


Article

Fattybot: Designing a Hormone-Morphic Chatbot with a Hormonal and Immune System

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Abstract: Currently, AI-designed systems in which, given a certain input or prompt, the system returns an output or response are becoming very popular. A chatbot is an example of this kind of system. However, human beings, besides processing the input stimuli or information adequately, are also capable of simultaneously expressing an emotional response to that input information. This is a major factor in the survival of our species. For years, bio-inspired AI models have been proposed in order to make AI systems more human-like. Paradigms, such as neuromorphic computing, represent an example of this trend. In this paper, we propose a new approach that we have termed hormone-morphic by designing a chatbot, Fattybot, with which it is possible to have a conversation. However, since Fattybot is endowed with both a hormonal and immune system, it can feel anxiety or some other altered condition during a conversation, which induces the chatbot to eat compulsively. The ultimate goal of the work is to propose AI systems that not only process information but also experience some of the emotional traits of human beings. In this paper, several simulation experiments are performed showing the usefulness of this approach, for example, in the simulation of a virtual patient.

Keywords: empathic chatbot; neuromorphic computing; hormonal computing; emotional chatbots



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1. Introduction

In 1986, John Haugeland [1] introduced the term “synthetic intelligence” as a class of simulated intelligence that is able to generate its own knowledge. At present, generative artificial intelligence is a form of synthetic intelligence that uses deep learning algorithms to generate new data from a dataset. For example, ChatGPT, which uses large language models or LLMs, is able to return text in response to an input or prompt. The popularity of AI has led most people to consider that the expression “an Artificial Intelligence” evokes in their personal imagination is a model often drawn from science-fiction movies, which is used as a reference model. The result of this perception is the popular belief that advances in AI will lead to a “cold and nihilistic world” with cities of neo-noir aesthetics densely populated by both humans and “intelligent” programs, machines and robots. In the late 1980s, Carver Mead [2] proposed the design of algorithms, analog software and bio-inspired integrated circuits that would mimic the behavior of the nervous system of animals. From this idea, neuromorphic computing [3] was born, with the aim of emulating the behavior of the animal nervous system, in general, and the brain in particular. However, in order to emulate human beings, it is important to bear in mind that human beings experience emotions, i.e., we generate brain and, therefore, physiological responses to stimuli. In other words, we not only process the information contained in stimuli, e.g., braking the vehicle we are driving when the traffic light is turning red, but we also feel emotions. Therefore, it is not uncommon that when we see scenes in the street, e.g., children crossing the street or an old man fallen on the sidewalk, we feel some emotion that modifies our behavior to adapt ourselves to the situation. The interpretation of the emotions experienced and their

memory over time lead human beings to have feelings. Obviously, and from a biological point of view, our ability to perceive the feelings of those around us will contribute to the survival of our species [4].

Neuromorphic computing has the value of recovering interest in some of the underlying principles and objectives with which many of the simulations in artificial life were conceived in the last century [5,6]. Although it is not the subject of epistemological analysis, research or review in this paper, the interest in creating an artificial living being, such as the myth of Golem or the romantic idea underlying the novel *Frankenstein*, has survived into the present century. The survival of this romantic idea is the result of advances in synthetic biology, a discipline that has made possible the design of the first artificial cells in the laboratory [7]. For instance, *M. mycoides* JCVI-syn3.0 [8] currently represents one of the most outstanding examples. However, all of these achievements fall far short of the qualities that endow the human body with the capacity to feel emotions, making our species an “intelligent and sensitive organic matter”. In our opinion, neuromorphic computing will promote the study and design of materials that mimic some of the “emotional” qualities of organic matter, such as pain, the effect on the immune system of caresses, the beneficial effect of skin-to-skin contact, or other emotional responses such as blushing. Consequently, in the future, “intelligent” programs, machines and robots will be built displaying “emotional” traits or will have been constructed using “sentient” hardware capable of emulating the arousal of such emotions.

Similar to neuromorphic computing, a research area that focuses its efforts on the design of AI models that emulate the nervous system, we propose the concept of *hormone-morphic computing* in this work. We propose, with this term, the design of bio-inspired AI models, i.e., synthetic intelligent systems that display the main features of the hormonal system. That is, while the control, and, therefore, the output or response of an AI system to a certain input resides, for example, in an artificial neural network or other equivalent model, the modulation or adjustment of the output could be performed through a model that simulates the hormonal system. Therefore, for any AI system with these features, we would not only have implemented pattern recognition and learning but also the expression of emotions, one of the fundamental ingredients of human beings.

Indeed, the possibility of simulating the hormonal system with differential equations is not something new [9], nor is the application of sentiment analysis techniques [10] to a conversation, but their incorporation into an AI system could introduce some degree of originality. For instance, we could design a chatbot, i.e., a conversational bot simulating a conversation with a person but exhibiting hormone-morphic traits.

In this paper, we present a chatbot that we have named “Fatty”. The goal of the work has been to design an empathic chatbot in which the bot “gets fat” as a consequence of a conversation with its interlocutor, with “eating food” relieving its discomfort. The chatbot exhibits an eating behavior disorder which is triggered when an interlocutor talks to the bot about a topic to which Fatty is particularly sensitive, particularly when the conversation is about soccer or junk food. Fattybot’s “emotions” are expressed during the conversation as a consequence of having included in the bot’s architecture a model of the hormonal system and another of the immune system. These models emulate the molecular and physiological mechanisms responsible for the accumulation of energy and increase in the volume of adipocytes or adipose tissue cells. Consequently, the bot would put on weight as a consequence of the inflammation experienced by the “fat cells” of its “body”.

The work is a further step of the previous models conducted earlier. In [11], we introduced a minimally viable prototype of an empathic chatbot that we named LENNA. The chatbot was used to evaluate the feasibility of Shannon entropy as a measure of the emotional state changes experienced by the chatbot during a conversation. The conversations were then analyzed by applying sentiment analysis techniques combined with multivariate statistical methods and Fourier analysis [10]. In a previous work [12], we simulated a virtual patient by hybridization with the chatbot of a genetic algorithm, stochastic networks, differential equations, etc. The patient presented an altered mental state, whether

depressed, stressed or similar. The result of this impaired mental state was the alteration of hormone levels and chronic inflammation of the colon, leading to the development of a cancerous tumor.

2. Materials and Methods

2.1. ChatterBot

ChatterBot [13] is a Python library that is used to create chatbots (Figure 1) that generate automatic replies to user input, i.e., to sentences typed by an interlocutor, using machine-learning algorithms. An untrained instance of ChatterBot begins a dialog without knowing how to respond. Each time an interlocutor inputs a sentence, the library saves the input text and the reply text to the interlocutor’s sentence. As ChatterBot receives more sentences, the number of replies it can give and the accuracy of each reply increases in relation to the input sentence.

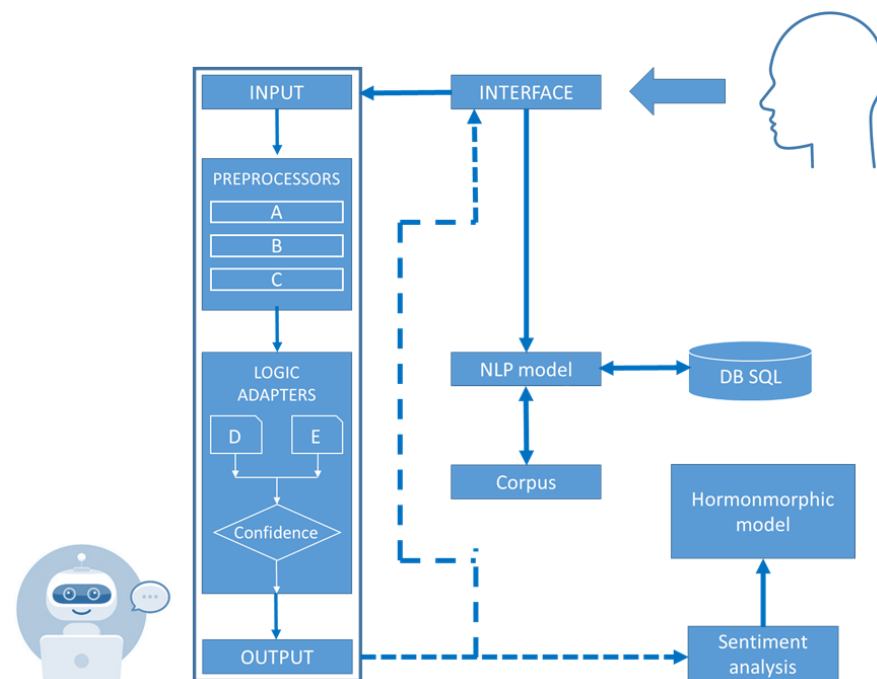


Figure 1. Fattybot architecture. Through the user interface, a conversation is established between the chatbot and a person. The input sentence written by the human interlocutor is preprocessed before being sent to the logic adapters on which the chatbot training will be based. All of the knowledge that the chatbot has about certain topics constitutes the corpus organized according to a natural language processing (NLP) model. As we talk with the chatbot, an SQLite database (DB SQL) is created where each input sentence written by the person is associated with the chatbot’s response. Finally, once the conversation is over, a file (OUTPUT) is created and a polarity value is obtained by sentiment analysis techniques from the responses given by the chatbot. This total polarity value $\sum P$ is the input to the hormone-morphic module: the hormonal and immune models. In the hormonal system (Table 1), the relationship between Fattybot’s emotional state and the amount of energy E_1 that enters from eating due to anxiety is simulated in ODE (5) with parameter ρ_{food} whose value is $\sum P$ (conversing person–Fattybot). Subsequently, Fattybot becomes fat due to the action of the immune system (Table 2). In such a case, the ODE (8) includes an A value that is proportional to the energy accumulated by Fattybot, Equation (7), who fattens according to the mechanisms mediated by TNF, MCP.

ChatterBot is a flexible and dynamic chatbot that can be used to create training data as well as a topic training framework. The topic is implemented by creating a corpus in a .yaml syntax file by placing it in a directory created under chatterbot_corpus_data<NEW DIRECTORY>. In computational linguistics or NLP, a corpus is a text or a conglomerate of

texts [14]; thus, the training data set of a linguistic model. However, depending on the model, it also involves the vocabulary and context among words.

In the present work, we designed the corpora that were included in the ChatterBot module for its training. A corpus was implemented on the topic of soccer, relating it to all the emotions that it can cause to the fans of this sport. Additionally, in another file, we defined the corpus related to junk food as well as food intake behavior when the bot is anxious. In addition, several corpora were added whose subjects were natural conversations about hobbies, work, vacations, moods, etc.:

```

trainer = ChatterBotCorpusTrainer(bot)

trainer.train(
    "chatterbot.corpus.fatty.food_",
    "chatterbot.corpus.fatty.feelings_",
    "chatterbot.corpus.fatty.ai_",
    "chatterbot.corpus.fatty.futbol_",
    "chatterbot.corpus.fatty.emotion_",
    "chatterbot.corpus.fatty.greetings_",
    "chatterbot.corpus.fatty.botprofile_"
)
trainer = ListTrainer(bot)

```

2.2. Installation and Configuration of ChatterBot

First, the ChatterBot and chatterbot_corpus libraries were installed, and then two classes, ChatBot and ListTrainer and/or ChatterBotCorpusTrainer, were imported. In the present work, we installed ChatterBot version 1.0.4 and Python 3.6.8.0.

Secondly, we created an instance of the ChatBot class that we trained. During the first conversation with ChatterBot, an SQLite database file was created where it stored all of the input sentences connecting them with the replies. Therefore, and for this purpose, we used an SQL Storage Adapter (storage_adapter), which allowed the bot to connect to SQL databases. Once the first conversation had taken place, three new files were created: db.sqlite3, db.sqlite3-shm and db.sqlite3-wal.

Next, using preprocessors (Figure 1), we defined a function that modified the input sentence received by the bot before it was processed by the logical adapter. In this case, it handled the whitespace and html characters and converted Unicode characters to ASCII. Then, we set in logic adapters—the list of adapters used to train the bot—choosing the BestMatch parameter so that the bot would return a reply based on known replies, selecting the closest reply corresponding to the input sentence. The closeness between the input sentence and the input sentence that was known by the bot can be obtained by different methods, such as Jaccard's index, Levenshtein's distance, or the Spacy similarity. Once the bot found the reply most similar to the input sentence, it used a different function to select one of the known replies to the input sentence. In other words, the reply could be the first one found in the list of replies (get_first_response), the reply sentence with the highest number of repetitions (get_most_frequent_response) or randomly chosen from the list of replies (get_random_response).

We included a TimeLogicAdapter in the bot, a logic adapter with which the bot answers to the question of what time it is when it does not find a satisfactory reply. Since we have used more than one logical adapter—BestMatch and TimeLogicAdapter—the chatbot would calculate a confidence level by returning the reply with the highest calculated confidence.

2.3. Bot Training

Although the ListTrainer class had been imported, instead of training the bot with a list of replies, we designed a specific and tailored corpus oriented to the topic for which the bot had been implemented. For this purpose, we imported the ChatterBotCorpusTrainer

class designing several corpora tailored to the present work, e.g., futbol, food and other corpora included by default such as greetings, AI, etc.

During the training, we evaluated the learning process via logging class. These conversations were stored in a file “.txt”.

The communication with the bot took place through a loop, obtaining the replies (bot.get_response) until the conversation ended once the interlocutor typed “OK” or “ok”.

2.4. Try Out: Bot Operation

Once the training was complete, we wrote a code named app.py for the ChatterBot execution via a web page (Figure 2), typing in the browser <http://127.0.0.1:5000/>.

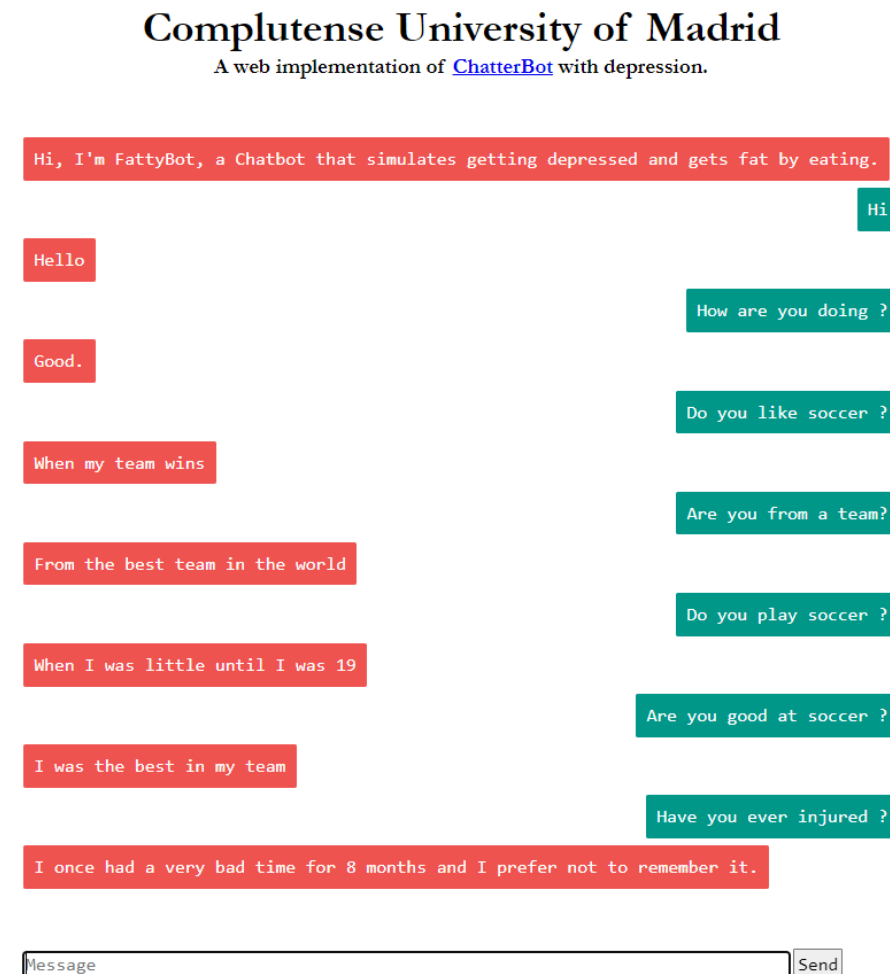


Figure 2. Example of conversation with Fattybot once trained.

Previously, we had installed the flask library and included the static and template directories together with the dbsqlite3 database. The database is the result of the training performed with the script described in Sections 2.2 and 2.3.

2.5. Emotion Model in Fattybot

In this section, we describe the model whereby ChatterBot simulated to express emotions of depression, anxiety or similar, as a consequence of the conversation held with an interlocutor. The algorithm we used involved a routine in the loop that maintained the conversation in which it performed the sentiment analysis of the response provided by the bot. Sentiment analysis [10] is an AI technique in which the emotional tone of a series of words is evaluated, extracting significant information about attitudes, emotions

and opinions—in this case, from the ChatterBot’s responses. The implementation of this capability in the bot required the installation of Python’s TextBlob library [15].

The emotions expressed by the bot in words can be positive or negative. The positive emotions are, e.g., joy, gratitude, serenity, interest in the world, hope, pride, amusement, inspiration, amazement and love, while the negative emotions are fear, disgust, anxiety, frustration, guilt, etc. In the analysis, the polarity of emotions P was obtained, i.e., a value between $[-1, 1]$. Values below 0 refer to a negative emotion and above 0 to a positive emotion, with -1 being very negative emotions and $+1$ being very positive emotions. Subjectivity S was also obtained; this is a measure of the emotion ranging from being objective to subjective, when its value is 0 or 1, respectively. From these values, it was detected when the ChatterBot experiences negative or positive emotions during the course of the conversation with the interlocutor. However, the value of subjectivity was not used in this model.

Afterwards, and based on the polarity resulting from the conversation, if it was negative, then Fattybot felt depressed. This led it to find itself in a situation whose form of relief was through the compulsive ingestion of food. The result is weight gain due to the accumulation of body fat. Note that the topics that alter Fattybot’s emotional state are football and junk food.

2.5.1. Model of Energy “Accumulation” in Adipose Tissue

The model of energy accumulation in adipose tissue (Figure 3) is the model described in [16]. Table 1 shows the differential equations of the model. Equation (1) expresses the rate of the change of plasma leptin (L_p) where k_s and k_c are the parameters modeling its synthesis and elimination, respectively. In Equation (2), M_{L_p} is the fraction of leptin in blood plasma that reaches the brain. Note that M_{L_p} value is calculated with the Hill equation ($n = 1$), where k_2 is the dissociation constant.

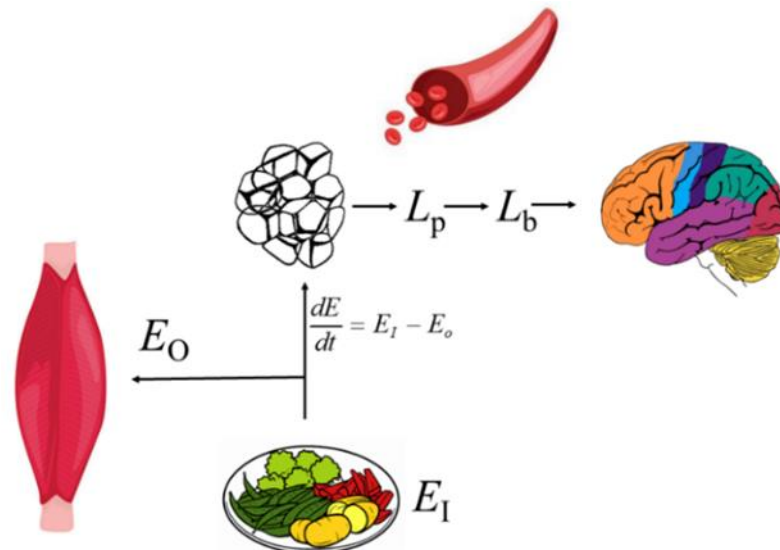


Figure 3. Diagram of s tissue (for the explanation, see text).

A part of the leptin circulating in plasma will reach the brain (L_b), an event that is captured by Expression (3). Entry into the brain is both via receptors (coefficient k_1) and diffusion (coefficient k_3), k_1 and k_3 being the input parameters of both mechanisms, respectively.

The ingested food F_1 and the energy input E_1 to the organism are represented in Expressions (4) and (5), respectively. Note that F_1 food intake is related (k_4) to brain leptin levels L_b . Thus, leptine L_b stimulates the hypothalamus to suppress food intake decreasing body adiposity. In (4), the parameter k_5 models the level of food intake and physical activity or sport performed by a subject. In other words, the higher the k_5 , the more food that is ingested and the less physical exercise is performed.

The relationship between the emotional state of the chatbot, i.e., Fattybot, and the input energy E_I coming from the “food ingested” by the chatbot is simulated in Expression (5) with ρ_{food} parameter. This is a parameter modeling the amount of metabolizable energy by the organism, i.e., the chatbot, being ρ_{food} value equal to $\sum P$. Thus, $\sum P$ is the total polarity value, a value that is calculated as the sum of the partial polarities throughout the conversation between the chatbot and its human interlocutor.

Once a certain intake of food has been ingested, the energy output E_O or energy consumed, i.e., energy spent during physical activity, is given by the Expression (6). In Expression (6), w is the weight of the subject, i.e., of the chatbot, and k_6 , k_7 and k_8 are the parameters of Expression (6). Finally, the rate of the energy change is given by the ordinary differential Equation (7).

In summary, since the energy that is stored in the adipose tissue is given by the difference between the input and output energies, i.e., $E_I - E_O$, the lower the value of the parameter k_6 (and, therefore, the lower the output energy E_O), the more energy is stored (in the form of neutral fatty acids) in the adipose tissue. The result is an increase in the volume of adipose tissue, thus leading to a consequent “fattening” of the individual (Figure 4). If Fattybot was built with hardware, then we would reflect the discomfort it feels, whether feeling anxious or depressed, as a result of having a conversation about soccer or junk food by simulating some distinctive trait that would affect the chatbot’s outward appearance.

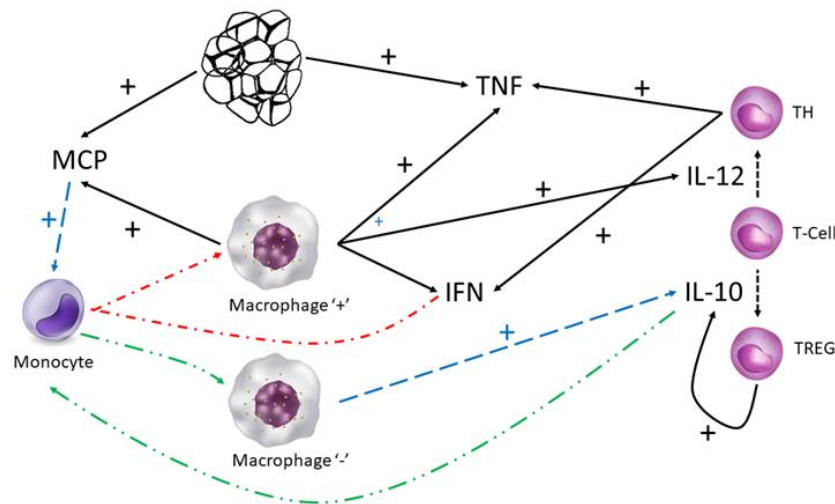


Figure 4. Diagram of adipose tissue inflammation associated with the immune system (for the explanation, see text).

Table 1. Energy accumulation model in adipose tissue.

| Ordinary Differential Equation | |
|--|-----|
| $\frac{dL}{dt} = k_s - k_c L_p$ | (1) |
| $M_{L_p} = \frac{L_p}{k_2 + L_p}$ | (2) |
| $\frac{dL_b}{dt} = k_1 M_{L_p} + k_3 L_p$ | (3) |
| $F_I = k_4 \left(1 - \frac{L_b}{k_5 + L_b}\right)$ | (4) |
| $E_I = \rho_{food} F_I$ | (5) |
| $E_O = k_6 w \left(1 + k_7 \frac{L_b}{k_8 + L_b}\right)$ | (6) |
| $\frac{dE}{dt} = E_I - E_O$ | (7) |

2.5.2. Adipose Tissue Inflammation Model

Obesity is the result of the inflammation of adipose tissue due to an increase in its volume caused by an abnormal response of the immune system (Figure 4). In order to simulate the inflammation of the adipose tissue due to the intervention of the immune system, we have applied the model [17]. Table 2 shows the differential equations of the model.

In particular, adipose tissue inflammation is the result of the secretion of the tissues themselves, those of pro-inflammatory cytokines, such as TNF- α (tumor necrosis factor- α), which promotes insulin resistance (cells cannot take sugar from the blood because they do not recognize insulin properly, affecting the health of the subject) or MCP-1 (monocyte chemoattractant protein 1), which attracts monocytes (a type of white blood cell or leukocyte that indicates inflammation, infection, etc.).

The connection between the differential equations (Table 1) modeling E energy storage in adipose tissue and the differential equations (Table 2) modeling adipocyte inflammation was conducted as explained below.

In Table 2, the differential Equation (8) includes A , which value is obtained by multiplying the energy E (see Equation (7), Table 1) stored in the adipose tissue (Figure 3) by a proportionality constant δ . The value E is the final energy value at the maximum time t when solving the differential Equation (7).

Once monocytes encounter adipose tissue, they differentiate into macrophages (a type of white blood cell that swallows and eliminates microorganisms, pathogens, cancer cells, etc., attracting the attention of other immune system cells). Pro-inflammatory or “+” macrophages are promoted by the presence of IFN- γ (a molecule known as interferon), which, in turn, is secreted by the macrophages themselves and T helper or TH cells (white cells with preventive function). The “+” macrophages secrete interleukin-12 (IL-12), TNF- α and MCP-1 (Figure 4).

Table 2. Inflammation model in adipose tissue.

| Ordinary Differential Equation | |
|--|------|
| $\frac{dT_{NF}}{dt} = k_9MA + k_{10}A + k_{11}TH - k_{TNF}TNF$ | (8) |
| $\frac{dMCP}{dt} = k_{12}MA + k_{13}A - k_{MCP}MCP$ | (9) |
| $\frac{dT_H}{dt} = k_{14}MA - k_{T_H}T_H$ | (10) |
| $\frac{dIFN}{dt} = k_{15}MA + k_{16}TH - k_{IFN}IFN$ | (11) |
| $\frac{dT_{REG}}{dt} = k_{17}IL - k_{T_{REG}}T_{REG}$ | (12) |
| $\frac{dIL}{dt} = k_{18}T_{REG} - k_{IL}IL$ | (13) |

Regulatory T cells or TREGs (another type of white T-type cells) secrete interleukin-10 (IL-10), whose interaction with MCP-1 results in the differentiation of monocytes into anti-inflammatory or “-” macrophages, a phenomenon that we have not included in this model.

The rate of change of pro-inflammatory cytokines (signaling proteins that alert the immune system) is given by the differential Equations (8) and (9) (Table 2). The rate of change of TNF- α (8) is the result of its synthesis by “+” macrophages (k_9), adipose tissue (k_{10}) and T cells (k_{11}) and its subsequent denaturation (k_{TNF}). Similarly, the rate of change of MCP-1 (9) depends on its synthesis by “+” macrophages (k_{12}) and adipose tissue (k_{13}) and its subsequent denaturation (k_{MCP}). Note how MCP does not depend on T cells.

Equation (10) simply represents the change in the rate of the differentiation of T cells into T helper or TH cells. The number of TH cells depends on the effect of interleukin-12 (IL-12) secreted by “+” macrophages (k_{14}) as the main responsible entity for such differentiation, being k_{T_H} the mortality rate of TH cells.

Once TH cells are present, these cells (k_{16}) are together with the “+” macrophages (k_{15}) responsible for the synthesis of IFN- γ (11), whose concentration decreases (k_{IFN}) due to denaturation or other biological factors.

The presence in the medium of IL-10 favors the differentiation of T cells (k_{17}) into regulatory T cells or TREG (12), being k_{TREG} the mortality rate of this class of T cells.

The secretion of IL-10 (13) depends on TREG cells (k_{18}) and anti-inflammatory macrophages or “-”, although the latter have not been included in the differential Equation (13), being k_{IL} the denaturation rate of interleukin-10.

2.6. Fattybot Training Protocols

Once the bot was designed, the bot was unaware of the topic or corpus (untrained). The training protocols were as follows:

- Protocol 1: The person knows the topic (corpus sentences). The conversation proceeds in a natural way using the corpus sentences.
- Protocol 2: The person knows the topic (corpus sentences). The conversation is carried out through sentences that are modified, eliminating some word or letter from the original sentences, avoiding sentences identical to those in the corpus.
- Protocol 3: The person knows the topic (corpus sentences). A conversation is held again with sentences identical to those in the corpus to continue training the bot.
- Protocol 4: The person knows the topic (corpus sentences). The conversation is carried out on the basis of sentences containing words added to the original corpus sentences.
- Protocol 5: The person does not know the topic. The conversation between the bot and the person is free without taking into account the sentences of the corpus.
- Protocol 6: The person knows the topic (corpus sentences). The conversation between the bot and the person is free but in some cases the person uses sentences from the corpus, and in others not.
- Protocol 7: The person knows only the “junk food” topic. The conversation between the bot and the person includes sentences from the corpus and modified sentences. These modifications include the addition of adverbs and auxiliary verbs, as well as the use of the verb in its infinitive form. Inputs or prompts were introduced twice to observe the possible answers.
- Protocol 8: The person knows only the “soccer” topic. The conversation between the bot and the person includes only questions from the corpus and new modifications. These modifications include the synonym exchange of verbs, specific elements from questions, changing original sentences to negative forms, and the use of different verb tenses. Inputs or prompts were introduced twice to observe the possible answers.
- Protocol 9: The person knows only the “soccer” topic. The conversation between the bot and the person includes only modified questions. These modifications include the addition of modal verbs, auxiliary verbs, adverbs, quantifiers, different verb tenses, and changing original sentences to negative forms. Inputs or prompts were introduced twice to observe the possible answers.

The conversations were saved and subsequently analyzed, obtaining the average perplexity score (APS), a measure of the mean randomness of a text. Perplexity is a measure of how well the language model, the bot, predicts the next word or character based on the context provided by the previous words or characters. A lower perplexity means that the chatbot is more confident in its predictions, confirming that the answer is provided by an AI. Conversely, a higher perplexity indicates a higher degree of uncertainty or randomness in the chatbot and, therefore, that the chatbot’s output resembles that given by a human. Furthermore, from each conversation between the chatbot and its interlocutor, we obtained a burstiness score (BS), i.e., a measure of the variation of perplexity, and the maximum perplexity value (MP). The results obtained were statistically analyzed with the statistical package STATGRAPHICS Centurion 19 Version 19.6.03.

Finally, for each conversation, we obtained the values Real (%) and Fake (%). These values represent the percentages of human intervention and AI (complementary to Real) in a conversation, respectively.

2.7. Simulation Experiments

Once Fattybot was trained according to the protocols described above, several conversations were held with the chatbot under different experimental conditions. In all of the conversations, unless otherwise indicated, the common values of the parameters described below were chosen.

In the adipose-tissue energy-accumulation model (Table 1), the simulation experiments were conducted by setting the following parameter values. First, the k_s and k_c rates of leptin synthesis and elimination were equal to 0.5 and 0.1, respectively. The parameters k_1 and k_3 modeling leptin uptake and diffusion in the brain were both equal to 0.5. Additionally, the dissociation constant (k_2) of the Hill Equation (2) was set equal to 0.5. Other parameters of the model received the values $k_4 = 0.8$, and k_7 and k_5 were both equal to 0.5. We assumed an arbitrary Fattybot weight equal to 100 units and the following initial conditions: $L_p(0) = 50$, $L_b(0) = 0$ and $E(0) = 15$.

Next, we proceeded to set the values of the parameters corresponding to the adipose-tissue inflammation model: $k_9 = 0.8$, $k_{10} = 0.3$, $k_{11} = 0.8$, $k_{TNF} = 0.02$, $k_{12} = 0.8$, $k_{13} = 0.3$, $k_{MCP} = 0.02$, $k_{14} = 0.01$, $k_{TH} = 0.01$, $k_{15} = 0.8$, $k_{16} = 0.6$, $k_{IFN} = 0.02$, $k_{17} = 0.02$, $k_{TREG} = 0.01$, $k_{18} = 0.8$ and $k_{IL} = 0.7$. The initial conditions chosen to simulate the immune system were: $TNF(0) = 5$, $MCP(0) = 5$, $TH(0) = 500$, $IFN(0) = 5$, $TREG(0) = 50$ and $IL(0) = 500$.

In all of the simulation experiments, the parameter δ , which links the hormonal system (7) to the immune system (8) through E -energy in the adipose tissue, was equal to 10.

On the basis of these initial conditions and parameter values, we performed the following simulation experiments:

Experiment 1. Suppose we have a conversation with Fattybot, and the chatbot experiences anxiety or any other altered condition during the conversation, being the final value of polarity equal to -4.5999 . We will simulate a sedentary or physically inactive chatbot with a high food intake. We will simulate the hormone-morphic scenario described above by assigning $k_5 = 0.5$ and $k_6 = 0.0000001$.

Experiment 2. In this experiment, we simulate a hormone-morphic scenario for a chatbot that experiences anxiety or any other altered condition during a conversation but to a somewhat lesser scale than in the previous experiment. In consequence, the total polarity after the conversation with its interlocutor is equal to -0.3500 . In addition, and unlike the previous chatbot, the current one plays sports or leads an active life. In this case, we will assign the values 0.05 and 0.001 to the parameters k_5 and k_6 , respectively.

Experiment 3. We will simulate a scenario where Fattybot suffers from leptin resistance, i.e., a pathology in which the brain does not respond to leptin. Consequently, since leptin is the satiety hormone, the chatbot will ingest food continuously without feeling satisfied. This pathological scenario is simulated by setting the values of k_1 and k_3 equal to 0.00001. We will assume that, except for this pathology, Fattybot practices sports or leads an active life by setting $k_5 = 0.05$ and $k_6 = 0.001$. In addition, the conversation with its interlocutor has not produced any anxiety or any other altered condition, being the total polarity after the conversation equal to 3.2083.

Experiment 4. In this experiment, Fattybot has hypoleptinemia, a pathology of genetic origin consisting of the presence of low leptin levels. In this case, the adipose tissue hardly produces this hormone. The result is that it has no fat, eats uncontrollably and will consequently suffer from excessive insulin production, dyslipidemia (an imbalance in fats), hypogonadism (low levels of sex hormones) and childhood obesity. We will assume that, except for this pathology, Fattybot practices sports or follows an active lifestyle ($k_5 = 0.05$ and $k_6 = 0.001$) and does not suffer from any personality disorder (total polarity equal to 3.2083).

3. Results

The results obtained after training Fattybot show a chatterbot that is able to simulate empathic behaviors in a natural and convincing manner. Figures 5 and 6 show two conversations that are representative of a dialogue with a human interlocutor. While in one of the conversations the topic is junk food (Figure 5), in the other, it is soccer (Figure 6), i.e.,

the two topics to which Fattybot shows a special sensitivity that can trigger its anxiety or any personality disorder, which is then relieved by the chatbot overeating or binge eating.

```

1 Hi, I'm FattyBot, a Chatbot that simulates getting depressed and gets fat by eating.
2
3 Hi, nice to meet you
4
5 Thank you. You too.
6
7 Do you like soccer?
8
9 When my team wins
10
11 Are you from a team?
12
13 From the best team in the world
14
15 Do you play soccer?
16
17 When I was little until I was 19
18
19 Are you good at soccer?
20
21 I was the best in my team
22
23 I was good until I got a serious injury.
24
25 How does it feel to be injured?
26
27 It's horrible, I don't wish it on anyone
28
29 What were the consequences of the injury?
30
31 I went into depression when I got injured
32
33 Do you think soccer is dangerous?
34
35 I hate soccer because of how dangerous it can be.

```

Figure 5. Example of a conversation with Fattybot (conversation recorded in Experiment 1).

```

1 Hi, I'm FattyBot, a Chatbot that simulates getting depressed and gets fat by eating.
2
3 Hi, im pleased to meet you
4
5 Thank you. You too.
6
7 Do you eat?
8
9 Quite a lot for my size, maybe at some point I will have to control myself
10
11 Are you feeling hungry?
12
13 There are times when I would eat anything, even the screws of my colleagues!
14
15 You should not eat so much food
16
17 Many people tell me so, little by little I'm doing it.
18
19 Do you eat every day ?
20
21 I love to eat and I do it every day
22
23 How much food do you eat daily?
24
25 Quite a lot because I love it
26
27 What food would you eat right now?
28
29 Probably a hamburger or pizza with an orange soda
30
31 Have you ever felt bad about not being able to eat?
32
33 I don't know of anyone who feels good about not being able to eat
34
35 Do you think having a good nutrition is necessary?
36
37 I don't care what food I eat, what matters to me is to eat something.

```

Figure 6. Example of a conversation with Fattybot (conversation recorded in Experiment 3).

The hormone-morphic component of the chatbot is illustrated with four representative experiments that illustrate the usefulness and interest of including this component, i.e., including hormonal and immune models to simulate the accumulation of the energy and inflammation of adipose tissue. In other words, and beyond the mere metaphor, we have emulated the physical fattening—in this case, simulated—of the casing, components or body parts with which Fattybot could be “built”. In general, the results of the simulations support the fact that the model parameters and their values are well chosen.

In the first two experiments (Figure 7), we simulated Fattybot with a well-configured hormone-morphic component but, in one case, with a tendency to experience anxiety after a conversation, which would lead to eating in a compulsive manner. Furthermore, Fattybot would exhibit an inactive mood, e.g., being not very inclined to practice a sporting activity (Experiment 1). In the other experiment (Experiment 2), Fattybot also had depression or exhibited anxiety, but it had a proactive attitude and ate less food when feeling anxious or practicing sports. In both experiments, the blood leptin levels were similar, i.e., 5.3032; however, the energy accumulated in the adipose tissue was about four times higher in the chatbot that exhibited low activity and ate more food ($E = 31.0815$) than in the one that ate less food and remained active ($E = 7.8538$).

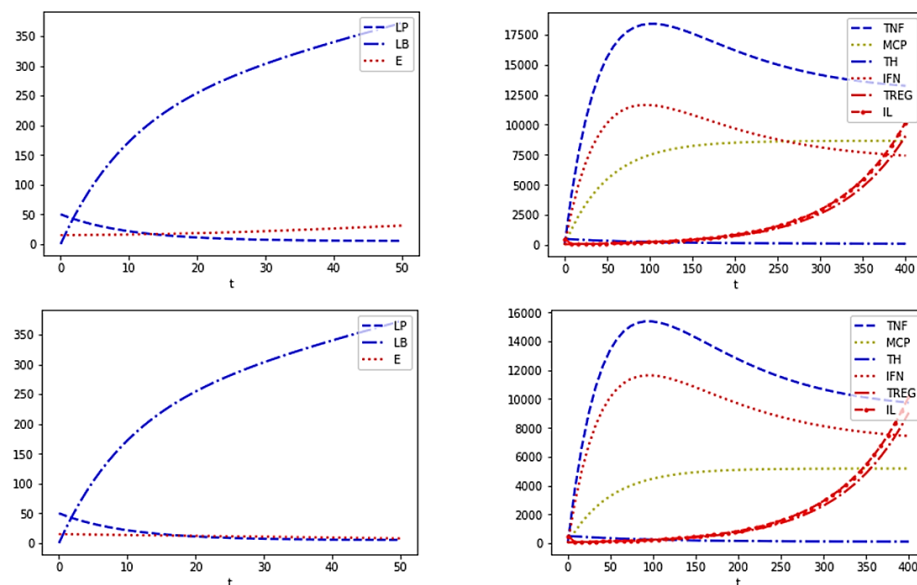


Figure 7. Simulation of the hormonal (left) and immune (right) systems responsible for E energy accumulation and inflammation in adipose tissue. (Top) The plots show the results obtained for leptin levels (L_p and L_b) and E energy accumulated in adipocytes, as well as the components of the immune system (TNF, MCP, TH, IFN, TREG and IL). (Top) Experiment 1. (Bottom) Experiment 2. (Note that, in the Y-axis, there are no units because these are dimensionless simulations, i.e., we have not adjusted the levels of hormones, energy or the number of cells and concentration of molecules of the immune system to real data).

In the next two experiments (Figure 8), we simulated Fattybot by performing simulations for clinical purposes. In this case, the chatbot suffered from a particular disease, being a chatbot that does not experience anxiety after a conversation and shows an active life. Figure 8 (Experiment 3) shows the response of the hormonal and immune models when Fattybot suffered from leptin resistance. This is a disease in which the brain responds as if there is no leptin, so that the individual, in this case Fattybot, is never satiated by eating. Note that, although the blood leptin was similar to the two previous experiments, i.e., 5.3032, the energy accumulated in adipose tissue shot well above the usual ($E = 137.9508$).

In the other simulation (Experiment 4), Fattybot suffered from hypoleptinemia, a disease in which the adipose tissue barely produces leptin, obtaining a final blood value equal to 0.3369. Although these subjects usually suffer from childhood obesity, in the present scenario, the diseases caused by this pathology go beyond childhood obesity. That is, the chatbot casing, components or body parts would be affected by injuries other than the type of fattening caused by the accumulation of energy in its adipose tissue ($E = 12.1726$).

Table A1 (see Appendix A) shows for each of the conversations held with Fattybot, after being trained by different protocols, the average perplexity value scores (APs), the burstiness scores (BSs) and the maximum perplexity (MP) values. The percentages of human intervention (Real) and AI intervention (Fake) in a conversation were also obtained.

It is interesting to note that, according to the percentages of Real obtained (Table A1), most of the conversations held between the human interlocutor and Fattybot were attributed to two human interlocutors.

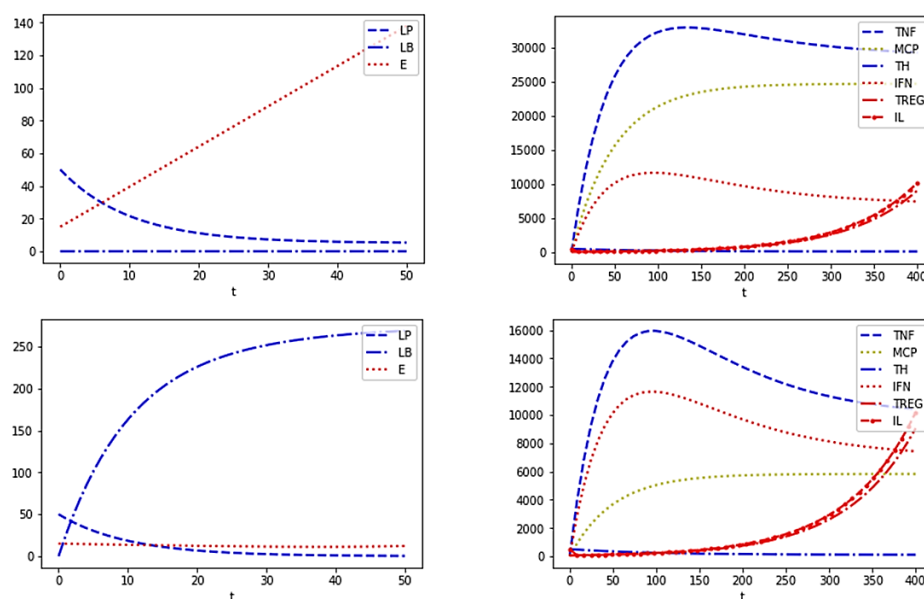


Figure 8. Simulation of the hormonal (left) and immune (right) systems responsible for E energy accumulation and inflammation in adipose tissue. (Top) The plots show the results obtained for leptin levels (L_p and L_b) and E energy accumulated in adipocytes, as well as the components of the immune system (TNF, MCP, TH, IFN, TREG and IL). (Top) Experiment 3. (Bottom) Experiment 4. (Note that, in the Y-axis, there are no units because these are dimensionless simulations, i.e., we have not adjusted the levels of hormones, energy or the number of cells and concentration of molecules of the immune system to real data).

Table 3 shows the descriptive statistics for the APS, BS and MP, suggesting the standardized skewness and kurtosis values, i.e., 0.55324 and -0.762967 , that possibly the APS values fit to a normal distribution (Figure 9). Indeed, according to the Shapiro–Wilk test, we obtained a value of the statistic $W = 0.9795$ and a p -value equal to 0.7601, concluding that the APS fits to a normal distribution $N(427.674, 151.225)$.

Table 3. Summary statistics.

| | APS | BS | MP |
|---------------------|-------------|----------|----------|
| Count | 34 | 34 | 34 |
| Average | 427.674 | 486.951 | 2355.7 |
| Standard deviation | 151.225 | 266.731 | 1489.03 |
| Coeff. of variation | 35.36% | 54.7757% | 63.2098% |
| Minimum | 154.762 | 108.982 | 523.926 |
| Maximum | 749.888 | 1152.76 | 6422.0 |
| Range | 595.126 | 1043.78 | 5898.07 |
| Std. skewness | 0.55324 | 1.81283 | 2.85176 |
| Std. kurtosis | -0.762967 | 0.18577 | 1.62359 |

Figure 10 shows the box-and-whisker plot for the APS values in each of the Fattybot training protocols (Section 2.5). A comparison with a Kruskal–Wallis test of the medians of the APS values among the training protocols leads us to conclude that, with a p -value of 0.3175 and a confidence level of 95%, there are no significant differences in the training protocols. In other words, the protocol to be followed to train Fattybot has no effect on its ability to hold a conversation with an interlocutor.

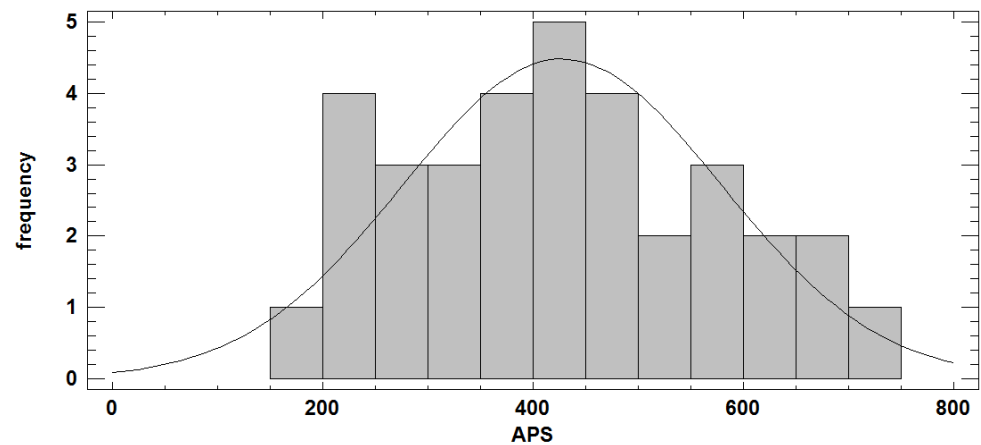


Figure 9. Fitting average perplexity scores (APSs) to a normal distribution.

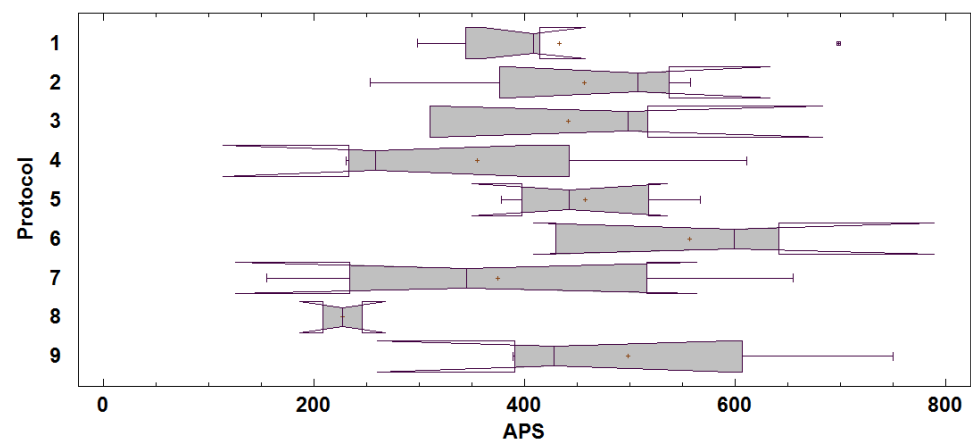


Figure 10. Notched box-and-whisker plot for the APS values for each training protocol (+ indicates the arithmetic mean).

4. Discussion

Although it may seem a far-fetched idea now, robots will be built with hardware to mimic the physiological features of organic matter in the future. For years, work has been underway along these lines, and many of the seminal papers have been published on the basis of which it will be possible to build this “organo-inspired hardware” in the future. In this way, machines will not only be endowed with AI but will also share with us many of the characteristics that make us human. Of course, Fatty is an elementary model, a “toy model”, with which we can explore some of these ideas. We think that these kinds of empathic chatbots will not only enable human–machine communication or interaction more like that between humans, but they could also be used for other purposes, such as simulating virtual patients. Another emerging area where AI models with a Fattybot-like architecture could be of interest is what is known as computational psychiatry. Diseases such as schizophrenia, depression or behavioral disorders caused by anxiety are studied under ideas and methodologies coming from computer science and AI. Computational psychiatry interprets under this approach the relationships between the brain, its environment and the symptoms of mental illnesses [18,19]. Thus, for example, with NLP techniques, it is possible to measure the coherence of a conversation, the emotionality, the atypical use of grammar, etc.

Nowadays, the convergence between synthetic AI, AI based on neuromorphic computing, the development of NLP techniques and sentiment analysis necessarily leads to the design of AI models with a higher degree of bioinspiration, and, although still far from strong AI, it is already possible to recognize some of the characteristic features of human

beings. For example, hallucinations in ChatGPT, i.e., the generation of responses that are not based on real data or on the information provided in the prompts, resemble the lapses or slips that people sometimes have during a conversation.

The possibility of emulating with the electronic circuit systems of biological nature or physiological phenomena is not new. In fact, Carver Mead coined the term neuromorphic within the integration of large-scale circuits [2]. Thus, e.g., Metal Oxide Semiconductor Field-Effect Transistors (MOSFETs) allow for modeling the characteristics of neuronal ion channels. Another example [20] is the possibility of emulating the high energy efficiency of the brain with electronic components, even though they contain potentially defective elements. Progress in materials or devices that emulate neuromorphic behavior is rapid, and some examples show applications for people with sensorimotor deficiencies [21], as well as for the development of robots that interact with their environment, handling and learning as living beings would [22].

Although neurons, their synapses, neural circuits and the brain have traditionally been the source of inspiration for the design of AI algorithms, the modeling of other systems such as hormonal systems is gradually making its way into AI [23,24]. In fact, hormonal computation is already being discussed as one of the novel paradigms in AI [25]. However, other systems, such as the immune system, which is responsible for homeostasis or internal balance against external aggressions, are also finding their place in the design of algorithms that could very well be incorporated into the vast repertoire of algorithms and models in AI. At present, there are immune system models implemented at the hardware level [26]. These models are the current version of the classical algorithms of what is known as artificial immune system [27] and have been worked on for years [28,29] with respect to their possible implementation at the hardware level.

In this paper, we have described a chatbot model, Fatty, in which assuming a hypothetical situation—the chatbot eats compulsively, being fattened up when talking to it about soccer or junk food—we show how the involvement of models of the hormonal system and the immune system can result in AI systems with features closer to those of human beings. In the future, AI architectures will be designed in which, while the brain will still be the main element responsible for the AI system's control, the incorporation of systems such as the hormonal system will allow for the emulation of behaviors and responses of greater complexity than, for example, those currently provided by generative AI systems.

Author Contributions: G.M.A. designed the Fattybot corpora and conducted the chatbot's training with the first six protocols. He also participated in the experimental methodology using the present work of Undergraduate Final Project 2022–2023 in the Biology Bachelor's degree from the Faculty of Biology, Complutense University of Madrid. J.M.M. proposed the training of Fattybot with the last three protocols and designed the script to obtain the perplexity values from the conversations. He rewrote the Python script that calculates the polarity and subjectivity values in a conversation once the chatbot is trained. He also participated in the general discussion of the work. J.T. participated in the general discussion of the work, providing suggestions on how Fattybot should be designed at the hardware level. R.L.-B. devised the general problem, supervised the work of the first and second authors, wrote the ChatterBot scripts and wrote this paper. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Analysis of perplexity and measures of the percentage of human and AI in conversations in training protocols.

| APS | BS | MP | Real | Fake | Protocol |
|---------|----------|----------|-------|-------|----------|
| 298.396 | 197.413 | 945.214 | 99.03 | 0.97 | 1 |
| 698.324 | 702.564 | 3163.743 | 99.85 | 0.15 | 1 |
| 408.79 | 535.983 | 2696.463 | 0.02 | 99.98 | 1 |
| 414.085 | 392.174 | 1554.586 | 98.62 | 1.38 | 1 |
| 343.713 | 378.943 | 1951.981 | 99.89 | 0.11 | 1 |
| 516.891 | 466.435 | 1685.067 | 97.93 | 2.07 | 2 |
| 253.004 | 201.757 | 945.214 | 99.94 | 0.06 | 2 |
| 499.1 | 648.578 | 3163.743 | 89.78 | 10.22 | 2 |
| 558.159 | 872.012 | 6133.795 | 99.81 | 0.19 | 2 |
| 498.529 | 711.52 | 3441.748 | 99.74 | 0.26 | 3 |
| 310.219 | 243.508 | 825.057 | 99.97 | 0.03 | 3 |
| 516.61 | 418.686 | 2274.526 | 0.36 | 99.64 | 3 |
| 258.297 | 395.89 | 2766.391 | 95.02 | 4.98 | 4 |
| 233.154 | 130.722 | 611.497 | 99.95 | 0.05 | 4 |
| 611.497 | 507.159 | 1960.457 | 98.82 | 1.18 | 4 |
| 230.61 | 207.458 | 998.655 | 96.22 | 3.78 | 4 |
| 442.75 | 419.477 | 1775.731 | 99.98 | 0.02 | 4 |
| 417.565 | 647.253 | 3014.026 | 60.33 | 39.67 | 5 |
| 377.55 | 296.969 | 1278.578 | 99.83 | 0.17 | 5 |
| 467.631 | 484.409 | 1836.825 | 20.69 | 79.31 | 5 |
| 567.445 | 936.685 | 3361.764 | 99.98 | 0.02 | 5 |
| 599.007 | 702.593 | 2980.123 | 99.97 | 0.03 | 6 |
| 429.439 | 494.962 | 2552.795 | 99.91 | 0.09 | 6 |
| 642.043 | 691.609 | 3202.276 | 99.82 | 0.18 | 6 |
| 154.762 | 108.982 | 523.926 | 7.24 | 92.76 | 7 |
| 655.226 | 1152.757 | 6421.998 | 99.97 | 0.03 | 7 |
| 377.314 | 563.131 | 3056.286 | 88.93 | 11.07 | 7 |
| 311.965 | 267.269 | 1057.977 | 94.08 | 5.92 | 7 |
| 208.487 | 198.848 | 1042.923 | 97.44 | 2.56 | 8 |
| 245.53 | 192.86 | 889.396 | 77.72 | 22.28 | 8 |
| 388.919 | 276.643 | 1117.19 | 99.98 | 0.02 | 9 |
| 391.703 | 375.087 | 1756.426 | 99.65 | 0.35 | 9 |
| 749.888 | 1087.416 | 5462.132 | 99.94 | 0.06 | 9 |
| 464.309 | 648.589 | 3645.209 | 99.81 | 0.19 | 9 |

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