" component examines the market data regardless of how the "Market Data Manager" component obtains and prepares the market time series to be used by the AAS. Similarly, the "Portfolio Analyzer" component obtains and evaluates different indicators of the current investment portfolio. The "Investment Decision Engine" component is responsible for each investment decision related to the portfolio. At this point, the definition of a policy function is a key aspect that guides both the level of consumption and the composition of the investment portfolio in accordance with market conditions and investment profile, the latter of which is defined based on technical parameters and a personality profile of the Big Five model.

The algorithm that describes the investment decision-making process shows the first part of setting the personality profile and technical parameters to define the investment profile and configure the first investment portfolio. Then, in a cyclical manner, the market time series are obtained, the market is analyzed, and the investment portfolio is evaluated (including in terms of the accumulated wealth and utility). Thus, it is possible to activate the steps associated with the "Investment Decision Engine" component, which finally defines the policy function and determines the investment decision.

The availability and use of a policy function within an AAS for investment decision-making allows the adjustment of the investment decision according to the characteristics of each personality profile and the market conditions. AAS can dynamically adapt its decisions to the market conditions while considering the investment and personality profiles. This is a clear difference and improvement in relation to the technology currently available in the market, where each system decision is usually necessarily based on a previous setting or approval by a human user.

The stock market presents a highly complex scenario, where the uncertainty and changes in the observed conditions require a permanent capacity for adaptation on the part of the decision maker. Therefore, the AAS represents a new proposal for addressing the stock market domain as it considers the possibility of defining technical investment parameters as well as the incorporation of personality profiles.

In this work, the personality traits are expressed in numerical terms by considering the definition of three variables (parameters σ, θ, and β) based on the models proposed by Thelken and de Jong (2017) and Adams and Nettle (2009). This research proposal does not pretend to infer personality traits nor capture them from humans; rather, it considers the Big Five model in terms of personality traits within an investment profile that makes each investment decision using technical criteria and personality traits. To the best of our knowledge, there are no proposals or studies that offer an analysis, design, or implementation related to the incorporation of the Big Five personality traits for conforming and testing an AAS devoted to the stock market domain while measuring both the accumulated wealth and utility obtained during investment decision-making processes.

7. Conclusions

This paper presented the design of an AAS for the stock market domain while considering an approximation from the Big Five model. The proposal designed the general architecture of an AAS, designed an algorithm for investment decision-making processes to be used by the AAS, and simulated an experimental scenario by considering official data from NYSE Composite Index.

The experimental scenario considered the definition of different investment profiles, each associated with a profile of the Big Five model, facilitating the analysis of both the accumulated wealth and variation in the utility perceived by each artificial investor during the investment process. The test results showed that a high level of accumulated wealth does not necessarily imply a high level of utility, which shows that the accumulated wealth effect is only one factor influencing the investor's well-being and that the variables associated with "risk exposure" must be incorporated into the decision models that support investment processes.

The incorporation of personality traits into an investment decision model facilitated the generation of different investment profiles that could be adapted to different market conditions, thus making the investment strategy more flexible according to the market conditions. Moreover, the existence of different investment profiles allowed the creation of a stock market operating structure equivalent to that operated by human investors. All of this was possible due to the use of a policy function that could adapt over time, considering both the market conditions and the Big Five model profile associated with an AAS.

The incorporation of a Big Five model approach into the AAS (both in the general architecture and the algorithm for investment decision-making process) allowed the development of a new methodology for the configuration of investment plans that also considers the elements – other than the accumulated wealth – that affect the well-being of the investor.

A potential future direction of research is the extension of the current decision model through the inclusion of restrictions that affect the investment decision, such as restrictions on indebtedness, liquidity, minimum or maximum amount of investment, and disposable income, or negative economic shocks to which the investor submits, among other situations that can affect the life cycle of the investor.

Another line of future research is the extension of this case study, including using the AAS with market data from other stock exchanges such as Shanghai Stock Market ("Shanghai Stock Market", 2020) and MILA ("MILA - Mercado Integrado Latinoamericano", 2020); considering the transaction cost (the cost derived from a business operation); or using other types of investment instruments (such as derivatives and mutual funds).

The use of AAS in other application domains is also a potential area of research; it can be used to consider an e-marketplace or electronic auction scenario where a decision-making system based on AAS can make purchases or sales decisions according to specific personality profiles or to consider an education scenario in which an intelligent tutoring system implemented using AAS can be sensitive to the personality profile of the student who is using it and can adapt the teaching–learning process accordingly.

CRediT authorship contribution statement

Daniel Cabrera-Paniagua: Conceptualization, Investigation, Methodology, Software, Supervision, Writing - original draft, Writing - review & editing, Funding acquisition. **Rolando Rubilar-Torrealba:** Conceptualization, Investigation, Software, Validation, Formal analysis, Writing - original draft, Writing - review & editing.

Declaration of competing interest

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