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ORIGINAL RESEARCH

Affective autonomous agents for supporting investment decision processes using artificial somatic reactions

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Abstract

Sometimes, the conscious act of decision-making in humans is dramatically interrupted by situations that warrant an immediate response (e.g. when there is an imminent risk). The human body somatizes this interruption such that an action could be taken without a rational analysis. The above is known as a somatic marker. According to the somatic marker hypothesis, somatic markers could directly influence several ambits of decision-making. This research work presents the incorporation of artificial somatic reactions into affective autonomous agents who implement decision-making in the stock market. This implies the design of a general decision architecture for stock markets considering artificial somatic reactions and the definition of a set of decision-making algorithms for supporting investment decisions performed by affective autonomous agents (considering artificial somatic reactions). Test scenarios were defined using official data from Standard & Poor's 500 and Dow Jones. The experimental results are promising and indicated that affective autonomous agents are able to experience artificial somatic reactions and achieve effectiveness and efficiency in their decision-making.

Keywords Somatic marker · Artificial somatic reaction · Affective autonomous agent · Investment decision process

1 Introduction

Autonomy is a key factor in the current and future generation of decision-making systems. Progressively, people have delegated a part of their decisions to objects, systems, and environments. An example of the above is the emergence of several proposals for autonomous systems under the concepts of the Internet of Things (Murugaveni and Mahalakshmi 2020; Qureshi et al. 2020; Casadei et al. 2021; Ravikumar and Kavitha 2021) and Smart City (Belhadi et al. 2020; Pajuelo-Holguera et al. 2020; Zhu et al. 2020; Dizon and Pranggono 2021). To make decisions autonomously, a system requires certain essential elements, such as baseline data from the decision domain, analysis procedures, evaluation and deliberation criteria, business rules, and performance and effectiveness metrics. A relevant aspect of analyzing autonomous systems depends on how they perceive the conditions of their environment, how they react to circumstances and the results of their own decisions, and how they adapt throughout the decision-making process to improve their efficiency and effectiveness.

Meanwhile, another expanding field that corresponds to affective computing is an area that studies both the recognition, interpretation, and processing of human emotions as well as the design, implementation, and evaluation of the use of artificial affectivity within systems. In particular, several works have suggested the incorporation of human affectivity and characteristics in artificial systems (Hou et al. 2021; Yan et al. 2021). Emotions, moods, and even personality profiles have been considered. In this sense, a little studied aspect corresponds to the incorporation of somatic markers in artificial terms within autonomous systems.

Sometimes, the conscious act of decision-making in humans is dramatically interrupted by situations that warrant an immediate response (e.g., when there is an imminent risk). The human body somatizes this interruption, leading to an action that is taken without rational analysis. The above is known as a somatic marker (Damasio 1994). According to the somatic marker hypothesis, somatic markers could directly

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influence the speed and accuracy of each human decision-making process (Linquist and Bartol 2013). In addition, they could also promote the identification of decision-making patterns, the generation of several courses of action, or the memory of emotions associated with past decisions.

Considering all the above, the present research work suggests the incorporation of artificial somatic markers in affective autonomous agents. The main objective is to analyze whether an affective autonomous agent with artificial somatic reactions can improve the effectiveness and efficiency of its decisions. For this, the design of a general decision architecture composed of three layers has been proposed: a somatic layer that is responsible for how the autonomous system reacts to circumstances and the results of its own decisions; an emotional layer that is responsible for the emotional effect that somatic reactions generate on the autonomic system; a decision layer that is responsible for deliberation and final decision-making while considering both the technical criteria and the affective criteria. To regulate the magnitude of the system's reactions depending on each stimulus, an artificial somatic function has been proposed. Likewise, the emotional effects have been defined using emotional regulation functions.

Accordingly, the novelties of the present research are as follows: (1) design of a general decision architecture that considers artificial somatic reactions in the stock market domain; (2) definition of a set of decision-making algorithms for supporting investment decisions taken by affective autonomous agents by considering artificial somatic reactions; (3) definition of test scenarios for decision-making using official data from Standard & Poor's 500 (Standard & Poor's 500 Index 2021) and Dow Jones (Dow Jones Index 2021); (4) analysis of the results by observing the behavior and decisions of affective autonomous agents.

The overall performance of the decision-making process has been measured in terms of the effectiveness of the decision (i.e., the increase in wealth or profitability over time) as well as the efficiency of the decision (i.e., the time required to achieve the aforementioned effectiveness). The use of artificial somatic reactions could partially drive the behavior and the decisions by activating specific actions or considering specific rules or knowledge, such as when events that warrant immediate action are perceived (e.g., a substantial economic loss).

The present research extends the knowledge frontier by incorporating a new artificial somatic marker approach in investment decisions. The design of a somatic layer, an emotional layer, and a decision layer—defined as a unified architecture that is flexible, specialized, and extensible—allow for the layers' potential application in other decision scenarios where complex decision-making is required or in the complex decision-making processes delegated to affective autonomous artificial systems.

The remainder of this work is organized as follows: the second section includes a literature review; the third section presents the design of artificial somatic reactions in stock markets in terms of general architecture and a set of algorithms that allow an affective autonomous agent to execute investment decision-making processes in the stock market domain; the fourth section includes the scenario description and experimental results; the fifth section presents a discussion on the results obtained. Finally, the sixth section presents the conclusions derived from the work and recommendations for future work.

2 Literature review

In the last few decades, a significant amount of work has been devoted by the research community to the use of rational reasoning in artificial agent systems (Cabrera and Cubillos 2008; Cubillos et al. 2010, 2013; Cabrera-Paniagua et al. 2011; Arokiasami et al. 2016; Mellado Silva et al. 2016; Acay et al. 2019; Ehab and Ismail 2020; Ismail 2020; Lv et al. 2020).

Particularly, regarding the use of artificial agents on decision-making systems, several approaches have been proposed to support agent negotiation in a power distribution system for demand reduction (Tom et al. 2020), to apply agents into the e-commerce (Liang et al. 2019; Cui et al. 2020), to simulate decision-making processes related to long-distance travel demand (Janzen and Axhausen 2018), to implement decision systems based on dynamic argumentation (Ferretti et al. 2017), to implement reactive, predictive, and adaptive processes within a virtual entity (Buche et al. 2016), to design a system for order management in heterogeneous production environments (Saha et al. 2016), and to design an agent-based model for a multimodal near-field tsunami evacuation (Wang et al. 2016) among others.

On the other hand, in relation to the inclusion of affectivity in artificial agent models, some works cover the following: the inclusion of emotional support from a digital assistant in technology-mediated services (Gelbrich et al. 2020); a multi-agent system for guiding users in on-line social environments using sentiment analysis (Aguado et al. 2020); simulation of human emotional behavior using intelligent agents (Pudane et al. 2016); simulation of the propagation of information among a group of individuals and its influence on their behavior (Bouanan et al. 2016); definition of an emotional life-cycle for autonomous agents (Jain and Asawa 2016); and design an affective algorithm for purchasing decisions in e-Commerce environments (Cabrera et al. 2015) among others. In Kaklauskas et al. (2020), the affective and biometrical states through a built environment with multisource data were analyzed. Meanwhile, in Sánchez et al. (2019), an affective framework for a BDI agent was presented. In Rosales et al. (2019), a framework for the design of artificial emotion systems was presented. None of the aforementioned cases consider the availability of artificial somatic reactions within decision-making systems.

Regarding the research line of somatic markers, several works have been devoted to analyze the neuroscience of the sadness (Arias et al. 2020), to analyze mood states and somatic markers (Steenbergen et al. 2020), to explore the relationship between somatic markers and behavior under stress (Huzard et al. 2015), to map the interconnected neural systems underlying motivation and emotion (Cromwell et al. 2020), to explore the existence of anticipatory feelings (Stefanova et al. 2020), and to analyze the impact of somatic markers in decision-making (Guillaume et al. 2009; Reimann and Bechara 2010; Gupta et al. 2011; Poppa and Bechara 2018; Sandor and Gürvit 2019) among others. General or abstract architectures for considering the use of emotions, artificial somatic markers, and moral aspects have been presented in Chandiok and Chaturvedi (2018), Dyachenko et al. (2018), Ichise (2018), Nagoev et al. (2018), Pessoa (2019), Reia et al. (2019), Kelley and Twyman (2020), Samsonovich (2020). It is noteworthy that when considering artificial somatic markers, the suggestions are general in terms of their use in decision processes and/or in terms of real application domains.

On the other hand, fewer works have explored the implementation of somatic markers within artificial systems for supporting decision-making processes. In Cominelli et al. (2015), an implementation of somatic markers for social robots was presented. The authors performed a set of tests using the Iowa Gambling Task as the analysis scenario in which the mood was the primary factor responsible for the activation of a somatic reaction. Therefore, the relationship between the triggering cause of a somatic reaction and the agent's judgment, perception, or consciousness level regarding said cause was found weak or non-existent. Furthermore, in Hoogendoorn et al. (2009), a computational decision-making model based on somatic markers was presented. Somatic markers were used as an alarm signal for a particular option and were described in algebraic terms. A non-standard simplified environment from the domain of a fighter airplane was used as the decision test scenario. Meanwhile, in Cabrera et al. (2020), an abstract framework for implementing artificial somatic markers within autonomous agent was presented. In order to illustrate the applicability of the framework, a conceptual case study on the transportation of people under a tourism context was presented.

In Hoefinghoff et al. (2012), an implementation of a decision-making algorithm based on somatic markers was presented. The agent had a set of S stimuli that could be recognized. The work presented a reduced study case in which the stimuli received were music or *joy pad,* and the possible actions triggered by stimuli were dance, videogames, and a specific action called *getofmyback*. The robot received rewards by pressing one of the three touch sensors. The robot danced when the music was recognized and talked and moved its arms when the joy pad was recognized. The proposal was extended in Hoefinghoff and Pauli (2012) by the inclusion of a frustration level and an evaluation of using the Iowa Gambling Task test and in Höfinghoff et al. (2013) in which a software architecture based on Nao robot technology (SoftBanks Robotics 2020) was presented.

Considering the available literature, and to the best to our knowledge, compared to the rational approach, minor effort has been devoted to consider the use of an affective dimension within artificial agent systems devoted to execute autonomous decision-making processes on stock markets (Cabrera-Paniagua et al. 2014, 2015; Cabrera et al. 2018, 2019; Cabrera-Paniagua and Rubilar-Torrealba 2021). Regarding the use of somatic markers, except the use of the Iowa Gambling Task, non-standard decision environments are usually used for implementing artificial somatic markers. Therefore, it is not possible to observe the use of artificial somatic markers within affective autonomous agents as decision-making systems for real-world decision environments (e.g. the stock market domain). Additionally, no works have explored whether the use of artificial somatic reactions within affective autonomous agents can improve the effectiveness and efficiency of their investment decisions. These aspects that the current research work seeks to explore and verify.

3 Design of artificial somatic reactions on stock markets

3.1 Human somatic markers

The somatic marker hypothesis proposed by Damasio offered a unified perspective of the body-brain system, explaining that the body serves as the basis for mental representations (Damasio 1994). The body (as a whole) can receive signals when a stimulus (internal or external) triggers it at the brain level. These signals can be translated into a series of body changes: sweating, heart rate increase, muscle twitching (momentary contraction), abdominal pain, paleness, paralysis, and so on. These signals are seen as sudden and immediate physical changes.

Although not entirely clear, a somatic marker could either be an incentive to act or be an inhibitor of action. Similarly, it can have an impact on the recognition of a decision point, generate alternative courses of action, and even give rise to feelings of reward or punishment when a decision is made (Linquist and Bartol 2013). People generate memories about events or circumstances and the sensations or reactions experienced at the body level from life experience. Such past feelings or reactions return or become visible in the present when similar events or circumstances are perceived. In other words, life experience is the means through which somatic markers are incorporated into people.

Somatic marker activation can have both positive and negative valence. An example of positive valence corresponds to experiencing pleasant sensations in the face of a fact or circumstance (e.g. meeting an old friend). On the other hand, an example of negative valence corresponds to experiencing unpleasant sensations in the face of a fact or circumstance (e.g. receiving bad professional or work news). It is noteworthy that in no case is it mandatory that a person must react in a certain way to a stimulus or that two people must react in the same way to the same stimulus. Each person, based on their own experiences, develops and extends their own somatic markers.

3.2 Stock markets

A stock market represents a physical and/or electronic space where investment instruments are traded. According to the specific objectives of each company, some decide to open up to the stock market through the sale of stocks. A stock represents a very small part of a company, and in addition to granting an idea of ownership over it, it allows its holders the eventual receipt of profits based on its performance in the market. The holders of such stocks are usually identified as investors. An investor uses capital to acquire investment instruments (including company stocks). An investment portfolio corresponds to a collection of investment instruments associated with a holder, that is, an investor.

The value of a portfolio is based on the performance of the investment instruments constituting it. Considering a portfolio of stocks, its value depends directly on the variation in the price of its stocks. The price variation over time is known as the profitability of the stock. When a positive variation in the price occurs, it is said that there was a positive profitability. On the contrary, when a negative variation in the price occurs, it is said that there was a negative profitability. In the present research work, the calculation of profitability is in accordance with Eq. 1:

$$prof_t = \frac{SP_t - SP_{t-1}}{SP_{t-1}} \cdot 100 \tag{1}$$

where SP_t: stock price in the current period t, SP_{t-1}: stock price in the previous period t−1.

Investment capital can increase over time through (positive) profitability. The successive occurrence of positive profitability allows an accumulation of wealth. In the same manner, the successive occurrence of negative profitability causes a loss of wealth. It is noteworthy that nothing can ensure an investment to consistently offer positive or negative profitability. There is an inherent condition to any investment that corresponds to the risk. In relation to a stock, risk represents the degree of fluctuation in its price. Similarly, in relation to a portfolio of stocks, risk represents the degree of fluctuation in the price of the stocks constituting it. In the present research work, the risk of a portfolio of stocks is calculated according to Eq. 2:

$$\sigma_P = \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_i \sigma_j C_{ij}}, \tag{2}$$

where σ_i: risk of the ith stock belonging to the portfolio. σ_j: risk of the jth stock belonging to the portfolio. w_i: weight of the ith stock belonging to the portfolio. w_j: weight of the jth stock belonging to the portfolio. C_{ij}: covariance between the ith and jth stocks belonging to the portfolio. N: number of stocks in the portfolio.

3.3 A general decision architecture for stock markets considering artificial somatic reactions

Figure 1 shows a general decision architecture for stock markets considering the incorporation of somatic reactions, all the above for affective autonomous agents. At the left end, it is possible to observe the entry of market data and investment results. Meanwhile, at the extreme right, it is possible to observe the output of an investment portfolio. At the center, three layers are identified: Somatic layer, Emotional layer, and Decision layer.

The somatic layer emulates in artificial terms the somatic reactions that can be triggered in humans. A set of somatic memories is required which corresponds to long-term memories of associations between objects, events, or past situations and the sensations experienced in each case. In addition, an evaluation mechanism (somatic appraisal) for triggering somatic reactions is necessary if the observed conditions warrant it. This gives rise to somatic rules defined in terms of activation criteria and functions that describe the behavior of a somatic reaction.

The emotional layer is responsible for interpreting somatic reactions and translating them into emotional effects. The present research work considers two pairs of emotions: joy–sadness and trust–fear, following the guidelines of Paul Ekman's basic emotions (Ekman 1982, 1992). An evaluation mechanism (emotional appraisal) that allows updating the emotional state according to the observed conditions is necessary. This gives rise to emotional rules defined in terms of updating criteria and functions that describe the behavior of an emotion.

The decision layer is responsible for analyzing the investment strategy to be followed. For this, it uses both the current emotional state as well as rational investment criteria. The application of investment rules is derived in decision-making about the investment portfolio, specifically, maintaining the current portfolio or applying changes to it.

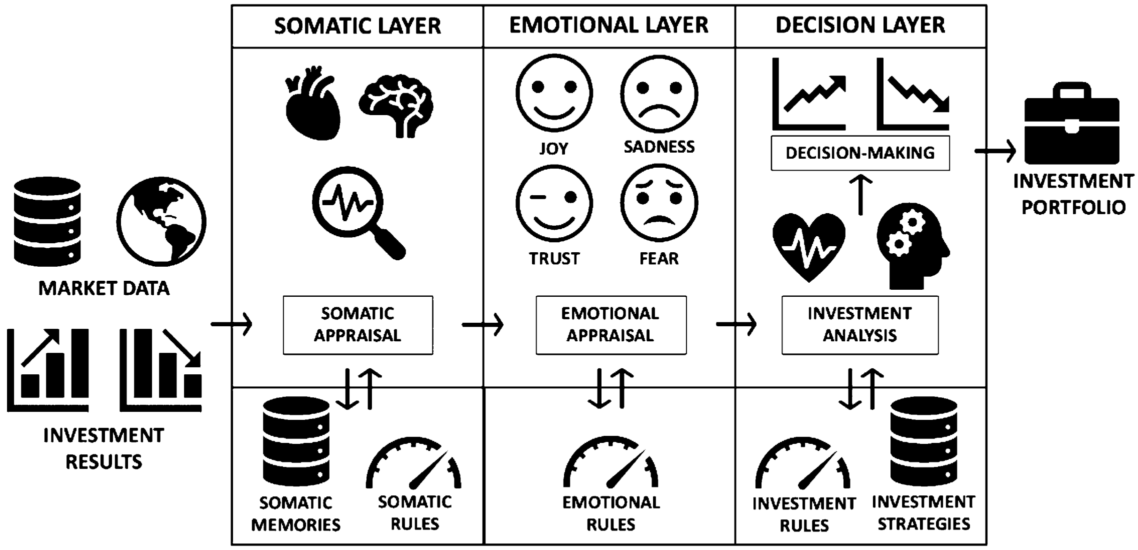

Fig. 1 General decision architecture for stock markets considering artificial somatic reactions

3.4 Autonomous decision-making processes on stock markets

This subsection includes a set of algorithms that allow an affective autonomous agent to make investment decisions in the stock market domain. Algorithm Nº1 represents the general investment decision process. During its execution, there are several calls to other algorithms that will be progressively explained. The algorithm begins by setting the initial investment strategy to use. The current research work considers two different investment strategies: a "*risk strategy*", which represents an aggressive investment strategy that seeks greater profitability or wealth and a "*moderate strategy*", which represents an investment strategy that seeks stability and to contain the investment risk. It is noteworthy that according to investment rules and the values of emotional variables, the investment strategy can be modified during the investment process.

The next step involves the analysis of market data, obtaining a list of candidate portfolios to invest. The next step is to verify the existence of somatic memories. This step seeks to verify the existence of associations between some characteristics of a candidate's portfolio and a somatic reaction. These somatic associations can inhibit the inclusion of a stock within a candidate portfolio (e.g., given its industrial sector) or promote the incorporation of a stock within a candidate portfolio (e.g., given its tendency to rise). Whenever it is required to configure an investment portfolio, it is mandatory to verify the somatic memories by calling Algorithm No. 2 (that will be explained below), which returns a refined list of candidate portfolios. Considering this refined list and investment strategy, the next step involves setting up an investment portfolio. Then, steps five, six, and seven indicate that for each investment period, the updated market data is received and the somatic reactions that these market results can generate in the affective autonomous agent are obtained, that is, a somatic appraisal (this requires a call to Algorithm No. 3, which will be explained later). Unlike Algorithm Nº2 in which somatic associations are verified to configure an investment portfolio, Algorithm No. 3 seeks to obtain the reactions of the affective autonomous agent from its own investment results. These reactions can be positive ('*Valence*+'), negative ('*Valence* −'), or neutral. These somatic reactions, received as a list from Algorithm No. 3, allow the next step that is the emotional appraisal of the affective autonomous agent through a call to Algorithm No. 4 (which will be explained later). Subsequently, investment rules are applied to determine a decision.

The investment rules correspond to a mixture between technical investment criteria and the state of the emotional variables of the affective autonomous agent. These rules will be discussed in greater depth when explaining the details of Algorithm No. 5. Anyway, at this point, it is important to note that the application of the investment rules within Algorithm No. 5 results in a decision composed of two aspects: a directive with two possible options (to sell or maintain the portfolio) and an investment strategy (concept explained at the beginning of this subsection). In step eleven, the directive is verified. If the directive corresponds to 'sell', then the portfolio is sold and the investment process goes to step 1, considering the last value of investment strategy. In the case the directive value does not correspond to 'sell', then the affective autonomous agent decides to maintain the current portfolio, going to the next investment period. The Algorithm No. 1 ends when the entire investment period is covered.

Algorithm 1 General investment decision process

Problem description: Dispose the investment decision-making process for an affective autonomous agent.
Preconditions: Data is collected from the stock market to start the process. For analysis purposes, past results derived from investment in the stock market are used.
Postconditions: There is a final portfolio to analyze its accumulated wealth till the last investment period. There is a record of the behavior of the results derived from the investment decisions made by an affective autonomous agent.
Input: Investment strategy.
Output: Portfolio with current prices (to the last period).

Begin
1: set {*investment strategy*} from {*input parameter*}
2: list_candidate_portfolios = analyze Market (*mkt_Data*)
3: refined_portfolios = verify Somatic Information (*somatic_memories*; *list_candidate_portfolios*) [*call to* Algorithm Nº2]
4: portfolio = configure Portfolio (*refined_portfolios, investment strategy*)
5: **For** each investment period:
6: mkt_Data = get Updated Market Data( )
7: somatic_reactions_List = Somatic Appraisal (*portfolio*; *mkt_Data*) [*call to* Algorithm Nº3]
8: Emotional Appraisal (*somatic_reactions_list*) [*call to* Algorithm Nº4]
9: decision = apply Investment Rules [*call to* Algorithm Nº5]
10: **Get** {*directive*, *investment strategy*} **from** {*decision*}
11: **If** (directive = 'sell')
12: sell (portfolio)
13: Go to step 1 {input parameter: *investment strategy*}
14: **Else**
15: Go to step 5
16: **End If**
17: **End For**
End Algorithm 1

On the other hand, Algorithm No. 2 describes the process of verifying somatic memories. The algorithm receives as input parameters a set of somatic memories and a list of candidate portfolios. For each candidate portfolio '*i*' belonging to the list of candidate portfolios and for each stock '*k*' belonging to a specific candidate portfolio '*i*', the algorithm verifies a set of somatic rules which aim to associate the stock to one of three different statuses: 'vetoed', 'promoted', or 'neutral'. If a stock '*i*' belongs to a company and/or an industrial/business sector associated with a 'bad or negative memory', the stock is labeled as 'vetoed'. If a stock '*i*' belongs to a company and/or an industrial/business sector associated with a 'good or positive memory', the stock is labeled as 'promoted'. The algorithm also allows one to promote uptrend or downtrend stocks. If the stock '*i*' is not associated with some somatic rule mentioned above, then its status is set as 'neutral'. The algorithm No. 2 returns a list of refined candidate portfolios in which each stock has one of the three statuses mentioned above.

Algorithm 2 Verify Somatic Memories

Problem description: Verify in the affective autonomous agent the existence of somatic memories associated with stocks that could be selected.
Preconditions: An autonomous investment decision-making process is performing.
Postconditions: The existing somatic associations with each stock are obtained. In the absence of a previous association, a neutral somatic association is denoted.
Input: Somatic memories; list of candidate portfolios.
Output: Refined portfolios.

```
Begin
For candidate_portfolio_i ∈ {candidate_portfolios_list}
  For stock_k ∈ {candidate_portfolio_i}
    If stock_k ∈ {somatic_memories: vetoed companies}
      Add (stock_k; vetoed) in {temporary_portfolio}
    Else If stock_k ∈ {somatic_memories: vetoed industrial/business sectors}
      Add (stock_k; vetoed) in {temporary_portfolio}
    Else If stock_k ∈ {somatic_memories: promoted companies}
      Add (stock_k; promoted) in {temporary_portfolio}
    Else If stock_k ∈ {somatic_memories: promoted industrial/business sectors}
      Add (stock_k; promoted) in {temporary_portfolio}
    Else If stock_k ∈ {somatic_memories: promotion of uptrend stocks}
      Add (stock_k; promoted) in {temporary_portfolio}
    Else If stock_k ∈ {somatic_memories: promotion of downtrend stocks}
      Add (stock_k; promoted) in {temporary_portfolio}
    Else
      Add (stock_k; neutral) in {temporary_portfolio}
    End If
    Add temporary_portfolio in {refined_portfolios}
End For
return (refined_portfolios)
End Algorithm 2
```

Algorithm No. 3 describes the process of somatic appraisal. For each investment period, it is necessary to verify the reactions that are generated in the affective autonomous agent when it knows the updated market data and the variations on own portfolio. Regarding the profitability, a somatic reaction of 'valence + ' (positive valence) will be triggered if the somatic function of profitability reaches an upper threshold. Conversely, a somatic reaction of 'valence −' (negative valence) will be triggered if the somatic function of profitability reaches a lower threshold. If both upper and lower thresholds are not reached due to the variation in portfolio profitability, a somatic reaction of 'neutral valence' will be observed (see Fig. 2).

Algorithm 3 Somatic Appraisal

Problem description: Activate the somatic evaluation, i.e., obtain the somatic reactions of the affective autonomous agent based on the results of its investment portfolio.
Preconditions: Updated data on the stock market are available.
Postconditions: Based on the variations in profitability and risk of the portfolio, the artificial somatic reactions are registered in the affective autonomous agent.
Input: Portfolio; market data.
Output: Somatic reactions list.

```
Begin
Get {profitability, risk} from {portfolio}
If {profitability}>= somatic_upper_threshold_Prof
  somatic_Reaction_Prof = 'Valence +'
  somatic_Reaction_Prof_Value = 'Value' (Using Eq. 3)
Else If {profitability}<= somatic_lower_threshold_Prof
  somatic_Reaction_Prof = 'Valence -'
  somatic_Reaction_Prof_Value = 'Value' (Using Eq. 3)
Else
  somatic_Reaction_Prof = 'Neutral Valence'
  somatic_Reaction_Prof_Value = zero
End If
If {risk}>= somatic_upper_threshold_Risk
  somatic_Reaction_Risk = 'Valence -'
  somatic_Reaction_Risk_Value = 'Value' (Using Eq. 4)
Else If {risk}<= somatic_lower_threshold_Risk
  somatic_Reaction_Risk = 'Valence +'
  somatic_Reaction_Risk_Value = 'Value' (Using Eq. 4)
Else
  somatic_Reaction_Risk = 'Neutral Valence'
  somatic_Reaction_Risk_Value = zero
End If
Add
  {somatic_Reaction_Prof, somatic_Reaction_Prof_Value; somatic_Reaction_Risk,
  somatic_Reaction_Risk_Value} in {somatic_reactions_List}
return (somatic_reactions_List)
End Algorithm 3
```

The somatic function of profitability is calculated according to Eq. 3. SFP describes the magnitude of the artificial somatic reaction as a function of profitability:

$$SFP\left(prof_t\right) = \frac{2}{1 + e^{-\alpha * prof_t}} - 1 + \gamma \quad (3)$$

where α corresponds to a sensitivity parameter to profitability and $\alpha \in \mathbb{R}_+$; γ corresponds to a random variable that represents the fuzzy characteristic of the somatic function of profitability and $\gamma : \mathbb{R} \to \mathbb{R}$; $prof_t$ corresponds to the profitability obtained by the portfolio in the period t according to Eq. (1).

Regarding the risk, a somatic reaction of 'valence + ' (positive valence) will be triggered if the somatic function of risk reaches an upper threshold. Conversely, a somatic reaction of 'valence −' (negative valence) will be triggered if the somatic function of risk reaches a lower threshold. If both upper and lower thresholds are not reached due to the variation in portfolio risk, a somatic reaction of 'neutral valence' will be generated (see Fig. 2).

On the other hand, the somatic function of risk follows Eq. 4. SFR describes the magnitude of the artificial somatic reaction as a function of risk:

$$SFR\left(risk_t\right) = \frac{2}{1 + e^{-\varepsilon * \left(risk_t - \kappa\right)}} - 1 + \theta \quad (4)$$

where ε corresponds to a parameter of sensitivity to risk and $\varepsilon \in \mathbb{R}_+$; κ corresponds to a parameter that adjusts the effect of the observed risk and $\kappa \in \mathbb{R}$; θ corresponds to a random variable that represents the fuzzy characteristic of the somatic function of risk, and $\theta : \mathbb{R} \to \mathbb{R}$; $Risk_t$ corresponds to the volatility measured as the standard deviation of the observed returns multiplied by 100.

The functional structure of Eqs. (3) and (4) makes it possible to model artificial somatic reactions as a function of profitability and risk, respectively. Through different assignments of the parameters, it is possible to configure the behavior of the affective autonomous agent where a higher value of α (in the case of SFP) and a higher value ε (in the case of SFR) implies a high-level sensitivity to stimuli (e.g., high variations in domain indicators), which can cause more recurrent somatic reactions. The role of the κ parameter corresponds to controlling the bias of the affective autonomous agent in the face of perceived risk. The parameter κ allows characterizing the risk aversion of the affective autonomous agent.

Algorithm No. 3 returns a list that contains the somatic reactions derived from the updated portfolio information of profitability and risk in terms of both conceptual reaction and numerical quantification of the somatic reaction. In the case of obtaining a somatic neutral reaction, 'neutral valence' is registered as the concept and 'zero' is registered as the numerical quantification of the somatic reaction.

For its part, Algorithm No. 4 describes the process of emotional appraisal. This algorithm receives as input parameter a list of somatic reactions (obtained after performing Algorithm Nº3). Considering the somatic reactions, the algorithm makes an emotional appraisal of the affective autonomous agent. If the somatic reaction of profitability has 'valence+' (positive valence) then the joy–sadness emotion takes 'valence+', that is, it turns to joy (using Eq. 5). Conversely, if the somatic reaction of profitability has 'valence −' (negative valence) then the joy–sadness emotion takes 'valence −', that is, it turns to sadness (using Eq. 5). Meanwhile, if the somatic reaction of risk has 'valence+' (positive valence), then the trust–fear emotion takes 'valence+', that is, it turns to trust (using Eq. 6). Conversely, if the somatic reaction of risk has 'valence −' (negative valence) then the trust–fear emotion takes 'valence −', that is, it turns to fear (using Eq. 6).

The functions to update joy–sadness and trust–fear emotions follow Eqs. 5 and 6, respectively. *SFP* corresponds to the somatic reaction value associated with profitability. *SFR* corresponds to the somatic reaction value associated with risk. *UTP* corresponds to an "*Upper Threshold Profitability*"; *LTP* corresponds to a "*Lower Threshold Profitability*".

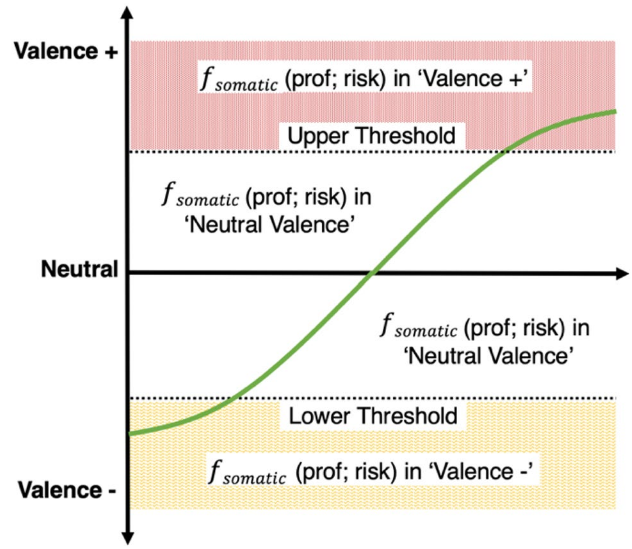

Fig. 2 Somatic reaction function for profitability and risk

It is important to highlight that investment results can generate different magnitudes of somatic reactions in the affective autonomous agent which in turn allows the appraisal of its emotional state. If the emotional update reaches some emotional threshold (each emotional threshold is represented by a variable that will be explained later) then the affective autonomous agent can modify its own portfolio. In other words, it is the emotional state that, according to the investment rules (that will be detailed later), can lead the affective autonomous agent to modify its investment portfolio.

$$JoySadness(SFP_t) = \begin{cases} \frac{2}{1+e^{-\eta*(SFP_t-UTP_{JS})}} - 1 + \phi, & if \quad SFP_t = \text{Valence} + \\ \frac{2}{1+e^{-\eta*(SFP_t-LTP_{JS})}} - 1 + \phi, & if \quad SFP_t = \text{Valence} - \end{cases} \tag{5}$$

where η represents a sensitivity parameter to the artificial somatic reaction derived from profitability and $\eta \in \mathbb{R}_+$; ϕ corresponds to a random variable that represents the fuzzy characteristic of the emotional function *JoySadness* and $\phi : \mathbb{R} \to \mathbb{R}$; SFP_t corresponds to the quantification of the artificial somatic reaction to profitability in the period t; UTP_{JS} corresponds to the Upper Threshold Profitability, which adjusts by the upper bound the effect of the artificial somatic reaction to profitability, and $UTP_{JS} \in \mathbb{R}$; LTP_{JS} corresponds to the Lower Threshold Profitability, which adjusts by the lower bound the effect of the artificial somatic reaction to profitability, and $LTP_{JS} \in \mathbb{R}$.

$$TrustFear(SFR_t) = \begin{cases} \frac{2}{1+e^{-\psi*(SFR_t-UTP_{TF})}} - 1 + \varphi, & if \quad SFP_t = \text{Valence} + \\ \frac{2}{1+e^{-\psi*(SFR_t-LTP_{TF})}} - 1 + \varphi, & if \quad SFP_t = \text{Valence} - \end{cases} \tag{6}$$

where ψ represents a sensitivity parameter to the artificial somatic reaction derived from risk and $\psi \in \mathbb{R}_+$; φ corresponds to a random variable that represents the fuzzy characteristic of the emotional function *TrustFear* and $\varphi : \mathbb{R} \rightarrow \mathbb{R}$; SFR_t corresponds to the quantification of the artificial somatic reaction to risk in the period t; UTP_{TF} corresponds to the Upper Threshold Risk, which adjusts by the upper bound the effect of the artificial somatic reaction to risk, and $UTP_{TF} \in \mathbb{R}$; LTP_{TF} corresponds to the Lower Threshold Risk, which adjusts by the lower bound the effect of the artificial somatic reaction to risk, and $LTP_{TF} \in \mathbb{R}$.

The functional structure of Eqs. (5) and (6) allows limiting the effects of the emotional pairs joy–sadness and trust–fear, respectively. The foregoing structure seeks to prevent the affective autonomous agent from having extreme episodes in the assessment of emotions. The parameters η (in the case of the *JoySadness* function) and ψ (in the case of the *TrustFear* function) allow controlling the sensitivity level of the affective autonomous agent to SFP and SFR variations. Meanwhile, UTP and LTP parameters controlling the bias in the generation of an artificial somatic reaction.

The functional form of the proposed Eqs. (3)–(6) is inspired by the logistic functions that are used in the

Algorithm 4 Emotional Appraisal

Problem description: Activate emotional evaluation, i.e., obtain the emotional reactions of the affective autonomous agent from the somatic reactions.

Preconditions: An updated list of artificial somatic reactions is available.

Postconditions: Considering the evaluation of the somatic reactions derived from the profitability and risk of the investment portfolio, the valuation of the emotional pairs joy_sadness and trust_fear is updated.

Input: Somatic reactions list.

Output: Record of the updated emotional state of the affective autonomous agent.

Begin

Get {*somatic_Reaction_Prof*, *somatic_Reaction_Risk*} **from** {*somatic_reactions_list*}
If {*somatic_Reaction_Prof*} = '*Valence +*'
  joy_sadness_state = '*Valence +*'
  joy_sadness_value = '*Value*' (Using Eq. 5)
Else If {*somatic_Reaction_Prof*} = '*Valence -*'
  joy_sadness_state = '*Valence -*'
  joy_sadness_value = '*Value*' (Using Eq. 5)
Else
  joy_sadness_state = '*Neutral Valence*'
  joy_sadness_state = zero
End If
If {*somatic_Reaction_Risk*} = '*Valence +*'
  trust_fear_state = '*Valence +*'
  trust_fear_value = '*Value*' (Using Eq. 6)
Else If {*somatic_Reaction_Risk*} = '*Valence -*'
  trust_fear_state = '*Valence -*'
  trust_fear_value = '*Value*' (Using Eq. 6)
Else
  trust_fear_state = '*Neutral Valence*'
  trust_fear_value = zero
End If

End Algorithm 4

statistical literature for the classification of events. The form of Eqs. (3) and (4) corresponds to a family of non-linear functions that allows relating the stimuli associated with profitability and risk to the activation of an artificial somatic reaction in an affective autonomous agent. This relationship makes it possible to guide the classification of events, which corresponds to the variation (or null variation) of the valence of the somatic function in the case of the SFP and SFR functions. Meanwhile, the form of Eqs. (5) and (6) corresponds to a family of non-linear functions that allows relating the activation of an artificial somatic reaction to its emotional effects. This relationship makes it possible to guide a portfolio change (or its maintenance without major changes, as the case may be).

On the other hand, Algorithm No. 5 describes the application of investment rules. It is important to remember that Algorithm No. 1 receives an investment strategy as the initial parameter, and that as mentioned previously, this parameter represents the first investment strategy to be used by the affective autonomous agent.

Algorithm 5 Apply Investment Rules

Problem description: Make an investment decision.
Preconditions: There is an updated emotional state in the affective autonomous agent.
Postconditions: From the application of investment rules, an investment directive and strategy are determined.
Input: Risk strategy; emotional state.
Output: Decision.

```
Begin
If (investment strategy = 'risk strategy')
  If (joy_sadness >= js_upper_threshold)
    set {directive} in 'sell'
    set {investment strategy} in 'moderate strategy'
  Else if (joy_sadness <= js_lower_threshold)
    set {directive} in 'sell'
    set {investment strategy} in 'risk strategy'
  Else if (trust_fear >= tf_upper_threshold)
    set {directive} in 'sell'
    set {investment strategy} in 'risk strategy'
  Else if (trust_fear <= tf_lower_threshold)
    set {directive} in 'sell'
    set {investment strategy} in 'moderate strategy'
  Else
    set {directive} in 'maintain'
  End If
Else If (investment strategy = 'moderate strategy')
  If (trust_fear >= tf_upper_threshold)
    set {directive} in 'sell'
    set {investment strategy} in 'risk strategy'
  Else if (trust_fear <= tf_lower_threshold)
    set {directive} in 'sell'
    set {investment strategy} in 'moderate strategy'
  Else If (joy_sadness >= js_upper_threshold)
    set {directive} in 'sell'
    set {investment strategy} in 'moderate strategy'
  Else if (joy_sadness <= js_upper_threshold)
    set {directive} in 'sell'
    set {investment strategy} in 'risk strategy'
  Else
    set {directive} in 'maintain'
  End If
End If
Add {directive; investment strategy} in {decision}
return (decision)
End Algorithm 5
```

Table 1 Experimental parameters

Parameter	SC-1	SC-2	SC-3
Somatic upper_threshold_Prof	1%	3%	5%
Somatic lower_threshold_Prof	− 1%	− 3%	− 5%
Somatic upper_threshold_Risk	0.8%	0.75%	0.70%
Somatic lower_threshold_Risk	0.9%	0.95%	1.0%
Emotional js_upper_threshold	0.075	0.22	0.36
Emotional js_lower_threshold	− 0.075	− 0.22	− 0.36
Emotional tf_upper_threshold	0.24	0.46	0.64
Emotional tf_lower_threshold	− 0.24	− 0.46	− 0.64

As will be shown later, the affective autonomous agent might modify the said strategy according to the verification of a set of investment rules. The investment rules considered in the present research work are the following:

Investment Rule 1: If the joy–sadness emotion reaches or exceeds an upper emotional threshold (i.e., an evident state of "joy"), a "*sell*" directive is triggered, and the investment strategy changes from "*risk strategy*" to "*moderate strategy*" to obtain the profits generated and, simultaneously, to moderate the risk to which the affective autonomous agent is exposed through its portfolio.
Investment Rule 2: If the joy–sadness emotion reaches or exceeds a lower emotional threshold (i.e., an evident state of "sadness"), a "*sell*" directive is triggered, and the investment strategy is maintained as "*risk strategy*" with the aim to increase the profitability or wealth and, simultaneously, to increase the joy of the affective autonomous agent.
Investment Rule 3: If the trust–fear emotion reaches or exceeds an upper emotional threshold (i.e., an evident state of "trust"), a "*sell*" directive is triggered, and considering the level of trust reached by the affective autonomous agent, the investment strategy is maintained as "*risk strategy*".
Investment Rule 4: If the trust–fear emotion reaches or exceeds a lower emotional threshold (i.e., an evident state of "fear"), a "*sell*" directive is triggered, and the invest-

Table 2 Stimulus sensitivity parameters

Parameter	Value
α	15
γ	$\sim U(-0.15,\ 0.15)$
ε	15
κ	0.85
θ	$\sim U(-0.15,\ 0.15)$
η	15
ϕ	$\sim U(-0.1,\ 0.1)$
ψ	15
φ	$\sim U(-0.1,\ 0.1)$

Table 3 Experimental results

SC	Inicial 2011 (USD)	Final 2011 (USD)	Final 2012 (USD)	Final 2013 (USD)	Final 2014 (USD)	Final 2015 (USD)	Final 2016 (USD)	Final 2017 (USD)	Final 2018 (USD)	Final 2019 (USD)	Profit average (%)
SC-1	10,000	12,447	15,657	18,545	24,044	27,039	28,097	31,351	36,873	38,378	31.53
SC-2	10,000	12,011	15,031	17,668	23,166	26,125	26,980	30,313	35,970	37,261	30.29
SC-3	10,000	11,900	14,847	17,175	22,666	25,862	26,669	29,872	35,874	37,130	30.14
BK	10,000	10,059	11,333	14,140	15,416	15,428	16,553	18,358	18,259	20,190	11.32

Table 4 Standard deviation on each scenario

SC	SDEV 2011 (USD)	SDEV 2012 (USD)	SDEV 2013 (USD)	SDEV 2014 (USD)	SDEV 2015 (USD)	SDEV 2016 (USD)	SDEV 2017 (USD)	SDEV 2018 (USD)	SDEV 2019 (USD)
SC-1	425	592	631	631	653	680	700	755	784
SC-2	182	231	460	462	489	501	504	631	632
SC-3	54	54	124	126	311	311	326	354	355

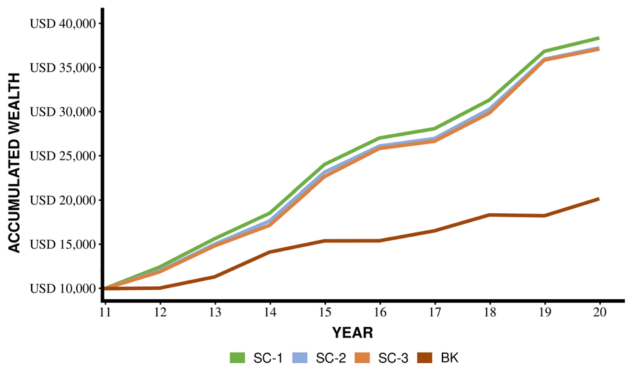

Fig. 3 Annual experimental results for the affective autonomous agent

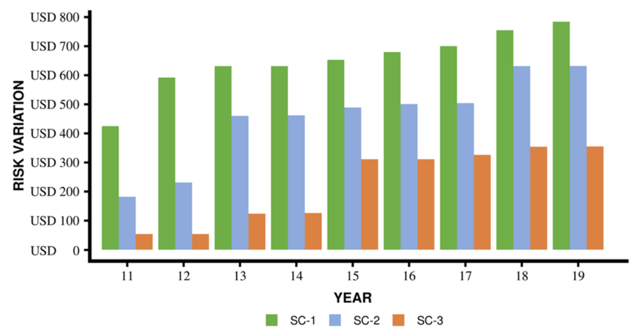

Fig. 4 Risk variation for each scenario

ment strategy changes from "*risk strategy*" to "*moderate strategy*" with the aim to increase the trust level for the affective autonomous agent.

In case any of the emotional thresholds mentioned above are not reached, the investment directive is defined as "*maintain*".

At this point, it is important to remember that somatic reactions derived from both profitability and risk have independent triggering mechanisms (Algorithm No. 3). Subsequently, it was defined that the somatic reaction derived from profitability has an effect on the variation of the joy–sadness emotion as well as on the variation of the trust–fear emotion (Algorithm No. 4). Thus, it is observed that a variation in profitability can trigger a somatic reaction which can influence the joy–sadness emotion. Similarly, it is observed that a variation in risk can trigger a somatic reaction which can influence the trust–fear emotion. In any case, the affective autonomous agent makes the decision to sell or maintain its portfolio considering its emotional state. Somatic reactions influence the emotional state, and the emotional state influences the investment decision.

In case the current investment strategy is "*risk strategy*" (aggressive strategy that seeks to increase profitability), the order of verification of the investment rules mentioned previously are, first, rules 1 and 2 (associated with the emotion joy–sadness), subsequently, rules 3 and 4. In case the current investment strategy is "*moderate strategy*" (strategy that seeks to control risk), the order of verification of the investment rules are, first, rules 3 and 4 (associated with the trust–fear emotion), and then, rules 1 and 2.

4 Test scenarios

4.1 General description

Regarding the general market data, the S&P500 index is considered from January 1, 2010 to December 31, 2019

Table 5 Annual profitability variation

SC	ΔProf 2011 (%)	ΔProf 2012 (%)	ΔProf 2013 (%)	ΔProf 2014 (%)	ΔProf 2015 (%)	ΔProf 2016 (%)	ΔProf 2017 (%)	ΔProf 2018 (%)	ΔProf 2019 (%)
SC-1	24.47	25.79	18.45	29.65	12.46	3.91	11.58	17.61	4.08
SC-2	20.11	25.14	17.54	31.12	12.77	3.27	12.35	18.66	3.59
SC-3	19.00	24.76	15.68	31.97	14.10	3.12	12.01	20.09	3.50

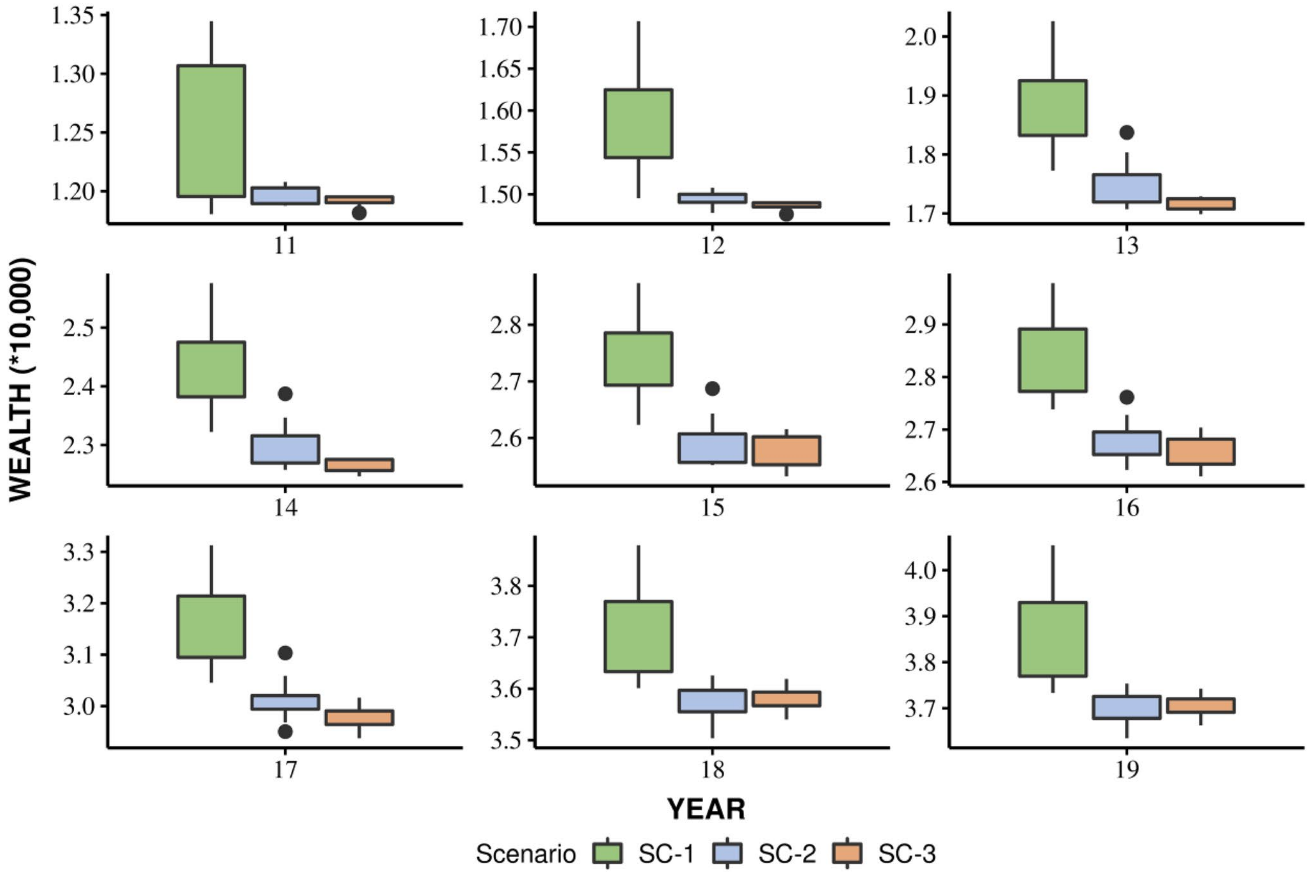

Fig. 5 Annual experimental results for the affective autonomous agent

(Yahoo Finance 2020). Meanwhile, the portfolio composition considers the time series of 30 stocks belonging to the Dow Jones index (Yahoo Finance 2020). The adjusted daily closing value of the stocks is used which considers the adjustment of splits and dividends of financial assets. The affective autonomous agent used the data of 2010 to configure its first investment portfolio. Thereafter, the experimental scenarios began on the first trading day of 2011.

Table 1 shows the parameters used in the test scenarios. It is important to remember that for observing a somatic reaction, it is necessary to reach some threshold (upper or lower). These somatic thresholds are represented by the first four parameters of the table (identifiable by the word “somatic”). Two threshold parameters are defined for a somatic reaction related to profitability (if profitability becomes too high or too low), and two threshold parameters are defined for a somatic reaction related to risk (if risk becomes too high or too low).

Furthermore, investment rules require an emotion to reach some threshold (upper or lower depending on each emotion) for promoting a change in portfolio. These emotional thresholds are represented by the following four parameters in the table (identifiable by the word “emotional”). Two threshold parameters are defined for an emotional reaction related to joy–sadness: an upper threshold if the emotion tends strongly towards joy and a lower threshold if the emotion tends strongly towards sadness. In addition, two threshold parameters are defined for an emotional reaction related to trust–fear: an upper threshold if the emotion tends strongly towards trust and a lower threshold if the emotion tends strongly towards fear.

Scenario 1 shows parameters with close values between the upper somatic threshold and the lower somatic threshold for a scenario in which the affective autonomous agent is highly sensitive to variations in profitability and risk. When one of the mentioned thresholds is reached, a somatic reaction is expected. Similarly, scenario 1 shows parameters with close values between the upper emotional threshold and the lower emotional threshold for a scenario in which the affective autonomous agent is highly sensitive to its emotional variations. With narrow or close emotional thresholds, the affective autonomous agent is more likely to reach them and thus its emotional valence is defined in a state that motivates a portfolio change. In contrast, scenario 3 shows parameters with more distant values between the upper and lower thresholds (both in the thresholds of somatic reactions and in the emotional thresholds). This makes the affective autonomous agent less sensitive to variations in profitability and risk. Similarly, an accentuated emotional variation is required to reach some emotional threshold, thereby promoting a portfolio change. Therefore, scenario 3 represents an intermediate point between the two scenarios mentioned previously.

In all the scenarios, the affective autonomous agent is considered to start with a "risk strategy". Similarly, by default, in all scenarios, there is a somatic memory that relates "uptrend stocks" to a "good or positive memory" such that the eligibility of this type of stock is promoted whenever a portfolio is configured.

On the other hand, Table 2 presents the valuation of the stimulus sensitivity parameters. These parameters are meant to establish and delimit the sensitivity of an affective autonomous agent to the variation of the domain indicators. The level of sensitivity of the agent is reflected in the intensity of its artificial somatic reactions.

The parameters (α, ε, η, and ψ) play an important role in the activation of artificial somatic reactions where values close to zero in these parameters are associated with less intense somatic reactions. Conversely, higher values in these parameters are associated with somatic reactions of greater intensity. In the case of the test scenario, it was decided to use values of $\alpha = \varepsilon = \eta = \psi = 15$ since this combination of parameters causes around 15% of artificial somatic reactions in relation to the total of the observed periods.

Meanwhile, it was decided to define the parameter $\kappa = 0.85$ whose purpose is that the somatic function associated with risk (SFR) takes a value equal to zero in the expected risk given the information using which this value was determined before initiating the general decision-making process.

The random parameters γ and θ allow one to generate changes in the valence of the somatic function when it is in the vicinity of the upper and lower thresholds as shown in Fig. 2. In the case of the present test scenario, these random parameters are allowed to have maximum values of 15% of the total spectrum that somatic functions can take. On the other hand, the random parameters φ and ϕ take values that represent 10% of the total spectrum of the *JoySadness* and *TrustFear* functions.

If the assessment of the somatic function associated with profitability is located in a neighborhood of the limit that activates a somatic reaction and an extreme assessment of γ is observed, the difference in amplitude with φ prevents the latter from counteracting the effect, triggering, in that case, a change in the *JoySadness* function.

If the assessment of somatic function associated with risk is in a neighborhood of the limit that activates a somatic reaction and an extreme assessment of θ is observed, the difference in amplitude with ϕ prevents the latter from counteracting the effect, triggering, in that case, a change in the *TrustFear* function.

4.2 Experimental results

Table 3 shows the results for each of the scenarios mentioned above for each investment year from 2011 to 2019. Additionally, the last row (BK) shows the benchmark results of investing on S&P500 index which corresponds to the investment performance that any investor could obtain an investment is directly made following the index. In other words, the BK results were not obtained using the proposal of the current research work, and they are only included to provide an investment referential trajectory.

Each scenario was independently tested 10,000 times, that is, the result of each cell corresponds to an average of 10,000 different experimental runs. Table 3 suggests that consistently over time, the affective autonomous agent shows a better performance in SC-1, followed by SC-2 and SC-3. With an initial investment capital of US10,000 at the beginning of 2011, in SC-1 an accumulated wealth of US$38,378 was reached at the end of 2019. Meanwhile, for the same initial investment capital, an accumulated wealth of US$37,261 and US$37,130, was reached in SC-2 and SC-3, respectively. In SC-1, an average annual profitability of 31.53% was observed. Meanwhile, SC-2 and SC-3 had average annual returns of 30.29% and 30.14%, respectively. Observing the results of Table 3, it is possible to affirm that overall, the affective autonomous agent has better investment performance than the BK investment strategy.

Figure 3 is a graphical representation of the behavior over time of the accumulated wealth as an average of the 10,000 independent executions carried out for each scenario. It can be observed that SC-1 (whose parameters are associated with greater recurrence in the activation of artificial somatic reactions) was consistently higher than the other configurations. However, despite positive results, the benchmark strategy was far below.

On the other hand, Table 4 presents the average standard deviation observed for each scenario for all investment periods. Similar to the previous table, it is possible to observe that consistently over time, investments made by the affective autonomous agent generate greater variance in SC-1 followed by SC-2 and SC-3.

Meanwhile, Fig. 4 shows the risk variation associated with each scenario. It is possible to observe that SC-1 consistently had a higher risk level over time, followed by SC-2 and SC-3. Furthermore, the risk level of the three scenarios showed an upward but not exponential trend over time.

On the other hand, Table 5 presents the average annual variation in profitability for SC-1, SC-2, and SC-3. It is possible to observe that SC-1 obtains the five best annual profitability results (years 2011, 2012, 2013, 2016, and 2019), SC-2 obtains the best annual profitability result in 2017, and SC-3 obtains three best annual profitability results (years 2014, 2015, and 2018). In 2011, SC-1 achieves a significant annual profitability of 24.47%. Compared to 2011, the results of SC-1 and SC-2 in 2012 are closer to each other. In 2013, the results of annual profitability show a significant difference of approximately 3% between SC-1 and SC-3. In the following year 2014, SC-3 obtained a significant increase in profitability in relation to SC-1. In 2015, SC-1 once again obtained the highest annual profitability. In 2017, SC-2 obtained the highest annual profitability. In 2018, SC-3 obtained clearly different results compared to SC-1. Finally, in 2019, SC-1 obtained the highest annual profitability.

Meanwhile, Fig. 5 graphically represents the variability and capital behavior for each investment year. The value of the abscissa axis corresponds to the investment year and the ordinate axis corresponds to the accumulated wealth at the end of the investment year. The size of each box represents the data set between the 25th and 75th percentiles of the simulation process. Therefore, the size of each box is representative of the dispersion of the data close to the mean value. Similarly, the outer boundaries of each box correspond to the data variability level both below the 25th percentile and above the 75th percentile.

Figure 5 graphically summarizes the information provided in Tables 3 and 4 according to which considering the mean value of the results, a better performance of the affective autonomous agent is observed in SC-1 compared to SC-2 and SC-3. However, compared to scenarios SC-2 and SC-3, the affective autonomous agent in SC-1 shows a higher level of variability of the results, which evidences a greater exposure to risk of the stocks belonging to the portfolio.

The results of accumulated wealth and risk variation showed that SC-1 obtained the best results with respect to accumulated wealth. However, this scenario steadily showed a higher level of risk. For its part, SC-2 presented better-accumulated wealth results compared to SC-3. Meanwhile, SC-3 showed the lowest risk levels for all scenarios. The foregoing points indicated that there is no absolute dominance of one scenario configuration over another and suggested the need to seek optimality criteria associated with each affective autonomous agent profile. An adequate investment strategy could require the combination of characteristics of different profiles within only one. The aforementioned idea can give way to the design of mixed decision-making systems by considering both artificial somatic markers and personality profiles.

5 Discussion

In SC-1, the affective autonomous agent is highly sensitive to variations in profitability and risk. A greater sensitivity has resulted in a greater capacity for adaptation by the affective autonomous agent to the new investment conditions, which ultimately translates into higher returns in the investment process. However, the better returns have as a counterpart a higher level of risk exposure, which can be observed in the greater variability of the results. This is fundamentally based both on the randomness of the prices observed in the stock markets as well as on the randomness of the functions that trigger the somatic reactions in the autonomous agent.

Compared to the results obtained in SC-2 and SC-3, the affective autonomous agent performed better in SC-1, which would suggest that a deep parameter calibration could generate even better results in the investment process. However, it is necessary to consider other types of restrictions that were not considered in the test scenarios, such as the transaction cost (e.g. payment of commissions for each share's purchase/sale operation). Incorporating transaction costs in a test scenario could eventually modify the performance of an affective autonomous agent and, ultimately, the final investment results. This implies that an affective autonomous agent could also evaluate the relevance of the change in the portfolio by observing the transaction cost involved.

The results show that the decisions of an affective autonomous agent are effective; these decisions allow the increase of the initial investment capital over time. Furthermore, it is also affirmed that investment based on SC-1 is more efficient as it achieves an increase in the initial investment capital in less time. However, although SC-1 obtains the best annual profitability in most cases, the results are not entirely conclusive given the proximity of some of the annual values obtained. This generates new possibilities for future research works which can correspond to exploring the use of artificial somatic reactions in autonomous investment processes in greater depth.

The results show that for an investment process, it is better to delegate investment decision-making to an affective autonomous agent than to simply invest after tracking a stock investment index. An affective autonomous agent obtains better results given its ability to feel artificial somatic reactions, which gives it greater sensitivity to the occurrence and nature of each event in the market. Based on the verification of its somatic memories, the affective autonomous agent can dynamically adapt its investment strategy to the market context.

The use of somatic memories in stock selection was fundamental to the investment process as it guided the investment options of the affective autonomous agent and, therefore, the potential returns that could be obtained during the investment process.

The test scenarios show the need to define an additional objective function in which the trade-off between the adaptive capacity of the affective autonomous agent and the costs produced by adaptation to the environment is determined, all the derivations obtained from the availability of artificial somatic reactions and considering a rational–emotional perspective. In other words, the type of autonomy, its range of action, and the mechanisms that sustain this autonomy of decision in an artificial agent offers, on the one hand, a direct benefit to humans who trust and delegate their decisions to artificial entities. On the other hand, it demands complex designs and implementations that effectively bring decisions closer to how a human might decide in the same context.

The general decision architecture for stock markets with respect to the investment decision-making process can be categorized into three primary layers. First, the somatic layer seeks to detect the reactions generated in the affective autonomous agent during the fluctuations in the stock market. This layer manages memories and somatic rules whose verification and evaluation delivers different levels of somatic reactions in the agent. The emotional layer receives the somatic reaction from the previous layer and translates it into emotional effects. This is accomplished through the application of emotional rules. Achievable emotional states (joy, sadness, trust, fear) require the emotional update process to reach any of the defined emotional thresholds. The third layer corresponds to the decision layer in which it is verified whether the current emotional state, along with investment rules, suggests planning regarding the change in the portfolio. At this level, the emotional and rational criteria converge to offer a rational–emotional perspective of the decision.

Separating the investment decision-making process into three layers allows each level to be specialized and decoupled from each other to facilitate the modification and extension of each level. The first layer (somatic) is extensible and allows the incorporation of new mechanisms of somatic appraisal, new types of somatic reactions, and different mechanisms of generation, registration, and use of somatic memories without affecting the subsequent layers of the investment decision process. The emotional layer allows the modification of the types of emotions, modifying the rules of emotional appraisal as well as the functions of emotional updating without interfering with how somatic reactions are generated or managed (previous layer) and without interfering with how the current emotional state is used in the investment decision (next layer). Finally, the decision layer allows the modification or extension of investment rules and investment strategies without altering the work of the previous layers. All this is verified through the availability of different algorithms that reflect the general decision architecture in procedural terms.

As indicated in Algorithm N°5, the autonomy of the affective agent allows it to dynamically modify its investment strategy according to its emotional state and market conditions. This represents a high potential of any decision domain in which complex decision-making can occur or is required to be delegated to artificial systems. It is possible to adapt the proposal of the present research work to other decision domains for which it would be necessary to modify the somatic layer and the somatic memories (related to the new decision domain) along with the somatic activation criteria. Meanwhile, it would be necessary to replace the set of investment rules and investment strategies based on the new application domain in the decision layer.

On the other hand, the present work has certain limitations. First, a single type of somatic memory was used (i.e., the promotion of "uptrend stocks"). Second, only two rational investment metrics were considered: the variation in profitability and the variation in risk. Third, the use of artificial somatic reactions was defined only in two senses: the configuration of investment portfolios (by promoting or inhibiting candidate stocks) and the recognition of a decision point, i.e., when the market results generate in the affective autonomous agent a somatic reaction that indicates that "something has happened" and that it is, therefore, necessary to evaluate a potential portfolio change. Fourth, the affective autonomous agent did not incorporate new somatic memories during the general investment decision-making process. The present research work followed an empirical approach based on the implementation of algorithms in R language, leaving the analysis of algorithmic correctness for a future study.

Some key advantages of the current proposal are as follows: a multilayer architectural design, which separates the artificial somatic reaction from its emotional effect, and consequently, from the final decision made by affective autonomous agents; the existence of parameterizable and adjustable somatic and emotional evaluation functions according to the context; a modular algorithmic design that guides the investment decision-making process in a comprehensive manner.

Additionally, some open challenges of the current proposal are as follows: having affective autonomous agents that are capable of interacting with each other during the decision-making process (whether for cooperation or competition); having affective autonomous agents with the ability to learn by observing the decisions and results obtained by other agents in the domain; extending the current proposal by incorporating personality profiles in affective autonomous agents.

6 Conclusion

The present research work suggested the incorporation of artificial somatic markers in affective autonomous agents. The main objective was to analyze whether an affective autonomous agent with artificial somatic reactions can improve the effectiveness and efficiency of its decisions.

The results of this proposal included the following: the design of a three-layered general decision architecture (somatic layer, emotional layer, and decision layer); an artificial somatic function to regulate the magnitude of the system's reactions according to each stimulus; emotional update functions based on somatic reactions; a mechanism for deliberation and decision-making; a set of algorithms to guide the decision-making process of affective autonomous agents in the stock market domain.

The test scenarios were defined using official data from Standard & Poor's 500 and Dow Jones. The overall performance of the decision-making process was measured in terms of the effectiveness of the decision (i.e., the increase in wealth or profitability over time) as well as the efficiency of the decision (i.e., the time required to achieve the aforementioned effectiveness). The experimental results were promising and indicated that affective autonomous agents are able to experience artificial somatic reactions and achieve effectiveness and efficiency in their decision-making.

Regarding the benefits of this research work, first, it is possible to indicate that the current proposal expanded the frontiers of knowledge on the design of autonomous decision-making systems, particularly through the incorporation of artificial somatic markers in affective autonomous agents.

Second, the current proposal suggested a novel mechanism for the design and implementation of investment decision support systems, which could potentially be applied to the current electronic investment platforms available in the market as Metatrader (MetaQuotes 2021) or xStation (Xtb 2021) whose processes operate in a context of partial autonomy based on permanent human instruction.

Third, the current proposal suggested a decision architecture potentially adaptable to other decision-making scenarios. Its layered structure ensures its flexibility at the design level. Meanwhile, the separation of the general decision-making process into different algorithms allows its internal structure to be adapted according to the data, domain profiles, and business rules.

Future research could extend the number of investment indicators considered in the experimental scenario, for instance, by incorporating the traded volume, the country risk, or indicators of central banks or regulatory entities. Furthermore, a mechanism can be designed to allow an affective autonomous agent to extend its list of somatic memories so that its experience in decision-making represents new knowledge that will potentially be used in future decisions. Finally, a general architecture could be designed to allow the incorporation of artificial somatic reactions at different moments of a decision-making process (e.g., the recognition of a decision point, the identification of courses of action, the evaluation of courses of action, the execution of a decision, and so on).

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Data availability The datasets used and analyzed during the current study correspond to S&P500 Index and Dow Jones Index, which are available in https://finance.yahoo.com/.

References

Acay DL, Sonenberg L, Tidhar G (2019) Formalizing tool use in intelligent environments. J Ambient Intell Humaniz Comput. https://doi.org/10.1007/s12652-018-0755-x

Aguado G, Julian V, Garcia-Fornes A, Espinosa A (2020) A Multi-Agent System for guiding users in on-line social environments. Eng Appl Artif Intell. https://doi.org/10.1016/j.engappai.2020.103740

Arias JA, Williams C, Raghvani R et al (2020) The neuroscience of sadness: a multidisciplinary synthesis and collaborative review. Neurosci Biobehav Rev. https://doi.org/10.1016/j.neubiorev.2020.01.006

Arokiasami WA, Vadakkepat P, Tan KC, Srinivasan D (2016) Interoperable multi-agent framework for unmanned aerial/ground vehicles: towards robot autonomy. Complex Intell Syst. https://doi.org/10.1007/s40747-016-0014-8

Belhadi A, Djenouri Y, Nørvåg K et al (2020) Space–time series clustering: algorithms, taxonomy, and case study on urban smart cities. Eng Appl Artif Intell. https://doi.org/10.1016/j.engappai.2020.103857

Bouanan Y, Zacharewicz G, Vallespir B (2016) DEVS modelling and simulation of human social interaction and influence. Eng Appl Artif Intell. https://doi.org/10.1016/j.engappai.2016.01.002

Buche C, Le Bigot N, Polceanu M (2016) Simulation within simulation for agent decision-making: theoretical foundations from cognitive science to operational computer model. Cogn Syst Res. https://doi.org/10.1016/j.cogsys.2016.03.001

Cabrera D, Cubillos C (2008) Multi-agent framework for a virtual enterprise of demand-responsive transportation. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). https://doi.org/10.1007/978-3-540-68825-9_7

Cabrera D, Araya N, Jaime H et al (2015) Defining an affective algorithm for purchasing decisions in e-commerce environments. IEEE Lat Am Trans. https://doi.org/10.1109/TLA.2015.7273796

Cabrera D, Cubillos C, Cubillos A et al (2018) Affective algorithm for controlling emotional fluctuation of artificial investors in stock markets. IEEE Access. https://doi.org/10.1109/ACCESS.2018.2802781

Cabrera D, Rubilar R, Cubillos C (2019) Resilience in the decision-making of an artificial autonomous system on the stock market. IEEE Access. https://doi.org/10.1109/ACCESS.2019.2945471

Cabrera D, Cubillos C, Urra E, Mellado R (2020) Framework for incorporating artificial somatic markers in the decision-making of autonomous agents. Appl Sci. https://doi.org/10.3390/app10207361

Cabrera-Paniagua D, Rubilar-Torrealba R (2021) A novel artificial autonomous system for supporting investment decisions using a Big Five model approach. Eng Appl Artif Intell. https://doi.org/10.1016/j.engappai.2020.104107

Cabrera-Paniagua D, Herrera G, Cubillos C, Donoso M (2011) Towards a model for dynamic formation and operation of virtual organizations for transportation. Stud Informs Control. https://doi.org/10.24846/v20i3y201106

Cabrera-Paniagua D, Primo TT, Cubillos C (2014) Distributed stock exchange scenario using artificial emotional knowledge. Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics). https://doi.org/10.1007/978-3-319-12027-0_52

Cabrera-Paniagua D, Cubillos C, Vicari R, Urra E (2015) Decision-making system for stock exchange market using artificial emotions. Expert Syst Appl. https://doi.org/10.1016/j.eswa.2015.05.004

Casadei R, Viroli M, Audrito G et al (2021) Engineering collective intelligence at the edge with aggregate processes. Eng Appl Artif Intell. https://doi.org/10.1016/j.engappai.2020.104081

Chandiok A, Chaturvedi DK (2018) CIT: Integrated cognitive computing and cognitive agent technologies based cognitive architecture for human-like functionality in artificial systems. Biol Inspired Cogn Archit. https://doi.org/10.1016/j.bica.2018.07.020

Cominelli L, Mazzei D, Pieroni M et al (2015) Damasio's somatic marker for social robotics: Preliminary implementation and test. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). https://doi.org/10.1007/978-3-319-22979-9_31

Cromwell HC, Abe N, Barrett KC et al (2020) Mapping the interconnected neural systems underlying motivation and emotion: a key step toward understanding the human affectome. Neurosci Biobehav Rev. https://doi.org/10.1016/j.neubiorev.2020.02.032

Cubillos C, Donoso M, Rodríguez N et al (2010) Towards open agent systems through dynamic incorporation. Int J Comput Commun Control. https://doi.org/10.15837/ijccc.2010.5.2223

Cubillos C, Díaz R, Urra E et al (2013) An agent-based solution for the berth allocation problem. Int J Comput Commun Control. https://doi.org/10.15837/ijccc.2013.3.465

Cui X, Lai VS, Lowry PB, Lei Y (2020) The effects of bidder factors on online bidding strategies: a motivation-opportunity-ability (MOA) model. Decis Support Syst. https://doi.org/10.1016/j.dss.2020.113397

Damasio A (1994) Descartes' error: emotion, rationality and the human brain. Putnam, New York

Dizon E, Pranggono B (2021) Smart streetlights in Smart City: a case study of Sheffield. J Ambient Intell Humaniz Comput. https://doi.org/10.1007/s12652-021-02970-y

Dow Jones Index (2021) Dow Jones Index. https://www.dowjones.com/. Accessed 1 Nov 2020

Dyachenko Y, Nenkov N, Petrova M et al (2018) Approaches to cognitive architecture of autonomous intelligent agent. Biol Inspired Cogn Archit. https://doi.org/10.1016/j.bica.2018.10.004

Ehab N, Ismail H (2020) LogAG: an algebraic non-monotonic logic for reasoning with graded propositions. Ann Math Artif Intell. https://doi.org/10.1007/s10472-020-09697-0

Ekman P (1982) Emotion in the human face. Cambridge University Press

Ekman P (1992) An argument for basic emotions. Cogn Emot. https://doi.org/10.1080/02699939208411068

Ferretti E, Tamargo LH, García AJ et al (2017) An approach to decision making based on dynamic argumentation systems. Artif Intell. https://doi.org/10.1016/j.artint.2016.10.004

Gelbrich K, Hagel J, Orsingher C (2020) Emotional support from a digital assistant in technology-mediated services: Effects on customer satisfaction and behavioral persistence. Int J Res Mark. https://doi.org/10.1016/j.ijresmar.2020.06.004

Guillaume S, Jollant F, Jaussent I et al (2009) Somatic markers and explicit knowledge are both involved in decision-making. Neuropsychologia. https://doi.org/10.1016/j.neuropsychologia.2009.04.003

Gupta R, Koscik TR, Bechara A, Tranel D (2011) The amygdala and decision-making. Neuropsychologia. https://doi.org/10.1016/j.neuropsychologia.2010.09.029

Hoefinghoff J, Pauli J (2012) Decision making based on somatic markers. In: Proceedings of the 25th International Florida Artificial Intelligence Research Society Conference, FLAIRS-25

Hoefinghoff J, Steinert L, Pauli J (2012) Implementation of a decision making algorithm based on somatic markers on the Nao robot. In: Levi P et al (eds) Autonomous mobile systems 2012. Springer-Verlag, Berlin Heidelberg, pp 69–77

Höfinghoff J, Steinert L, Pauli J (2013) An easily adaptable decision making framework based on somatic markers on the Nao-Robot. Kogn Syst. https://doi.org/10.1785/duepublico/31363

Hoogendoorn M, Merk R-J, Treur J (2009) A decision making model based on Damasio's Somatic marker hypothesis. In: Proceedings of the 9th international conference on cognitive modeling, pp 1001–1009

Hou Z, Ma K, Wang Y et al (2021) Attention-based learning of self-media data for marketing intention detection. Eng Appl Artif Intell. https://doi.org/10.1016/j.engappai.2020.104118

Huzard D, Mumby DG, Sandi C et al (2015) The effects of extrinsic stress on somatic markers and behavior are dependent on animal housing conditions. Physiol Behav. https://doi.org/10.1016/j.physbeh.2015.07.018

Ichise R (2018) A cognitive architecture consisting of human intelligence factors. Procedia Comp Sci 123:165–170

Ismail HO (2020) The good, the bad, and the rational: aspects of character in logical agents. Springer, Cham. https://doi.org/10.1007/978-3-030-15954-2_9

Jain S, Asawa K (2016) Programming an expressive autonomous agent. Expert Syst Appl. https://doi.org/10.1016/j.eswa.2015.08.037

Janzen M, Axhausen KW (2018) Decision making in an agent-based simulation of long-distance travel demand. Procedia Comp Sci 130:830–835

Kaklauskas A, Abraham A, Dzemyda G et al (2020) Emotional, affective and biometrical states analytics of a built environment. Eng Appl Artif Intell. https://doi.org/10.1016/j.engappai.2020.103621

Kelley D, Twyman M (2020) Biasing in an independent core observer model artificial general intelligence cognitive architecture. Procedia Comp Sci 169:535–541

Liang CC, Liang WY, Tseng TL (2019) Evaluation of intelligent agents in consumer-to-business e-Commerce. Comput Stand Interfaces. https://doi.org/10.1016/j.csi.2019.03.002

Linquist S, Bartol J (2013) Two myths about somatic markers. Br J Philos Sci. https://doi.org/10.1093/bjps/axs020

Lv Y, Zhu J, Jiang Y (2020) Using EGDL to represent domain knowledge for imperfect information automated negotiations. J Ambient Intell Humaniz Comput. https://doi.org/10.1007/s12652-020-02274-7

Mellado Silva R, Cubillos C, Cabrera Paniagua D (2016) A constructive heuristic for solving the Job-Shop Scheduling Problem. IEEE Lat Am Trans. https://doi.org/10.1109/TLA.2016.7555250

MetaQuotes (2021) MetaTrader 5. https://www.metatrader5.com/. Accessed 1 Mar 2021

Murugaveni S, Mahalakshmi K (2020) A novel approach for non-orthogonal multiple access for delay sensitive industrial IoT communications for smart autonomous factories. J Ambient Intell Humaniz Comput. https://doi.org/10.1007/s12652-020-02330-2

Nagoev Z, Lyutikova L, Gurtueva I (2018) Model for Automatic Speech Recognition Using Multi-Agent Recursive Cognitive Architecture. Procedia Comp Sci 145:386–392
Pajuelo-Holguera F, Gómez-Pulido JA, Ortega F (2020) Recommender systems for sensor-based ambient control in academic facilities. Eng Appl Artif Intell. https://doi.org/10.1016/j.engappai.2020.103993
Pessoa L (2019) Intelligent architectures for robotics: the merging of cognition and emotion. Phys Life Rev. https://doi.org/10.1016/j.plrev.2019.04.009
Poppa T, Bechara A (2018) The somatic marker hypothesis: revisiting the role of the 'body-loop' in decision-making. Curr Opin Behav Sci. https://doi.org/10.1016/j.cobeha.2017.10.007
Pudane M, Lavendelis E, Radin MA (2016) Human emotional behavior simulation in intelligent agents: processes and architecture. In: Procedia computer science. https://doi.org/10.1016/j.procs.2017.01.167
Qureshi KN, Iftikhar A, Bhatti SN et al (2020) Trust management and evaluation for edge intelligence in the Internet of Things. Eng Appl Artif Intell. https://doi.org/10.1016/j.engappai.2020.103756
Ravikumar S, Kavitha D (2021) IOT based autonomous car driver scheme based on ANFIS and black widow optimization. J Ambient Intell Humaniz Comput. https://doi.org/10.1007/s12652-020-02725-1
Reia SM, Amado AC, Fontanari JF (2019) Agent-based models of collective intelligence. Phys Life Rev. https://doi.org/10.1016/j.plrev.2018.10.004
Reimann M, Bechara A (2010) The somatic marker framework as a neurological theory of decision-making: review, conceptual comparisons, and future neuroeconomics research. J Econ Psychol. https://doi.org/10.1016/j.joep.2010.03.002
SoftBanks Robotics (2020) Nao-Robot. https://www.softbankrobotics.com/. Accessed 10 Jul 2020
Rosales JH, Rodríguez LF, Ramos F (2019) A general theoretical framework for the design of artificial emotion systems in autonomous agents. Cogn Syst Res. https://doi.org/10.1016/j.cogsys.2019.08.003
Saha C, Aqlan F, Lam SS, Boldrin W (2016) A decision support system for real-time order management in a heterogeneous production environment. Expert Syst Appl. https://doi.org/10.1016/j.eswa.2016.04.035
Samsonovich AV (2020) Socially emotional brain-inspired cognitive architecture framework for artificial intelligence. Cogn Syst Res. https://doi.org/10.1016/j.cogsys.2019.12.002
Sánchez Y, Coma T, Aguelo A, Cerezo E (2019) ABC-EBDI: an affective framework for BDI agents. Cogn Syst Res. https://doi.org/10.1016/j.cogsys.2019.07.002
Sandor S, Gürvit H (2019) Development of somatic markers guiding decision-making along adolescence. Int J Psychophysiol. https://doi.org/10.1016/j.ijpsycho.2018.12.005
Standard & Poor's 500 Index (2021) Standard & Poor's 500 Index. https://www.standardandpoors.com/. Accessed 1 Nov 2020
Steenbergen L, Colzato LS, Maraver MJ (2020) Vagal signaling and the somatic marker hypothesis: the effect of transcutaneous vagal nerve stimulation on delay discounting is modulated by positive mood. Int J Psychophysiol. https://doi.org/10.1016/j.ijpsycho.2019.10.010
Stefanova E, Dubljević O, Herbert C et al (2020) Anticipatory feelings: neural correlates and linguistic markers. Neurosci Biobehav Rev. https://doi.org/10.1016/j.neubiorev.2020.02.015
Tom RJ, Sankaranarayanan S, Rodrigues JJPC (2020) Agent negotiation in an IoT-Fog based power distribution system for demand reduction. Sustain Energy Technol Assess. https://doi.org/10.1016/j.seta.2020.100653
Wang H, Mostafizi A, Cramer LA et al (2016) An agent-based model of a multimodal near-field tsunami evacuation: decision-making and life safety. Transp Res Part C Emerg Technol. https://doi.org/10.1016/j.trc.2015.11.010
Xtb (2021) xStation. https://www.xtb.com/int/trading-services/trading-platforms/xstation. Accessed 1 Mar 2021
Yahoo Finance (2020) Stock market live, quotes, business & finance news. In: Yahoo Financ. https://finance.yahoo.com/. Accessed 1 Nov 2020
Yan F, Iliyasu A, Hirota K (2021) Emotion space modelling for social robots. Eng Appl Artif Intell 100:104178. https://doi.org/10.1016/j.engappai.2021.104178
Zhu J, Liu W, Liu Y et al (2020) Smart city oriented optimization of residential blocks on intensive urban sensing data based on fuzzy evaluation algorithm. J Ambient Intell Humaniz Comput. https://doi.org/10.1007/s12652-020-02104-w

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