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Resilience in the Decision-Making of an Artificial Autonomous System on the Stock Market

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ABSTRACT This paper presents the design of a resilience mechanism for supporting investment decision-making processes performed by artificial autonomous systems. In the field of Psychology, resilience is understood as the capacity of people to overcome adversity. Resilience has been determined to be a permanent necessary element for the life of an individual. In addition, different levels of intelligence, analysis capacities, and degrees of autonomy have been progressively incorporated within information systems that are oriented to support decision-making processes, such as those for stock markets. Particularly, the inclusion of affective criteria or variables within decision-making systems represents a promising line of action. However, to the best of our knowledge, there are no proposals that suggest the inclusion of a psychological approach to resilience within an autonomous decision-making system for stock markets. Specifically, the incorporation of a psychological approach to resilience allows the autonomous system to face special difficult investment scenarios (e.g., an economic shock) and prevent the system from achieving a permanent negative performance. Thus, psychological resilience can enable an artificial autonomous system to adapt its decision-making processes according to uncertain investment environments. Our proposal conducts experiments using official data from the Standard & Poor's 500 Index. The results are promising and are based on a second-order autoregressive model. The test results suggest that the use of a resilience mechanism within an artificial autonomous system can contain and recover the affective dimensions of the system when it faces adverse decision scenarios.

INDEX TERMS Resilience, artificial autonomous system, stock market.

I. INTRODUCTION

In the field of Psychology, resilience is understood as the capacity of people to overcome adverse scenarios [1]–[3]. Several studies have been developed related to the psychological approach to resilience, such as those related to Internet addiction [4], women and girls [5], children [6], adolescence [7], and workplace productivity [8], among others.

From a psychological perspective, resilience has been analyzed as a relevant and necessary element prior to the occurrence of an important event or circumstance (e.g., military operations), as a permanently necessary element for the living conditions of an individual (e.g., stressful work), or as a necessary element after the occurrence of an important event or circumstance (e.g., natural disasters) [9].

During the last decade, to improve the efficiency and the effectiveness of systems that operate in both public and private ambits, several technical and research works have been proposed, such as those aiming to improve logistics processes and e-commerce [10]–[16], to analyze urban demand-responsive transportation [17]–[21], and to improve learning processes [22], [23].

Progressively, different levels of intelligence and analysis and degrees of autonomy have been incorporated within information systems that are oriented to support decision-making processes [24]–[26]. In particular, the inclusion of affective criteria or variables within decision-making systems represents a promising line of action. In this sense, in the capital market domain, some proposals have been

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presented, such as those aiming to model the knowledge of the stock market using an affective-oriented ontology [27], to support decision making by incorporating artificial emotions within an investment decision model [28], and to control the emotional fluctuation of an artificial investor within an investment scenario [29].

However, to the best of our knowledge, there are no proposals that suggest the inclusion of a psychological approach to resilience within an autonomous decision-making system for the stock market domain. Specifically, the incorporation of a psychological approach to resilience allows an autonomous system to face special difficult investment scenarios (e.g., an economic shock) and can prevent the system from permanently turning negative. Thus, psychological resilience can enable an artificial autonomous system to adapt their decision-making processes according to uncertain investment environments. Thus, the novelties of the present research work are the following: 1) we design an artificial psychological resilience mechanism for the stock market domain, 2) we incorporate the artificial psychological resilience mechanism within a decision algorithm for the stock market domain, 3) we define an experimental scenario based on official data from the Standard & Poor's 500 Index (S&P500) [30], and 4) we analyze the promising results that are obtained from an experimental scenario.

The remainder of this work is organized as follows. Section 2 presents the related literature. Section 3 shows the artificial psychological resilience mechanism design and its inclusion within a decision algorithm for the stock market domain. Section 4 includes the scenario description and experimental results. Section 5 presents a discussion of the obtained results. Finally, Section 6 presents conclusions of the work done and future work.

II. RELATED WORK

Among the works that are related to resilience, one research area addresses to the engineering and sociotechnical system approach [31]–[33]. Sociotechnical systems represent different, varied and complex relationships between public and private entities (e.g., transportation systems, healthcare infrastructure, education services, organizations and communities, among others), where to achieve specific goals, these entities interact in terms of technical and social subsystems. Thus, resilience is understood as the capacity of a system to recognize, anticipate and absorb disturbances that can affect some function of the system. In addition, the concept is also associated with the capacity to recover any functionality or structural capability that is lost or damaged by the occurrence of a disturbance and adapt the system to future possible new disturbances. Some applications of the approach that were mentioned above correspond to transport [34], financial performance in tourism [35], and disaster management [36], [37], among others.

In contrast, other works related to resilience address the psychological approach [9], [38] and considering a broad spectrum of application domains, such as the following: health professionals [39], [40], resilience at work [41], resilience and immunity [42], resilience and sports [43], health professional students [44], [45], resilience in teenagers [46]–[48], resilience in young students [49], and resilience and cyberterrorism [50], among others.

It is generally accepted that psychological resilience is important for mental health and well-being [51], [52]. However, to the best of our knowledge, there are no research studies that examine the psychological approach to resilience for the stock market domain, particularly with respect to the investment decisions of individual investors. The evidence of the above is the extensive literature that is related to the stock market domain that is associated with technical and fundamental analysis [53]–[55] where the studies that are related to explicit sentiments within decision-making processes on stock markets have a secondary minor role.

Nevertheless, regarding the technological solutions that are used in the stock market domain, several commercial software platforms are available for supporting investment processes [56]–[60]. These commercial software platforms operate both online and offline and make different kinds of investment decisions according to the investment parameters that are defined by a real human investor. In this sense, all the investment decisions that are made by these commercial software platforms must strictly comply with the specifications that are defined by a human investor. In other words, commercial software platforms are not able to use their own decision criteria to make investment decisions, which represent a non-autonomous behavior. In addition, these platforms do not consider the affective variables within their own internal decision criteria. Thus, there is no stock market domain commercial software platform that considers both autonomous behaviors when performing investment decision-making processes and the inclusion of a psychological approach to resilience within the investment behavior.

Considering all of the above, the current research work tries to extend the available knowledge by exploring the effects of the incorporation of an artificial psychological resilience mechanism within an artificial autonomous system that is devoted to making investment decisions in the stock market domain. The theoretical value of the current research work is due to analyzing the psychological resilience of an artificial autonomous system, which is something that, to the best of our knowledge, has not been studied in the literature. Meanwhile, the practical relevance of the current research work lies, first, in the evaluation of the effectiveness of decisions that are made in the stock market domain by an artificial autonomous system with psychological resilience, and, second, in the potential applicability of an artificial autonomous system with psychological resilience in other decision environments. In this sense, several domains such as education (through the use of intelligent tutoring systems with psychological resilience to perform teaching-learning processes) or emergency and social crisis management (through the use of software to simulate individuals' resilience and behavior in the face of a crisis) could benefit from the results of the current research work.

In general, there are two application domains that can benefit from the results of the present research work. The first is decision scenarios in which people can delegate decision-making to artificial autonomous systems (where these systems incorporate artificial affectivity). The second is scenarios in which it is necessary to understand human behavior, and computational simulation technology is used to achieve this (where this technology incorporates the affective dimension within its internal processes).

III. PSYCHOLOGICAL RESILIENCE FOR AN ARTIFICIAL AUTONOMOUS SYSTEM

This section includes the following: an explanation of the design of artificial emotions, an explanation of the artificial psychological resilience mechanism's design, and, finally, an explanation for the inclusion of the mentioned resilience mechanism within a decision algorithm for investment decisions.

A. DESIGNING ARTIFICIAL EMOTIONS

The psychological approach to resilience considers the human affective dimension as a central component within human behavior and decision-making. In this sense, to design and implement a resilient artificial autonomous system, it is necessary to incorporate artificial emotions as a synthetic representation of real human emotions. Since the affective dimension influences human decision-making processes [61], [62], the observation, recording and analysis of the artificial emotions of an autonomous system becomes relevant since it allows us to explore the possible relationships between the emotional state of the decision-making system and the effectiveness of the decisions that are made by system and understand the effectiveness as the degree of compliance with specific defined goals. For example, in the stock market domain, decision effectiveness can be understood as the increase of investment capital in a specific period.

To incorporate artificial emotions within an artificial autonomous system, it is necessary to define the variables that represent specific emotional dimensions (as a synthetic representation of real human emotions), and they can be updated according to the fluctuations and conditions of the decision scenario. Thus, it is possible to define an artificial emotion as a numeric continuous variable that, starting from a neutral state (represented by a *zero* value), can have different values over time depending on the emotional reactions that are observed. For the purposes of the current research work, if the observed value of an artificial emotion variable is more than zero, it will be understood that the emotion has a positive valence. That is, it corresponds to a positive manifestation of an emotion. Conversely, if the observed value of an artificial emotion variable is less than zero, it will be understood that the emotion has a negative valence. That is, it corresponds to a negative manifestation of an emotion. To illustrate the above, considering the artificial emotion that is defined as "Trust-Fear", if the value of this variable is greater than zero, it is possible to affirm that the system is "confident". Conversely, if the value of this variable is less than zero, it is possible to affirm that system is "afraid". This functional schema can operate for other artificial emotions (e.g., Joy-Sadness and Tranquility-Angry). Fig. 1 graphically illustrates the behavior of an artificial emotion defined according to the above explanation. In this sense, it is possible to affirm that major confidence exists at time 3, and major fear exists at time 9. Since the present research work defines an artificial emotion as a variable with a "dual" nature, it is possible to affirm that if its valence is positive, it implies that some degree of "confidence" is observed, and, therefore, there is the absence of "fear". Conversely, if the valence of the emotional variable is negative, it implies that some degree of "fear" is observed, and, therefore, there is the absence of "confidence".

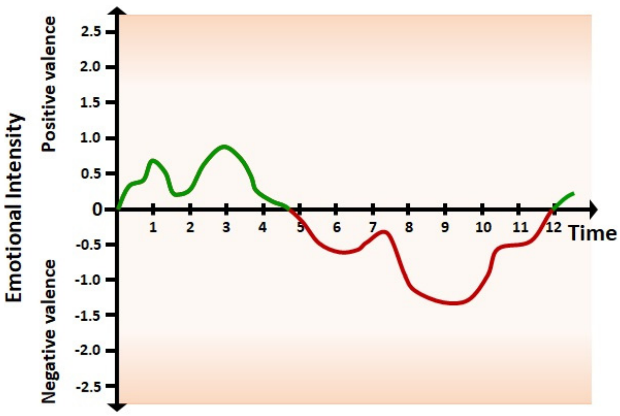

FIGURE 1. Emotional intensity variation.

In addition, several factors impact the valuation of a specific emotion. For example, receiving a prize or congratulations can be a reason to increase the level of joy, experiencing uncertainty or volatility may be grounds for decreasing the level of confidence, and being the subject of an act of injustice can be a reason to increase the level of anger. In this sense, when considering an artificial emotion as a numeric continuous variable, it is necessary to define a mechanism that updates the valence of an artificial emotional variable. The present research work defines an update function according to equation (1):

$$E_{xt} = E_{xt-1} + TAN^{-1}\left[\Delta EF\right] \cdot rand[0;1] \tag{1}$$

Here, we have the following:

$\mathbf{E_{xt}}$: Value of emotion x in period (t),

$\mathbf{E_{xt-1}}$: Value of emotion x in period (t-1),

$\boldsymbol{\Delta EF}$: Variation of the emotional factors between the previous period (t-1) and the current period (t), and

Rand[0; 1]: Uniform random value between 0 and 1.

Regarding the emotional factors (*EF*), their incorporation and degree of influence depend directly on each domain and how this domain is addressed and implemented. For the purposes of the present research work, to simplify the experimental phase, these factors will be associated with the stock price variations in the capital market. That is, emotional variation will be defined with respect to the profitability variation. A random value adds non-deterministic behavior to artificial emotions.

In [28] two mechanisms of emotional update were presented: a mechanism based on weights of each emotion, and another mechanism derived from the Prospect Theory [72]. Subsequently, in [29] the use of an emotional update factor called EIF (Emotional Influence Factor) was suggested, which operates using differentiated valuation for different emotional bands (in [29] three emotional bands were used: joy-sadness; confidence-fear; and tranquility-anger). It should be noted that each value of EIF associated to specific emotional band remained constant during each experimental scenario.

In contrast, the present research work suggests the use of a **Δ**EF (Emotional Factors) component, which seeks to reflect the variation of factors that influence the valuation of emotional variables. It should be noted that, in this case, emotional influence factors are essentially defined as "variable", and not as "constant". Considering the above, the present research work seeks to extend the mechanisms previously used, suggesting a modification that seeks to bring the decision criteria and emotional update to more real scenarios.

B. ARTIFICIAL PSYCHOLOGICAL RESILIENCE MECHANISM DESIGN

Considering the idea that an artificial emotion can be defined as a numeric continuous variable, it is necessary to establish some conditions for activating the resilience mechanism. In this sense, in the present research work, the essential activation condition corresponds to achieving an emotional threshold that is within the range of the negative valence emotional intensity. Fig. 2 shows an emotional function achieving the value of -1.0 in period 8. Since the resilience activation threshold was defined by -1.0, then the artificial psychological resilience mechanism is activated. The activation of the resilience mechanism supposes a trajectory change in the emotional function. Fig. 2 graphically shows that from period 8 there is a resilient trajectory that is a consequence of the resilience mechanism's activation and another non-resilient trajectory, which is assumed to be free to overcome the limits of the resilience activation (below the resilience trajectory). Since artificial affectivity is incorporated into a decision algorithm, the change of the emotional intensity valence along time becomes relevant for measuring its effect on the decisions that are made. The use of a resilience mechanism does not ensure that the decisions that are made over time will always be better than the decisions that are made without using some resilience mechanism or emotional containment. In this sense, is interesting for the present research work to explore and analyze the potential benefits of the

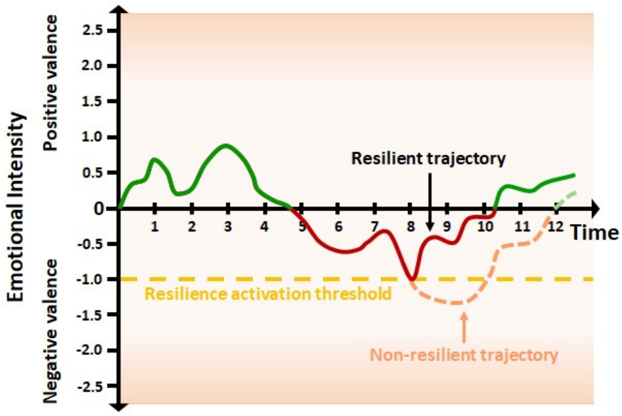

FIGURE 2. **Example of emotional behavior using a resilience mechanism.**

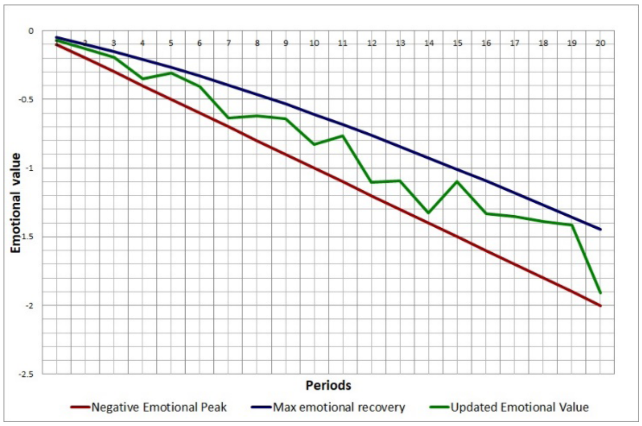

FIGURE 3. **Example of emotional behavior using a resilience mechanism.**

incorporation and use of such a resilience mechanism for decision-making.

The resilience mechanism can be activated only when the resilience activation threshold is achieved (always with the negative valence). For example, when considering a stock market decision scenario, if an investment portfolio's value has been decreasing over several investment periods, the valence of an artificial emotional variable can decrease its value. When using trust-fear as an artificial emotion, continuous losses along time can promote the tendency to feel fear. That is, it continues from a positive valence of emotional intensity (trust) to a negative valence of emotional intensity (fear). When the resilience activation threshold is reached, an artificial resilience reaction is generated.

Fig. 3 shows an example of emotional behavior for an artificial emotion "X" when the artificial resilience mechanism is activated. The line that is titled "Negative Emotional Peak" represents several possible threshold points for an artificial emotion "X", which are points where the resilience mechanism can be activated. In addition, the line that is titled "Max emotional recovery" represents the maximum recovery value that an artificial emotion can reach, which is associated with its specific negative valence peak.

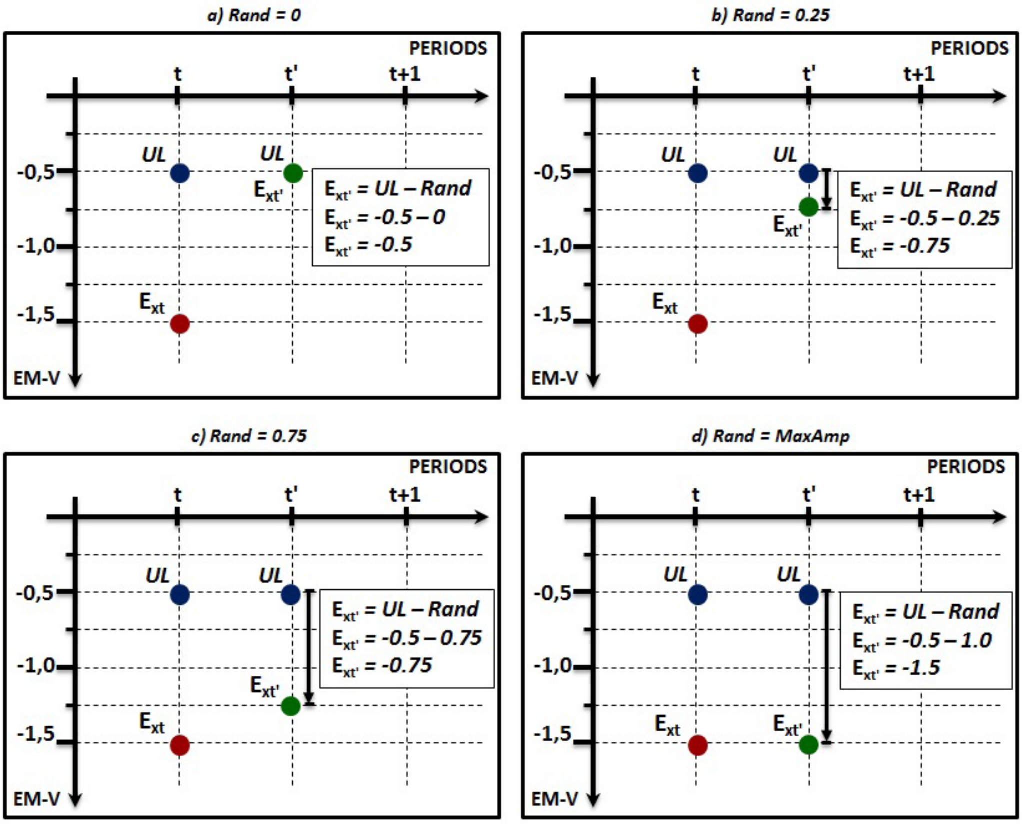

FIGURE 4. Example of scenarios for different values of the random component.

In other words, the maximum emotional recovery has an UpperLimit, which is calculated according to equation (2):

$$UpperLimit = E_{xt} + Tan^{-1}\left[Abs(E_{xt})\right] \cdot UFA \quad (2)$$

Parameter E_{xt} represents the emotional value for an artificial emotion "X" in period "t". That is, it corresponds to a negative valence peak. An arctangent function is used since as the negative emotional feeling becomes more intense, the emotional recovery process becomes more difficult. In other words, using an arctangent function allows one to obtain a more accurate recovery value based on the observed emotional state.

The parameter UFA is an update factor and its value is static during all periods. UFA is represented by a continuous value that is defined between [0,1]. When UFA is 1, the UpperLimit parameter reaches the maximum possible value. If only the last equation is used, the final value that is obtained by the emotional updating process always will be deterministic since there are no random parameters. Since human emotions are essentially non-deterministic, it is necessary to incorporate flexibility in each emotional update process. Fig. 3 shows a third emotional behavior titled "Updated Emotional Value", which represents a flexible emotional behavior. To generate this flexible emotional behavior, a random component is used to obtain a final updated emotional value. This random component adds a degree of freedom for the emotional reaction when the resilience mechanism is activated. The random component is generated within a range that is composed by lower and upper limits, which are represented by the lowest negative limit (Ext) and by the maximum value of emotional recovery (UpperLimit), respectively. In other words, the random value needs the maximum emotional amplitude that is available, which is calculated according to equation (3):

$$MaxAmp = Abs\,(E_{xt}) - Abs\,(UpperLimit) \quad (3)$$

With the MaxAmp value, it is possible to determinate the final updated emotional value. By considering the UpperLimit value as an initial point, the updated emotional value Ext' (artificial emotion "X" in period "t'") is calculated according to equation (4):

$$E_{xt'} = UpperLimit - Rand\,[0; MaxAmp] \quad (4)$$

Fig. 4 presents four different scenarios for the final updated emotional value. Each scenario is based on a specific value of the random component. When the random component is zero or the MaxAmp, the final updated emotional value corresponds to the UpperLimit or to the lowest negative limit (Ext), respectively. In other cases, the final updated emotional value is defined within the emotional limits that are mentioned above.

Considering the above explanation, the unified equation that updates an emotional value is represented as equation (5):

$$E_{xt'} = E_{xt} + TAN^{-1}[Abs(E_{xt})] \cdot UFA - Rand[0; MaxAmp] \quad (5)$$

C. A RESILIENT DECISION ALGORITHM FOR STOCK MARKETS

First, profitability corresponds to the percentage variation of a stock price within a specific investment period. Profitability can be positive, negative, or neutral (equivalent to zero). Profitability can be calculated using equation (6):

$$r_t = \frac{D_t + P_t - P_{t-1}}{P_{t-1}} \quad (6)$$

Here, P_t corresponds to the stock price at period "t" and D_t corresponds to the dividends at period "t". The present research paper considers the dividends as $D_t = 0$ because the stock prices are already corrected by dividends (the modeling considers the obtained dividends along time in its calculation).

Meanwhile, risk is associated with the volatility, which is the variation of the stock price along time (a high variation implies high risk), and it is measured using the standard deviation.

To build an investment portfolio, Markowitz's Mean-Variance Portfolio Theory is considered [63], and an efficient frontier of available portfolios is defined. To calculate each point belonging to this efficient frontier, it is necessary to minimize the standard deviation (risk) of the portfolio, subject to a certain expected return, as follows:

$$Min\ W^T \mathrm{Mcov}\ W \quad (7)$$

This is subject to the following:

$$R^T W = \mu \quad (8)$$

$$\sum_{i=1}^{n} w_i = 1 \quad (9)$$

Here, we define the variables as follows:

W: It corresponds to the weight vector that describes the stocks distribution within an investment portfolio (i.e., the portfolio composition).

w: It corresponds to the weight of each specific stock that is considered within an investment portfolio.

Mcov: It corresponds to the variance-covariance matrix, which is associated with the returns of each stock within an investment portfolio.

R: It corresponds to the expected profitability vector of each stock that belongs to the portfolio. It is important to mention that to calculate the expected profitability of a stock, the historical profitability is considered.

μ: It is a value that is defined by an investor that corresponds to a final profitability goal that is derived from the investor's own investment portfolio.

In addition, the variation of the emotional factors (ΔEF) that is used in equation (1) is calculated according to equation (10):

$$\Delta EF = \Delta price \cdot AC \quad (10)$$

Here, we define the variables as follows:

ΔEF : Variation of emotional factors, between the previous period (*t-1*) and the current period (*t*). ***ΔEF*** is related to the variation of stock prices that belong to investment portfolio.

Δprice : Variation of stock price, between the maximum and the minimum value observed in the last year.

AC: Adjustment constant.

Table 1 shows a resilient algorithm for supporting artificial investors in investment processes. First, it is necessary to initialize the emotional profile of an artificial investor. Then, the investment parameters are defined (e.g., the amount of investment capital and the investment horizon). Subsequently, the data set is obtained, and the investment strategy is defined. An example of an investment strategy defines pre-selected candidate stocks that are to be chosen using the Dow Jones Industrial Average [64]. There are several strategies to face investment processes in stock market [70], [71]. First, passive strategies suggest tracking investment portfolios configured by other investors. Thus, it is possible to track a specific stock index, or also set up an investment portfolio that replicates the behavior of a stock index. Meanwhile, there are discretionary trading investment strategies, where an investor takes active investment positions through the configuration of investment portfolios using historical market information. Within this type of investment strategies are classic models such as Markowitz, CAPM, APT (extension of CAPM). Other examples of investment strategy are: "Value", in which the stocks undervalued by the market are identified; "Momentum", which identifies the stocks with the best performance in a specific period of time; "Size", in which stocks of relatively small companies are acquired and stocks of relatively large companies are sold; "Multi-factor", which combines the strategies described above.

After choosing an investment strategy, an initial investment portfolio is defined considering all the previous steps. While the last investment period has not been reached, the investment indicators of the portfolio are obtained, and the performance of the investment portfolio is verified. The last step involves updating the emotional state of the artificial investor using equation (1). If emotional assistance is required, then the resilience mechanism is activated, forcing emotional stabilization (using equation (5)).

IV. SCENARIO DESCRIPTION AND EXPERIMENTAL RESULTS

This section describes a scenario and provides the experimental results that are obtained from simulations.

A. SCENARIO DESCRIPTION

The experimental scenario considers official data from the Standard & Poor's 500 Index [30] from 2010 to 2018. To configure the investment portfolios during experimental

TABLE 1. Resilient decision-making algorithm for investment processes.

```
BEGIN
 1. INITIALIZE EMOTIONAL PROFILE
 2. DEFINE INVESTMENT PARAMETERS
 3. GET MARKET DATA
 4. DEFINE INVESTMENT STRATEGY
 5. CONFIGURE INITIAL INVESTMENT PORTFOLIO
    [USING EQUATIONS (6) (7) (8) (9)]

 DO
    6. GET INVESTMENT PORTFOLIO INDICATORS
    7. CHECK INVESTMENT PORTFOLIO PERFORMANCE
       [USING EQUATIONS (6) (10)]
    8. UPDATE EMOTIONAL STATE [USING EQ. (1)]

    IF (EMOTIONAL STATE = "ASSISTANCE REQUIRED")
       9. ACTIVATE RESILIENCE MECHANISM
          [USING EQ. (5)]
    END_IF

 WHILE (THE LAST PERIOD HAS NOT BEEN REACHED)

END_BEGIN
```

scenario, official data from the Dow Jones Industrial Average were specifically used [64]. The Dow Jones index is composed of 30 representative stocks of the economy.

The experimental scenario considers three different types of artificial investors: the resilient investor (RI), the non-resilient investor (NRI), and the trend-follower investor (TFI). The RI can use the resilience mechanism. Meanwhile, the NRI and TFI cannot use the resilience mechanism. In turn, the TFI invests according to the Standard & Poor's 500 Index. That is, the TFI is a permanent follower of the trend of the index.

Each artificial investor has US$10,000 of investment capital. The investment process begins with the analysis of the market data that were observed in 2010 and the subsequent configuration of a first investment portfolio on the first business day of investment in 2011. From that moment, the investment horizon is one calendar year and is renewed until 2018 (inclusive). At the end of each investment year, the artificial investors withdraw their profits (or materialize their losses). At the beginning of a new investment year, each investor makes an investment equivalent to US$10,000.

The experimental scenario considers that all artificial investors have the same information about the prices and volatilities of stocks and start their investment processes at the same time. In the cases of the RI and NRI, the composition of the investment portfolio is determined using the algorithm that is described in Table 1. Since the TFI is limited to investing in the S&P500 index, it does not build an investment portfolio.

The present experimental scenario considers that the RI and NRI use a single pair of emotions called "joy-sadness", and its variation is defined depending on the observed profitability of an investment portfolio. The variation of the emotional factors (ΔEF) in equation (10) is determined considering the variation of stock prices (Δ prices). Then, ΔEF is used in equation (1) to update the emotional state.

The joy-sadness pair of emotions is defined within a continuous interval $[-10,10]$, where 10 represents joy, -10 represents sadness, and 0 (zero) represents a neutral emotional state. At the beginning of the investment process (first business day of investment in 2011), a neutral emotional state was considered. In relation to the activation threshold of the resilience mechanism, during all investment periods, the threshold has a value of -1.0. The above means that sadness increases (that is, emotional neutrality is lost by the increasing the negative emotional valence), and the resilience mechanism could be activated if the threshold (-1.0) is reached.

Tables 2, 3 and 4 show the statistical parameters of the simulation for the RI, NRI and TFI. It is considered that the time series of the returns of the portfolios that are associated with the RI, NRI and TFI profiles follow a process that is based on an second-order autoregressive model with a moving average of order 0 (ARMA(2,0)). This implies that the profitability data that are observed in period t are determined by the following: a constant, the observed profitability in period $t-1$ (L.ar), the observed profitability in $t-2$ (L2.ar), and a random number of Gaussian characteristics. N corresponds to the number of observations that are used to estimate the simulation parameters for each year.

Each table shows the disaggregated estimation parameters for each year of operation. The column indicates the year in which the estimated parameters were obtained using the data that were collected during that year, which is the information that is relevant for the simulation of the investment process of the following year.

There are multiple approaches to face simulation scenarios. In the present research work, the ARMA model approach was considered due to the wide use of such models in the literature for the definition of the stochastic processes that govern the financial price series [73]–[77]. The ARMA model, in the definition of the stochastic processes, is presented as a standard to contrast the results of the strategies followed by the different artificial investors in a simulated process; however, it is not part of the algorithm for supporting investment decision-making.

B. RESULTS

Table 5 shows the observed investment capital at the end of each year. It is important to mention that, for each year from 2011 to 2018, 10.000 simulations were carried out. In this sense, the values in Table 5 for the RI, NRI and TFI (for each investment year) correspond to the simple average of 10.000 runs and the obtained experimental results.

Moreover, it is important to remember that the year 2010 was considered only to configure the first investment portfolio (at the beginning of 2011). For the above, the three artificial investors have the same values.

TABLE 2. Statistical parameters of simulation for RI.

	2010	2011	2012	2013	2014	2015	2016	2017
Constant	0,000954 (0,000606)	0,0000506 (0,000499)	0,00116 (0,000414)	0,000804 (0,000474)	0,000207 (0,000633)	0,000166 (0,000466)	0,00109 (0,000343)	0,000332 (0,000638)
ARMA(2,0)								
L.ar	-0,151 (0,0496)	0,0513 (0,0764)	-0,0428 (0,0571)	-0,0255 (0,0534)	0,00867 (0,0495)	-0,0376 (0,0534)	-0,0397 (0,0465)	-0,000301 (0,0532)
L2.ar	0,0979 (0,0474)	-0,00780 (0,0675)	-0,0492 (0,0627)	0,0732 (0,0560)	-0,0687 (0,0533)	-0,00762 (0,0567)	0,0480 (0,0696)	-0,101 (0,0562)
N	250	250	250	250	250	250	250	250

Standard errors in parentheses.

TABLE 3. Statistical parameters of simulation for NRI.

	2010	2011	2012	2013	2014	2015	2016	2017
Constant	0,000556 (0.000528)	0,000240 (0,000371)	0,00102 (0,000393)	0.000461 (0.000425)	0,0000783 (0,000578)	0,000320 (0,000398)	0,000884 (0,000225)	0,000330 (0,000567)
ARMA(2,0)								
L.ar	-0,132 (0,0508)	0,0374 (0,0636)	-0,0571 (0,0572)	-0.00785 (0.0476)	0,00399 (0,0460)	-0,132 (0,0531)	-0,0687 (0,0638)	0,0584 (0,0492)
L2.ar	0,0842 (0,0503)	-0,0607 (0,0580)	-0,0397 (0,0580)	0.0621 (0.0566)	-0,0674 (0,0489)	-0,0261 (0,0572)	-0,000257 (0,0595)	-0,121 (0,0551)
N	250	250	250	250	250	250	250	250

Standard errors in parentheses.

TABLE 4. Statistical parameters of simulation for TFI.

	2010	2011	2012	2013	2014	2015	2016	2017
Constant	0,000141 (0,000979)	0,000490 (0,000535)	0,00104 (0,000427)	0,000530 (0,000485)	-0,0000143 (0,000651)	0,000437 (0,000514)	0,000676 (0,000233)	0,00000802 (0,000657)
ARMA(2,0)								
L.ar	-0,101 (0,0499)	0,0209 (0,0730)	-0,0772 (0,0616)	-0,0140 (0,0495)	0,0511 (0,0479)	-0,0838 (0,0453)	-0,136 (0,0721)	-0,0293 (0,0483)
L2.ar	0,101 (0,0436)	0,00992 (0,0623)	-0,0417 (0,0608)	0,0482 (0,0532)	-0,0919 (0,0491)	0,0125 (0,0505)	-0,0587 (0,0644)	-0,0579 (0,0487)
N	250	250	250	250	250	250	250	250

Standard errors in parentheses.

TABLE 5. Variation of accumulated wealth and profitability.

Year	Investment capital (US$) RI	ΔProf (%) RI	Investment capital (US$) NRI	ΔProf (%) NRI	Investment capital (US$) TFI	ΔProf (%) TFI
2010	10.000	-	10.000	-	10.000	-
2011	12.371	23,71%	11.627	16,27%	10.862	8,62%
2012	12.916	4,41%	12.486	7,39%	12.537	15,42%
2013	16.376	26,79%	15.652	25,36%	15.584	24,30%
2014	18.413	12,44%	17.105	9,28%	16.963	8,85%
2015	19.094	3,70%	17.479	2,19%	17.184	1,30%
2016	19.542	2,35%	18.369	5,09%	18.399	7,07%
2017	22.506	15,17%	21.051	14,60%	20.239	10,00%
2018	23.589	4,81%	22.208	5,50%	20.405	0,82%

According to the results, it is possible to observe that the RI obtains the highest final result, followed by the NRI and then by the TFI. From the beginning of 2011 until the end of 2018, the RI, NRI and TFI obtained final investment capital of US$23.589, US$22.208, and US$20.405, respectively. In percentage terms, the final values that are obtained by the RI, NRI and TFI represent increases of 135,89%, 122,08% and 104,05%, respectively, from the initial investment capital. The greatest percentage variation was associated with the RI (26.79%) at the end of 2013, and the lowest percentage variation was associated with the TFI (0.82%) at the end of 2018. The standard deviations of

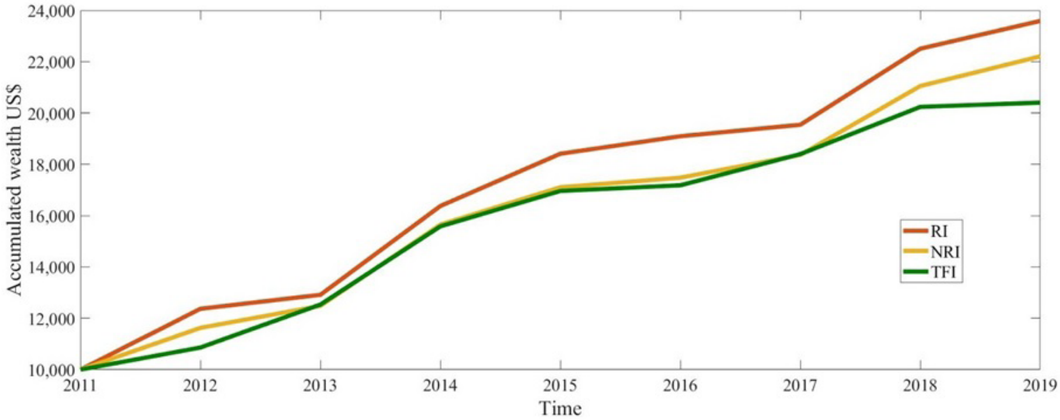

FIGURE 5. Accumulated wealth from 2011 to 2018.

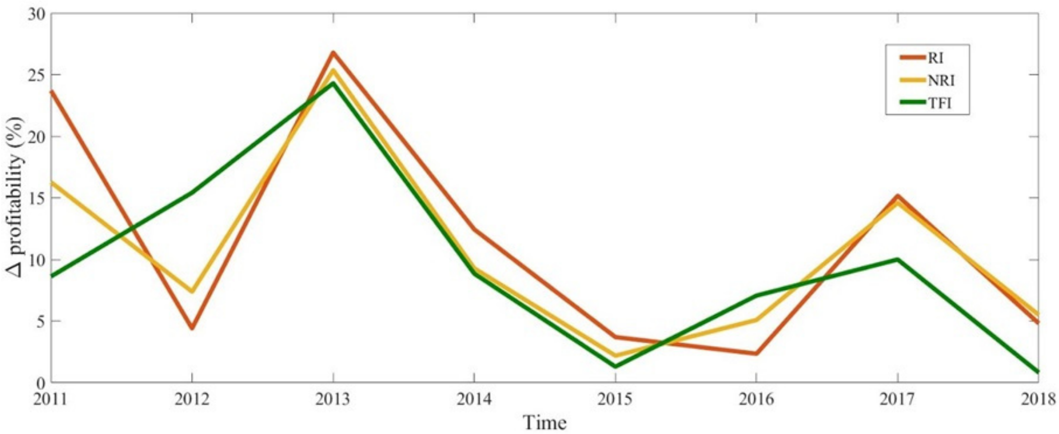

FIGURE 6. Variation of profitability from 2011 to 2018.

the RI, NRI and TFI were 8,92%, 7,11%, and 7,10%, respectively.

Fig. 5 shows the variation of the accumulated wealth for each type of investor. It is observed that the RI has sustained better performance than the NRI. Similarly, from 2011 until 2013, the NRI has better performance than the TFI. A similar situation is observed in 2018 where the accumulated wealth of the NRI is greater than that of the TFI. The periods with the greatest difference between the RI and the other profiles are observed at the end of 2014, from 2015 to 2017, and in 2018.

Furthermore, Fig. 6 graphically shows the profitability variation in each investment period. Since the beginning of 2011, an important decrease in profitability is observed until the end of the same year. The same situation is observed for the NRI. Meanwhile, the TFI shows sustained growth until the end of 2012. Since the beginning of 2012, both the RI and NRI show significant increases until the end of the same year. From the beginning of 2013, there are sustained declines for the three investment profiles and those of the NRI and TFI continue until the end of 2014. For the RI, the decreased profitability continues until the end of 2015. Subsequently, profitability growth is observed for the three investment profiles until the end of 2016. From 2017, a sustained decrease in profitability is observed for the three investment profiles. In general, the profitability of the RI and NRI investment profiles present similar trends. With respect to the TFI investment profile, it contains two countertrend profitability behaviors in relation to the RI and NRI investment profiles. These specifically occur from 2011 until the end of 2012 and from 2015 until the end of 2016.

Fig. 7 graphically shows an example of the emotional behavior of the RI and NRI investment profiles during all investment periods, which were obtained from one simulation. In relation to the ''Joy-Sadness'' pair of emotions, it is observed that positive emotional valence (that is, joy) has its highest valuations at the end of 2013 and 2017. Meanwhile, negative emotional valence (that is, sadness) has its highest valuation during 2015. In general, it is possible to observe that the positive emotional valence does not exceed 5.0 and the negative emotional valence does not exceed −4.0. Since the investment horizon that is considered in all simulations corresponds to one calendar year (renewable year by year),

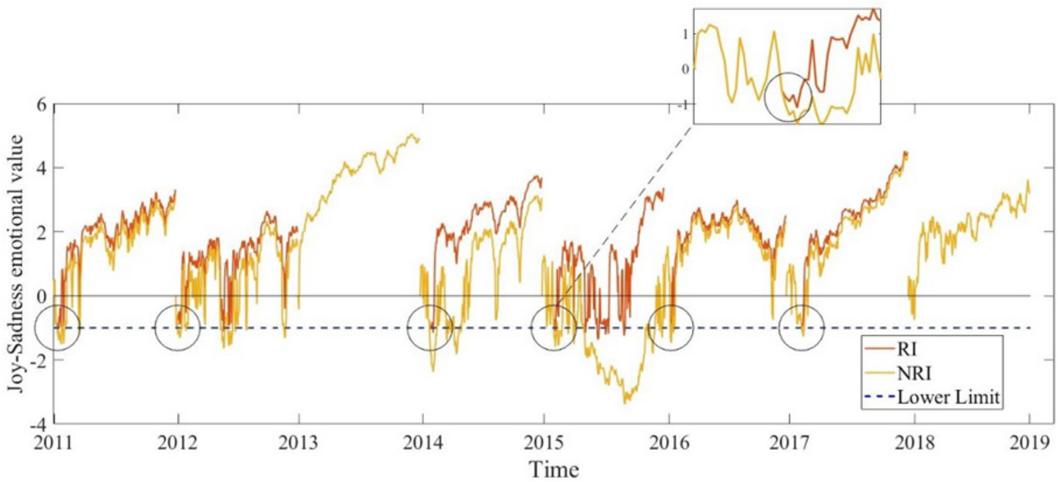

FIGURE 7. Resilience mechanism activation from 2011 to 2018.

at the beginning of each investment year, both the RI and NRI investment profiles begin their investment processes from a neutral emotional state (which is graphically observed using the discontinuous lines between investment years). Additionally, Fig. 7 shows the activation points of the resilience mechanism during all investment periods (each activation is represented by a circumference). It is important to remember that the resilience mechanism is associated exclusively with the RI investment profile, and its activation is triggered after reaching a threshold of negative emotional valence. Since the experimental scenario considers the ''Joy-Sadness'' pair of emotions, each time that sadness increases and reaches -1.0, the resilience mechanism is activated. As an example, the activation of the resilience mechanism that is observed in 2015 is amplified. In this case, while the NRI emotional trajectory is not contained, the RI emotional trajectory is redirected according to the activation of the mechanism. During that same year, the NRI investment profile reaches its lowest point in the negative emotional valence.

V. DISCUSSION

During 2011, the European Debt Crisis occurred, which generated a global slowdown and financial asset price instability. During this period, the RI investment profile performs better overall than the NRI investment profile, achieving more effective investment decisions in the face of high financial market volatility. In addition to the European Debt Crisis, from 2011 to 2018, other events that generated high instability in financial markets were observed, although they had lower impacts than the debt crisis that was mentioned above. An example of this corresponds to 2015, which was the pre-voting stage of the United Kingdom's exit referendum from the European Union (Brexit) in 2016. In this case, the RI investment profile performed better than the NRI and TFI. Meanwhile, in 2018, there were moments of high stock market tension due to the trade war between China and the USA. In this case, the RI maintained its superiority in terms of accumulated wealth, even though the NRI obtained slightly higher returns.

The experimental scenario demonstrates that the investment decisions that are made from a rational-emotional perspective (the RI and NRI investment profiles) are more effective than a purely rational perspective (the TFI investment profile). In addition, the experimental results show that the use of a resilience mechanism makes it possible to adapt decision making in periods with economic shocks. In this way, the RI investment profile has better long-term performance than the NRI investment profile. The resilience mechanism prevents investment decision making from being carried out with information that is biased by emotional states of greater sadness, and, therefore, it tries to maintain a certain degree of rationality in decision making (i.e., the decision-making does not have an intensely emotional perspective). Similarly, the mechanism does not allow for a complete restoration of the emotional state (from a state of sadness to a state full of emotional neutrality), as occurs in people within real life scenarios.

The emotional state year after year (i.e., beginning the investment process from a neutral emotional state) in the RI and NRI investment profiles was restored to verify the possible effects of having a resilience mechanism under equivalent individual emotional conditions for investing.

In the industry there is a widely used investment strategy called ''Stop Loss'', which comes from the Technical Analysis and considers that the investor defines a lower limit on the price of a financial asset. Once that lower limit is reached, the financial asset acquires the status of ''saleable''. On the other hand, the resilience implementation proposed in the present research paper suggests the use of a mechanism for restoring artificial emotional variables within an artificial autonomous system for stock market. In this sense, once a weakened emotional scenario is detected, the resilience mechanism is activated to restore that state. Considering all above, both strategies operate on different variables

(Stop Loss operates on the price, and the resilient mechanism operates on emotions), and in addition, they act in different circumstances: Stop Loss acts based on a direct instruction from a human investor, who sets a lower price limit for a financial asset; on the other hand, the resilience mechanism uses lower limit on the emotional state of an artificial autonomous system. Thus, the reaction of the artificial autonomous system becomes more weighted and gradual according to the emotional reactions observed (which are generated by prices fluctuations).

Technological development systematically advances systems to which humans can delegate decision-making. For example, autonomous transportation systems based on agents were being designed about a decade ago [65]–[67], and it is currently possible to observe real advances of autonomous vehicles and systems in urban transportation [68], [69]. In this sense, the incorporation of the affective dimension into autonomous decision-making systems becomes important to complement rational and objective criteria with other emotional and subjectivity aspects that are natural in humans, which allows one to form and configure a rational-emotional perspective closer to how a human would make a decision. Likewise, it is necessary to define mechanisms for the evaluation and control of artificial affectivity in order for both the system behavior and the effectiveness of each decision that is made by the system to comply with the quality metrics and performance criteria. The above reinforces the central objective and the contribution of the present research work. That is, this paper analyzes new mechanisms and criteria for promoting and guiding the development of technology that incorporates artificial affectivity in autonomous decision-making systems. In this way, people can progressively increase their level of confidence in technological systems, and, in particular, in affective artificial systems that face real decision scenarios from a rational-emotional perspective. These systems would then have the competence to manage the high complexity existing at present and have the ability to face and overcome adverse decision scenarios. The above description can be represented by a resilient artificial autonomous system.

VI. CONCLUSION

An artificial psychological resilience mechanism for supporting investment decision-making processes in the stock market domain was presented. The resilience mechanism required the inclusion of an artificial emotional dimension within a decision algorithm for investment decisions and was tested considering free-access data from the Standard & Poor's 500 Index.

Regarding the limitations of the present research work, first, the experiments exclusively considered stocks belonging to the mentioned investment index. In this sense, a possible future research line would be to test the resilience mechanism using more diverse data. These data would extend the evaluation period and also incorporate the globality of companies operating on the NYSE Composite. Second, the experiments only used numerical data from the Standard & Poor's 500 Index and did not consider other "environmental" antecedents (e.g., information about country risks and signals coming from "trade wars", among others).

Third, the experiments were based exclusively on defining the affective variation considering the variation of the profitability of an investment portfolio. In this sense, another possible complementary work corresponds to extending the affective dimension by incorporating other emotions in an artificial way (such as the trust-fear pair) and, in turn, relating these additional artificial emotions with other capital market variables (such as volatility, probability of loss, or economic shocks). Then, the resilience mechanism can be tested in scenarios with greater affective complexity.

Four, the joy-sadness values exclusively depend on the observed stock price variations. In real world, joy-sadness is affected by many more dimensions than those considered in this simulation scenario (some examples): at market level, market liquidity, country risk, production and manufacturing indicators; at the international level, policy contexts such as the USA-China trade war or Brexit in Europe; or on the other hand, variables related to the personal sphere (personality profile, personal affective life). Considering the above, the focus of the present research work is to define and test the use of a resilience mechanism to contain and restore the emotional state of an artificial autonomous system for stock market. In this sense, the use of additional information (such as the comments available on social networks) can be incorporated into a subsequent version of the present study, for example: for analyzing different mechanisms devoted to update emotional variables (giving different degrees of relevance to personal variables, related third party recommendations, and open comments available on social networks); to define other approach of an emotional restoring mechanism that considers the formation of an "external emotional scenario" derived from the state of financial markets, when the comments available on social networks can have a central role in obtaining a market perception.

Another possible future line of work corresponds to extending the scope of the current experimental scenario. This work can include the following: incorporating more artificial investors, adding other capital market indexes within the experimental scenario (e.g., Shanghai, Nikkei, Dax, and FTSE), and adding special information for the markets (i.e., signals from the central banks of countries or global regulatory entities).

Another possible future line of work corresponds to extending the current resilience mechanism to support decision-making processes, including adding other additional criteria for activating the resilience mechanism, adding other methods or criteria to activate the emotional transition, or incorporating Fuzzy logic. As example, the Sharpe ratio could be used as a mechanism for updating emotional variables; or also, to use the Sharpe ratio as a criterion for activating the resilience mechanism (e.g., that the variation in a specific magnitude on the Sharpe ratio can activate the resilience mechanism).

Another possible future line of work is to use artificial investors with different personality profiles, where each personality profile includes a different resilience profile. In this way, the effects of different levels of resilience on the effectiveness of decision making could be comparatively analyzed.

Another line of future work corresponds to the implementation of a resilience mechanism adapted to other domains or decision scenarios. For example, the mechanism can be used in intelligent tutoring systems that teach different disciplines, decision-making assistants in management scenarios (e.g., decisions in project management), or customer relationship management systems (e.g., smart chatbots).

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