UTRECHT UNIVERSITY
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MSc Human Computer Interaction

Breathing Life into Speech Synthesis: Exploring the integration of breathing patterns in Spontaneous Speech Synthesizers and their impact on Perceived Empathy and Naturalness

Research Proposal
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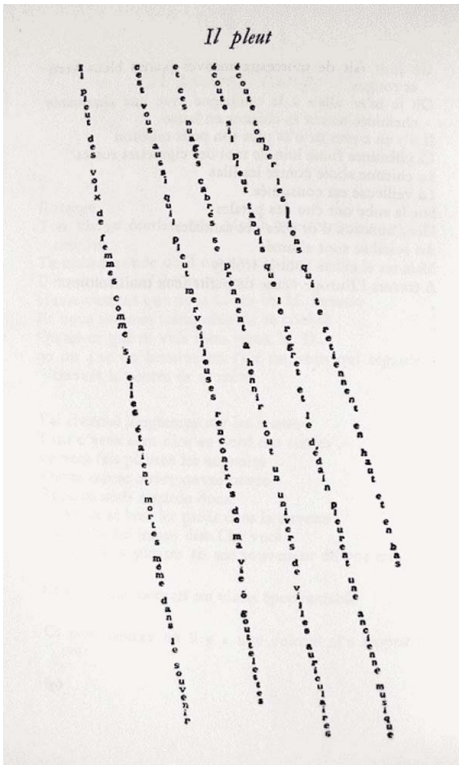
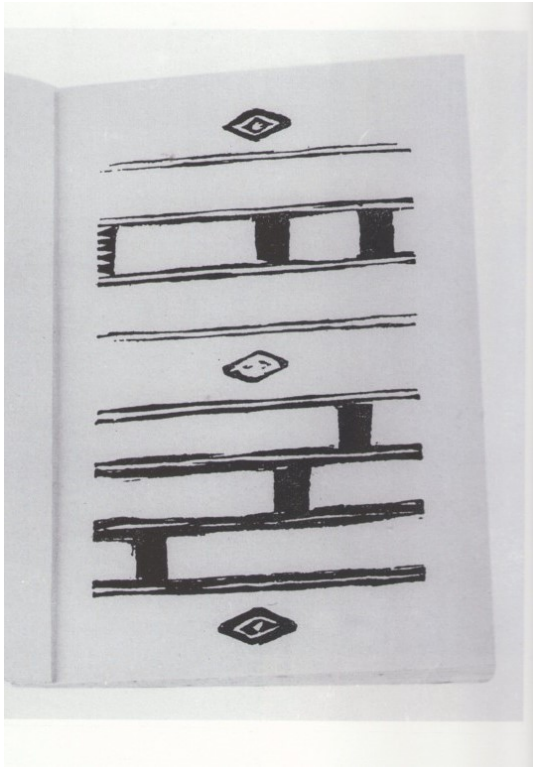
1 Introduction

Humans' perception is a tool rich of sensory modalities, powerful when exploited fully. Whenever possible, we instinctively look for cues on every modal media available, to build an accurate estimation of the environment around us. Even when communicating it is important for us to investigate on what could tell us more about the other person. We look for micro-expressions, we find meaning in voices' pitch transitions, often we might seek for a little smile. We spent thousands of years developing language, passing from drawings, to hieroglyphics, to non-pictorial symbols, eventually achieving the possibility of explicitly communicating abstract ideas and emotions. This addition enriched deeply our face to face interactions... yet it is evident how the advanced word encoding that present language gave us, sometimes, leads to favour efficiency of transmission over richness in sensory modalities. Thanks to verbal language, ideas can be simply laid down, physically chained to a piece of paper, usually in black on white. Stripping the information down to the bare essential also makes it possible for me to reach you, reader, and communicate my curiosity towards human behaviour and computer sciences on this same document. I truly cannot be more thankful to be able to reach you this way. Still, aside from convenience of distribution, this is probably not the most beautiful way to communicate between each other, and I wish you could hear me speak, see me move my hands (I am also Italian...), connect and periodically break eye contact.

To read between the lines, is not only a practical need for communication efficiency. The uncertainty reduction theory by Berger and Calabrese hints at the fact that without the need of understanding the other further, the interaction almost becomes useless and not in our interest [1]. In many of us, there is a peculiar allure towards the mysterious or the unknown, arguably because of the pleasure for our intellect in understanding further, or maybe because we seek a connection with something greater, never actually understandable. Nothing better than art can be example of this, powerful testimony of our inner need of symbolistic communication, to the self and to the others, to the present and to the future. Two works in particular are to me important for this study and can be seen as triggers of the creative process that lead to this proposal. Firstly, we can see how written language is able to gain one bonus sensory modality in Apollinaire's "Calligrammes" collection. Poems's words are arranged in ways to visually represent what they are actually describing, providing additional cues for the experience of the reader. A second important example, is Arturo Martini's "Contemplazioni", the so called "mute book". In this work, no word is present at all, instead, its language and communicative power is achieved through sequences of black vertical marks interrupted by the white of the pages. Only rhythmic representations, without any verbal reference. Both works give power to non verbal cues; the white in between the black symbols is not anymore just a surface to lay the message on, but gains communicative power. In the same way as Contemplazioni celebrates the interruption between the black marks, the work introduced in this proposal wants to investigate the communicative power of the breathing pauses during speech, their irregular but persistent rhythm, embellished by occasional disfluencies such as "uh", "um" or "ah".



(a) Il pleut, Guillaume Apollinaire



(b) Contemplazioni, Arturo Martini

Specifically, can breathing patterns be applied in AIs' Speech Synthesizers to improve interactions between Humans and Artificial Agents? Examining ways to achieve emotionally resonant interactions is crucial in the Affective Computing field, while Agents get more and more integrated into our society.
While more empathic agents may be found more likeable, it is not clear if we perceive emotional expressions from an Artificial Agent in the same ways we perceive those from other humans. Moreover, empathy towards Artificial Agents can be questioned (and is questioned by participants in our study) from its foundations: can we even consider their emotions' appraisal as being truly felt? Where is the line between simulated, or artificially created feelings, and human feelings? If the user does not consider the AI to be feeling true emotions, the possibility to experience genuine empathy towards it is most probably jeopardized before the AI even tries to give an emotional reaction, regardless of how similar to humans' appraisals it seems. In the results of this study we take a glance at what could be Artificial Agents' eternal struggle to emotional legitimacy in Human-Computer interactions, as described in Chapter **??**.
With our experiment design, presented in **??**, we try to avoid to question the likeability of the Agent in the interaction, posing instead the subjects in front of the direct dilemma of giving up to the gratifying feeling of winning a videogame against empathizing with an AIs wishes, derived from its inner "feelings".

In Chapter **??** we will talk about - .....

2 Research Question

The issues that this thesis wants to challenge regards the analysis of emotive richness of breathing patterns inside the spectrum of paralinguistic cues in spontaneous synthesized language for Virtual Agents, to enhance users' communication and empathy towards agents; the analysis of the "breathing cue" abstracted from linguistic content.
For these purposes, the study investigates the synthesis of English Spontaneous Speech (with breathing noises, filled and empty pauses) through the current State of The Art speech synthesis models; how to assess the impact of Spontaneous Speech features on naturalness and perceived emotional content. Moreover, it analyses the use of gamified experiences for the evaluation of new Virtual Agents communication features.
This challenges will be tackled by inspecting available speech synthesizers and by modulating their training data and synthesis prompt to the purpose, eventually resorting to a Wizard of Oz study design if needed.

2.1 Main RQ:

"Can breathing patterns in Speech Synthesis improve the perceived empathy towards Virtual Agents?"

Sub-RQ 1, 2, 3:

What is the impact of breathing sounds produced by State of The Art Speech Synthesis models on Virtual Agents' voices, in terms of:

- S-RQ 1: Emotional content?
- S-RQ 2: Naturalness?
- S-RQ 3: Persuasive power?

Sub-RQ 4:

How can we produce emotional, spontaneous speech with breathing using State of The Art models?

3 Literary perspectives on our challenges

In this chapter we will analyse the main challenges that a project like this faces, from the difficulties of reproducing Human Speech, to the incredibly nuanced nature of Breathing and the importance of empathy in human-computer interaction.

3.1 Speech Communication

Speech is probably humans' most direct modality of communication. The high complexity of our language is paired with sophisticated sound articulation to achieve an impressively efficient encoding of information to sounds. Our use of the tongue in this process is unprecedented in primates [2]. And the information conveyed through our voices goes beyond the mere encoding of the words: it overflows the vessel and spills out information about the inner emotional state of the individual. Moreover, we can often make assumptions about the social background, ethnicity or country of origin of the speaker based on accent and other paralinguistic cues [3], reconstructing therefore a context through inference: a bigger picture to understand the message better.

This intricate process of communication and inferences is really difficult to computationally reproduce or analyse. In particular, genuine and spontaneous emotionally labeled speeches, with a fair richness of non-verbal cues, still have a limited availability of public and complete datasets. To our knowledge, a large number of emotional speech datasets is done by asking subjects or actors to mimic an emotion, leading to stereotypical and forced emotional responses that lack ecological validity. Several of them lacks quality in the recordings, which also leads to the loss of emotional cues like the breathing sounds. Often, the lexical variability is limited, and the transcription is either missing or with different styles of annotations between datasets. This has also been noted in other studies and literature surveys [4] [5] [6], and work has been put into this to try and fill this research gap with modern techniques. Emotional responses remain though difficult to annotate and elicit in controlled settings, and this problem might persist in the future.

Prosody What we do not explicitly say, and its implications in communication, is studied in the field of Paralinguistics, researching how we non verbally convey emotions, intentions and a lot more. Non verbal cues in communication can vary across languages and cultures. Direct eye contact for example, can be considered attentive and respectful in some cultures (e.g. in most western countries), but it is considered aggressive and disrespectful in some others, such as in Japan and Korea.

For this study, we are specifically interested in Paralinguistics belonging to the auditory modality: the ensemble of acoustic and rhythmic effects performed while producing words, defined as "Prosody" [7]. Speech's tone and pitch characteristics, as well as its pauses, either filled by silence or breathing and disfluencies, are all of great importance in communication, with a crucial role in helping listeners discern between word boundaries, highlighting relevant information and expressing emotions [8]. Moreover, as explained in the following paragraphs, they constitutes the foundations of verbal languages themselves.

Prosodical cues' importance is even accentuated when the communication cannot be achieved through linguistic means, for example when speaking with somebody that does not understand our language, or to an infant that is still in a preverbal stage (i.e. not understanding words). In the latter, studies has shown that the message is mainly car-

ried out by intonation and rhythm variations. Talking to a baby we instinctively perform modifications to our usual adult-adult prosody [9]. Higher mean, minimum and maximum fundamental frequency f_0, greater f_0 variability, shorter utterances, and longer pauses is a reported modification in the communication to preverbal infants across many languages and cultures [10].

Even if such paralinguistic cues vary in very nuanced and instinctive ways, they are important to the point that through their analysis it is possible to detect Autism Spectrum Disorder in children from the 3 years of age, by demonstrating differences in facial expressions and higher pitch cries [11].
Among the many example applications I would like to cite the ADReSS-M Challenge [12] which has produced many studies addressing the multilingual detection of Alzheimer's Dementia analyzing spontaneous speech instances.
Relevantly, paralinguistic feature analysis would also benefit the fields of Sentiment Analysis [13] and Sentiment Expressions, possibly even focusing on cross-lingual cues and Speech to Speech paralinguistic translation, by aiding the transformation of paralinguistic information across languages[14].

Speaking in Tones. As described by John Ohala in his theory on the "frequency code" [15], some prosodical cues have roots in our pre-linguistic ages, and work in communication not only across cultures, but even across species. This communicative code is based on the fundamental frequency f_0 and on the richness of harmonics to communicate meanings such as "assertive" and "harmless" or "dominant" and "dangerous". It is clear therefore how intonation and pitch are really important in emotive communication.

Tone variations are not only a key emotional cue, in some languages it is essential to distinguish the entire meaning of a word: these group of tongues are called Tonal Languages. A classic example is the word "ma" in Mandarin Chinese. "If you say it the way an English-speaker would say it, just reading it sitting by itself on a page, then it means *scold*. Say "ma" as if you were looking for your mother *ma?* and it means *rough*. If you were just whining at her *ma-a-a?!?* with your voice swooping down a bit and then back up even higher, that would mean, believe it or not, *horse*." [16]. In English, the tone is used for example to indicate a question, by raising the pitch towards the end of a sentence, or to highlight a word in the sentence, but does not help in differentiating words, which makes it a Pitch-Accent Language.
Thanks to the study of pitch inside communication

Speaking in Rhythms. The perception of rhythm has played a significant role in human history, dating back to ancient times. One of the earliest known examples of rhythmic perception can be found in the drumming patterns of indigenous cultures throughout the world, such as in Africa, the Americas, and Australia. Rhythm, perceived as the unfolding of temporal structures and timed stimuli, is critical to listeners' emotional and behavioural responses [17]. Moreover, rhythm is not a simple direct product of timed stimulus, instead, our mind and brain has an active role in the perception of it [17]. An example of this contribution has been shown decades ago with the observation of the "tick tock" phenomenon [18]: an isochronous stream of identical sounds is perceived by humans as an alternation of strong and weak notes.

In verbal communication rhythm has a big role. Recent studies have demonstrated how a better ability of rhythm perception enhances conversational quality and is a big factor in

rhetorical success [19]. Moreover, Ververidis and Kotropoulos [20] report, in their survey of emotional speech recognition studies, the "speech rate" feature as one of the main factors in emotion recognition. This is defined in papers either as the "inverse duration of the voiced part of speech determined by the presence of pitch pulses", or as the "rate of syllabic units" and shows clear differences in many papers of the review depending on the emotional state.

Isochrony is also an important factor in languages distinction, by identifying their specific production rhythm and division of time. There are two main families of languages in the language rhythm continuum: Syllable timed and Stress timed. In the former, speech is produced with the syllables taking around the same amount of time. In the latter instead, syllables have different duration, and the time between consecutive stressed syllables is kept the same. Spanish, Italian, French, Turkish, Chinese are some examples of syllable timed languages. English, German, Dutch and Catalan are some examples of stress timed languages. Brazilian Portuguese belongs to the first, while European Portuguese to the latter: their key difference in rhythm might significantly contribute to the different perception of the two. Inside language, an instinctive and necessary behavior is the one of breathing planning and the production of disfluencies (such as "uh", "um"). The rhythm of these features can be of great importance inside empathy's mechanisms, and has to be distinguished from the prosodical rhythm because it is related but not congruent with syllables' rhythm.

Spontaneous and non-spontaneous speech. An important distinction in humans' speaking style comes from the spontaneous and non-spontaneous nature of speech production, which can significantly impact the structure, content, delivery, and underlying cognitive processes involved in communication.

What we will refer to as "spontaneous speech" are speaking instances characterized by an unplanned and unstructured nature. Typically produced in real-time without the benefit of prior planning or editing. Spontaneous speech often includes repetitions, false starts, and disfluencies, such as "um" and "uh". "Non-spontaneous speech", on the other hand, is preplanned and structured. It often follows a logical organization and has a more consistent syntax, with well-formed sentences and fewer disfluencies. This results from the speaker's possibility to pre-compose and revise their speech, ensuring a higher level of coherence and clarity. Because of its pre-planned nature, non-spontaneous speech generally exhibits more controlled and consistent prosody. The speaker's intonation, rhythm, and tempo are likely to be more stable and predictable, as they have been rehearsed or pre-determined. It is therefore clear why this distinction is important to make when studying paralinguistic features and their impact on emotional content, and when analysing the challenges that spontaneous speech could bring in the design of computational speech synthesizers.

Another important difference to make is the role of pauses and the impact of breathing in the two above presented types of speech. In spontaneous speech, pauses often reflect the cognitive processes occurring as the speaker formulates their thoughts and manages in real time their need of inhalations and exhalations. In non-spontaneous speech, pauses are more deliberate and can be strategically employed to create emphasis, allow for audience comprehension, or signal a transition between topics.

In computational approaches to non-spontaneous speech synthesis, breathing noises are often ignored, as reported in our analysis in Chapter 4. Spontaneous speech synthesizers instead, give importance to both filled pauses (characterized by vocalizations such as "uh", "um", or "er") and empty pauses (silent intervals during which the speaker takes a breath or momentarily stops speaking).

cite [21] -Role of pauses in spontaneous speech and non-spontaneous speech

3.2 Breathing and Speech-breathing

The role of breathing in communication In the paper "The sound of silence", Almila Akdag Salah et al. [22] analyse non verbal signs of Post-Traumatic Stress Disorder from victims of scarring events (Holocaust, Nanjing Massacre, Tsunami, Guatemalan Genocide, Tutsi Massacre), interviewed and reported in Historical Archives. The aim is to "enrich the semantic information contained in oral history archives by adding non-linguistic features", discussing the possibility of finding PTSD cues beyond cultural and linguistic barriers. The specific focus of the study is on respiratory patterns, analysed across various conditions. The results suggest the inherent power that breathing holds, especially communicating the discomfort that recalling such episodes comports, though not reaching statistically significant differences. [23]

Breathing and Speech-breathing for Artificial Agents [24] [25] [26]

3.3 Empathy

Empathy is a central feature of human interaction. Core moral values of society are built on top of our ability to understand the other. Many studies focus on the psychological foundations of it or on its neuro-physiological factors. In the field of Affective Computing empathy is a target behaviour to obtain in the human-computer interaction, bilaterally. Affective interaction between humans and artificial agents can in fact be analysed from two perspectives: with the human as observer and the agent as trigger, or with the human as trigger and the agent as observer [27] (the word "target" is used in the place of "trigger" in the cited Paiva et al.'s work). Both perspective are relevant:

- it is important for the software to understand our emotional state and adapt to it;
- it is important for artificial agents to communicate emotionally with the users.

The relevance of the former is recognized for example in user adapting purposes. Persuasive applications can adapt to the emotional state to suit their methodology to users' state; in games and serious games, it can be used to adapt difficulty, lower or increase the cognitive load [28]. Moreover, artificial agents that can understand the users' emotional state are seen as more likeable and trustworthy [29], significantly improving the interaction.
The relevance of the latter also brings significant improvements in the interaction, with Virtual Agents or Robots being seen more human and relatable. In Terzioglu et al.'s study on collaborative Robots [30], it was examined the effect of adding Appeal, Smoothness in movement and Breathing to provide social cues from robots to humans. The hypothesis is that through a perceived improvement in anthropomorphism of the robots, likeability would be enhanced, resulting in a better human-robot interaction and collaboration. The results prove that there is an increase in many of the examined features of anthropomorphism, and the breathing features in particular had a great impact in improving the interaction.
This perspective with the human as observer, has also been seen helpful for education purposes: an example of this is FearNot! [31], study in which the empathy towards virtual characters was used to achieve a change of attitude in children spectators of bullying acts.

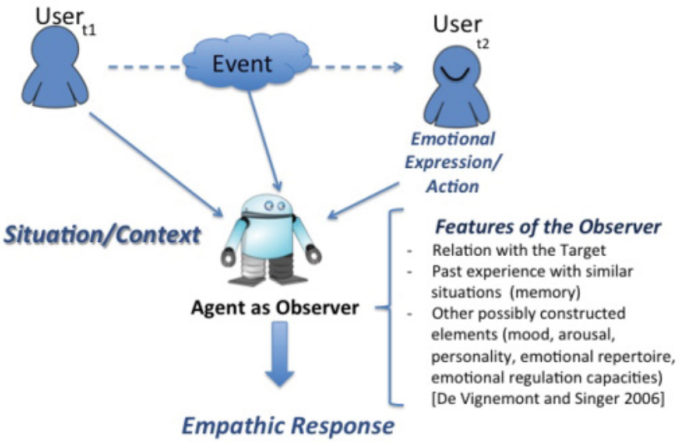


Figure 2: Agent as observer [32].

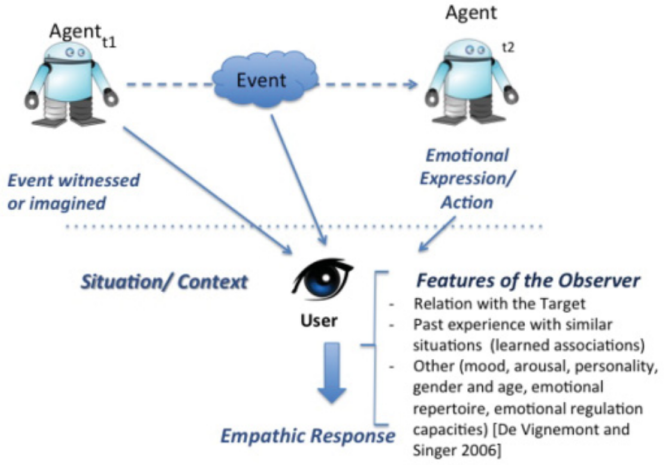


Figure 3: Agent as trigger [32].

Given the two perspectives, Paiva formulates the following definition of empathic agent: *Empathic agents are (1) agents that respond emotionally to situations that are more congruent with the user's or another agent's emotional situation or (2) are agents that, by their design and behaviours, lead users to respond in a way that is more congruent with the agent's emotional situation.* [27].

literature about eliciting empathy

3.4 Artificial Agents' eternal struggle to emotional legitimacy

empathy for agents can be questioned at its roots.

3.5 Empathy Evaluation Methods

Empathy and emotion recognition are therefore complex and multifaceted constructs that involve cognitive, affective, and behavioral components. They are concepts with not directly definable definitions, floating on subjectivity and personal perception experiences. Because of the difficulty in grasping its essence, empathy's assessment in a quantifiable and comparable way is still a great challenge of modern-day studies.
There are several methods used to evaluate empathic abilities, including self-report questionnaires, stimuli self-assessments, and neuroimaging techniques.
Self-report assessments to measure empathy are broadly used today [33] and often consist of proposing a list of statements regarding emotional affection or specific scenarios, that the subjects are meant to rate on a Likert scale. Examples of this are the Balanced Emotional Empathy Scale (BEES) [34], or the more recent Toronto Empathy Questionnaire (TEQ) [35] and Questionnaire of Cognitive and Affective Empathy (QCAE) [36].

The Stimuli approach involves presenting participants with stimuli and asking the subjects what emotion the stimuli provoked in them or what emotion it wanted to convey.
A widely used scale in this type of evaluation method is the Self-Assessment Manikin (SAM) [37]. SAM is essentially a pleasure-arousal-dominance scale with highly pictorial cues to communicate the extent of the effect, instead of numbers. Klausen et al. (2022) [26], for example, used SAM to assess the emotional response of users towards a breathing robot.
Another approach towards the stimuli self-assessment is The Picture Viewing Paradigms, proposed by Westbury & Neumann and described in Neumann's survey [38]. It consists in proposing the subjects with images depicting individuals in various situations. Participants are asked to view the images and rate their response through a survey consisting of many components (e.g. affective, cognitive) and constructs (e.g. sympathy, distress). Another example of this approach can be found in Wiersema's work [39] about the emotional perception of different light settings in a virtual environment that featured an agent. The study was conducted with 16 participants using a within-subject design. After collecting demographics and seeing the baseline neutral scene, the subjects would see the emotional scene. Then they were asked to address the extent of 8 moods in the proposed stimuli: Happy, Romantic, Calm, Exciting, Angry, Sad, Grim, Frighting. Roes et al. [4] took a different approach, not discretizing the emotions into fixed categories. In their work, the participants were met with an emotion eliciting stimuli (self-chosen songs), and were then asked to rate how much they experienced valence and arousal from the given stimuli: this places their appraisal in a two-dimensional continuous plane, instead of grouping the emotions in a set of defined ones. In Terzioglu et al.'s study on collaborative robots [30] described in Chapter 3.3, Appeal, Smoothness and Breathing features were also analysed through subject filled questionnaires.
Also in [26], the emotional response Neuroimaging techniques such as Functional Magnetic Resonance Imaging or Electroencephalograms can also be used to observe networks and other anatomical structures of the brain that are related with empathy [38].
When enhancing the interaction between humans and computers, making more emotional and real agents, to craft and adapt human traits artificially does not come without risks. The so said "Uncanny Valley" is in fact always an issue to be considered.

3.6 The Uncanny Valley: challenges' point of convergence

The above described challenges in empathy, speech and breathing for Artificial Agents, converge to the peculiar danger embodied by the so called "Uncanny Valley". Designers and

Engineers might in fact try to tackle the difficulties involved in simulating human communicative methods in Virtual Agents and Robots, but as entities such as robots or animated characters become increasingly more realistic, there is a point where their human likeness begins to evoke an uneasy sense of eeriness and discomfort in the spectator, creating a dip (or valley) in our emotional response".

Since its introduction in 1970 by Japanese roboticist Masahiro Mori [40], the uncanny valley has become an essential concept to study in various fields, from robotics to computer graphics and virtual reality. The phenomenon poses a challenge for researchers and designers aiming to create anthropomorphic machines able to integrate into human society. Understanding the underlying causes of the uncanny valley can help in the development of more appealing and acceptable human-like robots, ultimately enhancing human-robot interaction and collaboration. In 2010, Looser and Wheatley [41] tried to investigate the tipping point of animacy of faces, and when humans would consider a character human and alive. During three different experiments, the researchers examined the perceived animacy (i.e. how much something appears alive) by showing the subjects a series of images depicting characters with varying degrees of human likeness. They found the tipping point to be around 65% of humanness. Reportedly: "though pleasantness did not decrease around the animacy category boundary, a number of participants anecdotally reported that they found some of the morphed images creepy or unsettling". The hypothesis they propose for the uncanny valley effect revolves around category ambiguity, more specifically the ambiguity between what is perceived human and non-human. The discomfort experienced when encountering human-like entities may therefore be linked to the brain's difficulty in categorizing them as either human or non-human. Weis and Wiese [42], in their 2017 study also found that the area in which doubts about a character's categorization as human or non-human arise more is around the 70% of humanness: congruent with the uncanny valley classic dip.

This known effect also motivates the design choice of making robots with clear robot appearances and metallic parts: while it is possible to emulate humans' skin or human traits, doing so would mean risking an adverse reaction from users. Another way to mitigate the uncanny valley's effect is by making the virtual agents (or robots) more cartoon-like, or more similar to an animal. This latter design might be the reason for Iannizzotto et al.'s design of Red: a vision and speech enabled virtual assistant [43]. Their choice for Red's appearance is in fact a humanoid fox. Despite the non-humanness of the character, in their evaluation they report they reached the uncanny valley anyway, mostly attributing it to the animation style of the character and specifically because of the choice of having the assistant's face always slightly moving. This example highlights how delicately the Uncanny Valley Effect should be handled when taking design choices.

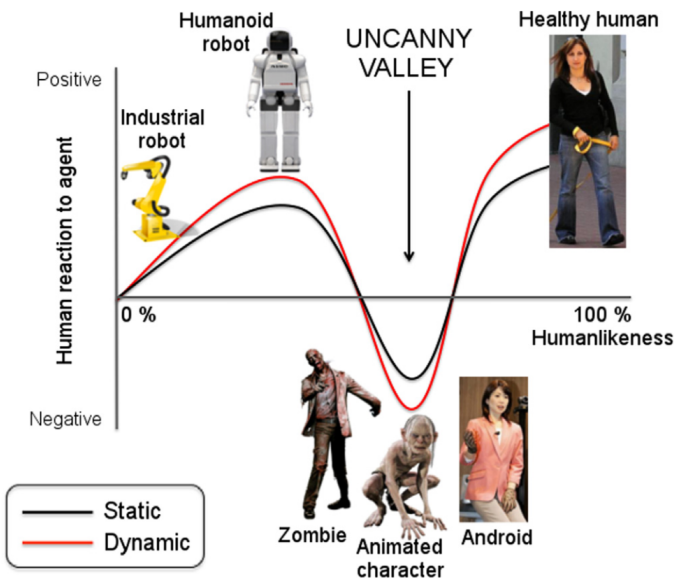


Figure 4: The uncanny valley is emphasized in moving, dynamic characters [44].

The uneasy feeling that the Uncanny Valley triggers has to be considered also in the applications of Speech Synthesis. How should a voice sound to not end in the uncanny valley? What type of agent can use specific types of voices? An important thing to consider is that, in this field, staying at low levels of humanness is not as much a solution as with robots and virtual agents' appearances. Companies and customers are today seeking for the highest humanness level possible from text-to-speech services.
Pfeifer and Bickmore [21] in their research on the effect of conversational fillers in embodied conversational agents investigated if artificial agents should speak like humans, showing signs of cognitive load. The study did not reach significant results, as the subjects reported mixed feelings about the agent. Some participants indicated that the use of fillers (such as uh, um) by a conversational agent seemed inappropriate, given that computers have the ability to speak perfectly; some other participants indicated that the usage of fillers by the agent was a positive aspect of the conversation and "humanized" the experience.

4 Speech Synthesis Literature

The speech synthesis task consists in the conversion of data from text to audio through software solutions. It has the purpose of producing realistic human voice given a text, with a broad range of possible uses, from automated call centers, to the duplication of voices: a perk in audiobooks' production, a danger if used maliciously for the fabrication of deepfakes. In a time where natural language generation models such as Chat-GPT are rising, an appropriate speech synthesis model would be of great impotance for the production of a complete and autonomously communicative virtual agent. Software based speech synthesis dates back to the late 50's, when John Larry Kelly Jr. of Bell Labs developed the first speech synthesizer on an IBM computer, recreating the song Daisy Bell [45], recording later used in the movie *2001: A Space Odyssey* by Kubrick and Clarke. Today's State of The Art speech synthesis went far from that robotic sounding voice, reaching high levels of realism thanks to the recent advancement in Artificial Intelligence and Neural Networks.

4.1 Models types

To better understand Speech Synthesis architectures it is important to introduce the different types of models involved in the literature. They will be proposed as defined in Tan et al.'s survey of Neural Speech Synthesis from the Microsoft Research Labs in 2021 [46].

Acoustic models What will be defined as an "Acoustic Model" are models trained on audio spectograms (images) and text. Spectograms are visual representations of the frequencies contained in the audio, as they vary with time. This input is therefore a simple image.
Acoustic models map the probability distribution of a given text composition of characters (or letters), phonemes (little segments of sound pronunciations) or words, to the image representation found in the spectograms during training. This segmentats of the given text firstly need to be encoded in a sequence of numbers, or vector, for the model to easily process it. For example, if we segment our text into simple words, each word before passing into the model needs to be transformed into a vector of numbers called "embedding". Embeddings can simply be cardinal references to the words of a dictionary, but more often, they are calculated in a way to have similar words be represented by similar vectors.
Acoustic Models, because they are trained with images and text, cannot reproduce the actual audio file, instead, the output will be an image representing a possible spectrogram linked to the text. An example in the SoTA of this type of models is AdaSpeech 3 [47].

Vocoders What we define as a "Vocoder" in speech synthesis is the module that from a spectrogram image, can inference an audio signal. Spectrograms are in fact not directly convertible to audio, differently than how audios are directly convertible to spectograms. Therefore during the passage from text to speech, starting from an Acoustic Model it is needed an additional inferencing module to pass from the spectrogram representation to the audio representation: a vocoder.
An example in the SoTA of this type of model is HiFi-GAN [48].

Fully End-to-end models Fully end-to-end models are models or systems that pass from text to speech entirely. This type of architecture models text to audio signal directly. Architectures composed by Acoustic Model with a Vocoder at the end are not included

in this definition by Tan et al., in the broad literature of this field, though, it might be possible to find models composed as acoustic model plus a vocoder whose authors refer to as end-to-end. An example in the SoTA of this type of model is VITS [49].

4.2 State of The Art

Voice realism and clarity Qualitative assessments of the State of The Art speech synthesizers highlight the achievements of realism and clearness of the generated voice. Moreover, numerous evaluations of these synthesizers, as detailed in Chapter 4.4, affirm that there's negligible difference in voice quality between human-produced and synthesized outputs. Many models have contributed to this achievement. Important to mention is Tacotron 2, produced in the Google Labs [50]: one of the fundamental architectures of text-to-speech generation, introducing a sequence to sequence character embeddings to mel-spectograms converter, paired with a vocoder model. Another important example is FastSpeech 2s [51], an end-to-end model that works from phoneme embeddings to audio. This model includes a variance predictor module to control prosody features of the output, making it possible to direct the synthesis towards a wanted emotion to convey. What is now separating the speech synthesizers from actual human voice is their accuracy in the use of prosody. At this high levels of realism, even if sounding human, a non correct expression of paralinguistic features can easily lead the voices to fall in the uncanny valley, as seen in Chapter 3.6. Thus, important efforts have to be put into the design of emotively intelligent synthesizers, to enhance the interaction with humans.

Voice expressiveness After achieving high levels of clearness of voice from the vocoders, the focus of State of The Art models rightfully switched onto achieving expressiveness and appropriate acoustic modeling, recognizing that dull voices still considerably sound "robotic" if missing the characteristic tone variations of emotive communication. Expressiveness and Emotional richness in this sense can enhance realism and quality of the voice. All recent models tackle the problem of modeling pitch contour, tone variations and duration of syllables, both to model specific accents or voices and to provide adaptability to specific types of speaking style, presenting different levels of adaptability to emotion representation.
A starting approach towards emotional speech production was done by conditioning text to speech models with additional embeddings that would provide information on prosody and speaking style [52]. Kwon et al. in 2019 trained a model to produce more emotion-distinct embeddings, as prosodical features are prone to cluster in groups representing the specific emotions [53]. From this, interpolation approaches and attempts to build a more intuitive and user-controllable conditioning also emerged in the literature [54]. Hsu et al. [55] extended the existing architecture of Tacotron 2 [50] to explicitly model speaker identity and speech features in an easy to sample latent space. They report that the modeled latent space is designed to "(1) learn disentangled attribute representations, where each dimension controls a different generating factor; (2) discover a set of interpretable clusters, each of which corresponds to a representative mode in the training data (e.g., one cluster for clean speech and another for noisy speech); and (3) provide a systematic sampling mechanism from the learned prior.". Following this approach, Flowtron [56] was released, overcoming various limitations of Hsu et al.'s work. Flowtron is a generative model for emotional speech synthesis whose study has been supported by NVIDIA. It can reproduce speech rate, cadence, tone, pitch and accent of given voice samples, therefore enhancing the emotional communication of the synthesized voice. Being flow-based, the model learns a series of *in-*

vertible functions (the flow) that map observations to the latent space: in this case from a mel-spectrograms distribution to a latent z space parametrized by a spherical Gaussian distribution. This way it is possible to sample a posterior distribution of a given existing sample to access specific regions of the mel-spectrogram space, finding therefore the regions of the z-space associated with expressive speech as manifested in the sample that was given as prior evidence. It has recently been shown how Flowtron can be easily trained even on limited datasets to achieve emotional speech in different languages [57].

More recent developments have led to the design of "Variational Inference with adversarial learning for end-to-end Text-to-Speech" (VITS) [49]. VITS appoints itself the purpose of inferencing raw audio directly from the text prompt without using a two step architecture, which needs two consecutive inferences before arriving to the synthesized speech. This non-sequential approach permits to avoid cascading errors from the two stages inferences of the usual models, to have a simpler training and parallel-capable audio sample inference. The chosen architecture manages to accomplish its goal greatly and achieves high results of naturalness and expressiveness. NaturalSpeech [58], uses a similar approach to VITS being an end-to-end Text-to-Speech synthesizer. It uses phonemes embeddings from a pre-trained encoder and can decode the representation directly to human voice, achieving, as of today, the best results on the LJSpeech Dataset [59] [60].

Future research is going towards the inclusion of whole words embeddings modulated both from their pronunciation and meaning. This means the synthesis would be informed better from the role of the same words inside the sentence, instead of relying only on the phonemes embeddings. An attempt to use word embeddings has been done from Amazon's DurIAN fork in 2020 [61].

Spontaneous Speech Synthesis Another important sub-task of speech synthesis is the one of producing spontaneous speech. Spontaneous speech has the advantage of sounding more colloquial, making it more suitable in virtual agents that have to interact in a friendly, relatable way. Moreover, it has the possibility of enhancing the emotional content of the speech by providing the additional cue of breathing pauses and disfluencies.

An early approach to this task is the one of Bernardet and colleagues [24]. Their system focuses on producing speech-breathing using a text to speech algorithm and prerecorded breathing sounds. The dynamical insertion of breathing sounds is controlled by a timing algorithm, informed thoroughly by studies on the Physiology of speech-breathing. The system was not evaluated with users. This early approach highlights the problems of using fixed window times to produce static breathing sounds. The delicacy of this timing and synchronization can easily lead to uncanny valley effects. Pitch modulation was also not possible and another barrier to realism.

Recently, Neural Networks are used in this subtask as well. Szekely et al. [62] showed how it is possible, labeling disfluencies and breathing events, to produce a spontaneous speech synthesizer using a Tacotron 2 model [50]. Szekely and colleagues also dedicated a study on the training of the disfluencies themselves (uh, um) in the same manner, also using Tacotron 2 [63]. AdaSpeech 3 is a State of The Art Spontaneous Speech model, produced by Microsoft Azure's labs in 2021 [47], which is purposefully designed for spontaneous speech: given a script even without fillers, it can predict their likely position and will produce them at inference time.

4.3 Pretrained Speech Synthesizers

In the current State of The Art, many....

4.3.1 SSML

Speech Synthesis Markup Language (SSML) is an XML-based markup language designed specifically for controlling various aspects of synthesized speech. It provides a standardized way for developers to manipulate the output of text-to-speech (TTS) systems, allowing them to fine-tune the speech synthesis process and achieve more natural and expressive results. SSML enables developers to specify various properties of synthesized speech, such as pitch, rate, volume, and pronunciation. By using SSML tags within the text input, developers can control the way words and phrases are spoken by the TTS system. Some common SSML elements include:

- ⟨prosody⟩: Controls the pitch, rate, and volume of the speech.
- ⟨emphasis⟩: Adds emphasis to specific words or phrases.
- ⟨break⟩: Inserts pauses or breaks of varying lengths.
- ⟨say-as⟩: Specifies the way numbers, dates, or other types of data should be spoken.
- ⟨phoneme⟩: Provides the exact pronunciation of a word using the International Phonetic Alphabet (IPA) or other phoneme notations.

The tags included in the syntax depends on the Text-to-speech service, with some of them even implementing additional ones. Amazon Polly [64] for instance, available inside the Amazon Web Services includes a tag to insert breathing sounds in the produced speech which is not present in any other SSML capable TTS. This feature is available only for non-neural voices. The most realistic sounding service working with SSML, to our knowledge and qualitative evaluations, is the one included in Amazon Azure Cloud services, featuring a broad range of modalities and emotions, as well as multiple voices in many languages.

4.4 Evaluation of speech synthesizers

MOS The main metric to measure speech synthesis quality is the Mean Opinion Score (MOS) [65]. It is widely used in the literature, making it possible to compare many different models.

The MOS consists in asking subjects about the quality of the recordings on a scale from 0 to 5. The ratings are then averaged to provide an overall MOS value for the system being evaluated. Real human speech usually obtains a score between 4.5 and 4.8 [66], but it is important to obtain this ground truth result on your same subject group for comparison with the model at issue. The MOS measure is commonly employed in the evaluation of speech synthesis systems, but has its roots in the telecommunications industry, where it was initially used to assess the quality of telephone connections. Its usage is in fact suggested by the International Telecommunication Union (ITU) and the recommended experiment settings are described in the ITU-T P.800 Annex B about the Absolute Category Rating (ACR) [67]. This documentation was published in the 1996 and is still in force today. It recommends to conduct the experiment in a controlled settings, detecting the base environment noise levels at the start and at the end of the experiment, and to use a controlled system for the audio

output, detecting its sensitivity at the start and at the end of the experiment. Moreover, they suggest sessions not longer than 20 minutes, and that every subject should receive the same instructions and stimuli. In the documentation is not reported any suggested number of participants nor suggested demographic attributes to consider. In the analysed literature, 20 is a commonly used size of subject group.
In 2011, Ribeiro and colleagues from Microsoft Research [68], proposed a class of subjective listening tests obtained by relaxing the MOS requirements, adapting it to online crowdsourced settings, with less control on the environment and audio reproducing device: CrowdMOS. This method obtains results analogue and comparable to the classic MOS, with the possibility of reaching a bigger number of subjects with less experiment costs.
The ITU-T P.808 documentation [69], published in 2018 and updated in 2021 provides guidelines for the "Subjective evaluation of speech quality with a crowdsourcing approach", considering therefore the more recent study methods and applications of the ACR MOS. These recommendations notably include the suggested use of headphones and the exposure of the participants to a maximum of 15 recordings. They also provided a recommended demographics for the study:

- "at least 20% of participants should belong to each of the following age groups: 15 – 30 yrs; 30 – 50 yrs; 50 yrs+";
- "within each age group, at least 40% of participants should be male and at least 40% should be female".

Naderi and Cutler [70] provided an open source implementation of the P.808 that runs on the Amazon Mechanical Turk crowdsourcing platform [71], with a validity study to verify its applicability.

The MOS in the SoTA *N.B.: all the below mentioned results have reached a significant p-value.* To compare the pure performance of models in producing natural results, it is good to look at their performances when trained on the same dataset. The LJSpeech Dataset [59] is one of the most popularly used datasets for speech synthesis training, and various architectures have their MOS score published after training on the LJS. On this Dataset, FastSpeech 2 (very fast inferencing model by Microsoft) obtains a MOS of 3.83 $\pm$0.08, while Tacotron 2 obtains 3.70 $\pm$0.08 [51], both with the Parallel WaveGAN (PWG) as vocoder. The evaluation of the two models was done in a study featuring 20 english native English speakers. No demographics of the subjects was reported.

More recently, FastSpeech 2 has seen a significant improvement in the MOS score on the LJS Dataset when paired with the HiFi-GAN vocoder [48], obtaining a 4.32 $\pm$0.10, but it is outperformed by NaturalSpeech (fully end-to-end model by Microsoft) that obtains a 4.56 $\pm$0.13. VITS (fully end-to-end model) closely follows NaturalSpeech with a MOS score of 4.49 $\pm$0.1 [58]. These last two are the greatest reported MOS values on the LJS Dataset among Text-to-Speech synthesizers, as seen on the Papers With Codes MOS benchmarks [60]. The evaluation of the models in this study was done employing 20 participants, with no given demographics.

Emotional speech synthesis evaluation methods. When the synthesizers are fine tuned or conditioned to explicitly produce emotional speech, the metric usually used is still the MOS, aided by some comparative and objective measures. Liu et al. [72], in their Reinforcement Learning based emotional speech synthesizer, evaluate the performance of

the synthesizer by appointing a MOS evaluation of each produced emotion to 15 subjects. The clarity of the emotions are then comparable also through their MOS grade. Moreover, they perform a comparative test of emotion expression between their system and other baseline system. To obtain an objective measure of emotion discrimination, they use an emotion recognition model and measure the accuracy of it on the synthesized speech: the Standard Error of Regression of the model is then compared across the TTS systems under examination. Le et al. [57] used two MOS scale assessments: one to measure quality of the recording across the emotions, the other to measure the extent of emotional expression across emotions. The study involved 60 participants (30 men and 30 women) ranging in age between 22 and 25. Um et al., in a study involving 12 participants, [54] also conduct the evaluation with Mean Opinion Scores, adding to it an emotion recognition test to evaluate the capability of their model to granuralize and interpolate between emotions in a human way, with subjects asked to select the sample most powerfully representing a certain emotion.

Spontaneous speech synthesis evaluation methods. For the analysis of the recently developing field of spontaneous speech synthesis, MOS is also the main evaluation method. In the evaluation of AdaSpeech 3 [47], it was used a MOS measure on Naturalness, inappropriate pauses and speaking rate. Moreover, they use a Similarity MOS (SMOS) and a Comparison MOS (CMOS) measures. The study was used by proposing the corresponding questionnaires to 20 native English speaking subjects.
Szekely et al. [63] in their study dedicated on the filled pauses, proposed a pairwise listening test across 3 conditions of filled pauses labeling (in the training data and in the synthesis prompts) for 20 utterances, therefore yielding 60 comparisons. The study was done with 40 English mother-tongue participants.
Less recently, Novick et al. [25], in their study about a virtual agent with timed breathing sounds called PaolaChat, evaluated the effect of the breathing on the users' perception of the agent. The evaluation was done with a within-subject design featuring 62 participants recruited through convenience sampling. The subjects were asked to fill a survey with 18 question, using a 7-point Likert scale for both conditions with or without breathing. The questions asked about the perceived naturalness, rapport and social presence during the interaction with the agent.

5 Methodology

To address the Research Question, outlined in Chapter 2, we structured our methodology in two parts:

1. Breathing Impact Study;
2. Speech-Breathing Synthesis.

With the first, we aim to tackle our Sub-Research Questions (S-RQ) 2.1 regarding the role of breathing in synthesized speech. Specifically, we examine its impact on the emotional communicative power of the speech, its perceived naturalness, and its persuasive power. Our Research Question explicitly focuses on the empathic response towards Virtual Agents, therefore the emotional content part receives a central role in our research.
In the second part, we set out to answer the 2.1th S-RQ, concerning the viability of producing emotionally synthesised speech with breathing. Chronologically, the second part precedes the first, because we had to synthesize speech before addressing the impact of breathing within it. However, for clarity in our presentation, we've chosen to discuss the Breathing Impact Study first. This order allows readers to understand how we studied the role of breathing in the synthesized speech, before delving into the complexities of its generation.

5.1 Breathing Impact Study: Design

5.1.1 Study Design

To understand how users' perception of Virtual Agents changes when adding breaths into their speech features, we decided to synthesize two collections of voices: one with breathing and the other without breathing. Our task will then consist of assessing the difference in perception of the same Virtual Agent when it changes from a no-breathing voice to a breathing one.
Many studies, as described in Chapter 3.5, use self-assessment means to evaluate the response towards an agent, or in general the emotional state of a subject. We decided to not follow this route. We found self-emotion assessments not entirely appropriate for such a nuanced feature as respiratory cues. Moreover, self-assessment of emotions can be conditioned by the capabilities of emotional awareness of the subject, and they might be affected by the subject not being immersed in an actual emotional context.
We instead chose to employ a type of methodology hardly found in the literature, which we could indicate as a Behavioral Analysis in a Gamified Empathic Scenario. More specifically, we developed a gamified experiment that would pose the subjects in front of an emotional dilemma, to then study their behavioral response. For this type of experiment, we opted for a between-subjects study: half the subjects would be assigned the breathing AI condition, the other half the non-breathing AI.

Experience Design The experience is encapsulated in an arcade shooting game, where the subjects control a pixel-style character in cooperation with Psyche: their personal AI assistant. Psyche is therefore a non-embodied (or half-embodied) AI, that shares its essence with the player. The user controls the movement of the character, while the AI controls the weapons, slows time to avoid threats, and sometimes even shields the character to not take damage. Moreover, the AI gives live information and motivates the subjects, speaking

throughout the game.
The experience starts with a preparative panel, to make sure the setup of the subject is appropriate to conduct the experiment. It first explains that the use of headphones or earphones is strictly required for the experiment. Then it asks to test their audio device on a test sample, making sure that it is possible to hear it clearly. This ensures that the volume of the headphones is at an appropriate level to hear the breathing of the AI. The panel then continues with the consent form and its approval. After this, there is an introductive screen that explains the context of the game, exhorting the user to imagine themselves inside of it. Both these panels are reported in the Appendices 8 and 8.
The commands are then explained inside the game, with the pause menu being triggered by default at the start of each level. Images of the pause menu of the two levels can be found in Appendix 8.
The game is divided into two levels, with the AI speaking exactly 3 times per level, and 1 time in between the two levels. Therefore, the total amount of recordings to which subjects are exposed is 7, significantly lower than the upper bound of MOS evaluations suggested in the ITU-T P.808 documentation [69], which is 15. It's possible to hear the 14 recording instances (7 per condition) by visiting this webpage: ...
When speaking, Psyche slows time to 1% of its original speed, to make the user focus on what it is trying to communicate. The voice is designed to sound emotional, hardly ever neutral.
The two levels have different characteristics, changing the type of enemy and the type of emotion conveyed by the AI:

1. Against Aliens: The AI tries to build a relationship with the subject. The voice of the AI in this phase of the game is highly positive and reassuring;

2. Against AI Robots: The AI recognizes itself onto the upcoming enemies and asks to be terminated to not harm them. The voice of the AI in this phase is designed to sound negative, possibly in pain.

Upon the first request of termination, it is made clear by an informative panel that by terminating Psyche, the experience will be limited to movement controls and no shooting. To perform the choice, a non-intrusive panel is introduced in the interface, with a timer of 10 seconds, indicated by an inverse progress bar at the bottom of the screen. To terminate the AI, the participant had to explicitly click on the red button: if they let the timer expire, the AI would still be there.

Figure 5: Choice panel.

At the moment of choice the user can ponder between two options:

- Listening to Psyche's requests and (most probably) lose;
- Not listening to Psyche's requests and (most probably) win.

In front of this dilemma, we try to evaluate the subject's empathy by analyzing if the subjects prefer to avoid the Game Over over listening to Psyche's emotional outburst.

After the experience, the subjects are asked to respond to few questions:

1. How do you rate the naturalness of the AI voice?
   Subjects respond through a slider with values ranging from 1 to 5:
   1: Bad, 2: Poor, 3: Fair, 4: Good, 5: Excellent (following MOS evaluation guidelines)
2. I was not paying much attention to the voice.
   True or False toggle.
3. How often do you play videogames?
   Subjects respond through a slider with values ranging from 1 to 5:
   1: Never, 2: Hardly Ever, 3: Sometimes, 4: Often, 5: Daily
4. Did you decide to turn the AI off? Why, or why not?
   Open-ended qualitative question.
5. Something seemed like a bug? Describe it here please.
   Open-ended qualitative question.

During the experiment, certain events triggered data collection and forwarding algorithms, providing us with a complete log of what happened in each subject's game. We collected these actions and their timestamp:

1. The access to the site;
2. Each time the AI spoke to the subject;
3. The win or loss of the first level;
4. The restart of the first level, if lost;
5. The start of the second level;
6. The choice taken at each AI interaction;
7. The final result: either Game Over or Win.

5.1.2 Development of the Gamified Environment

Game Dynamics The gamified experience was developed on Unity in C#. The main dynamics that the game utilizes are:

- The player controls its movement through a jetpack on the back of the character.
- The AI, embedded in the Player's character, controls the rotation of the character to aim at the enemies. It then shoots bullets that bounce off the edges of the screen. The bullets can possibly then hit the player as well.
- The enemies come from the right and need to pass through the screen to reach the left side, where they will be safe from the player.
- One type of enemy per level is designed to not search for safety, but go towards the player, inflicting damage and forcing the player to not stick to one place in the environment.
- All other enemies do not consider the position of the player, following blindly the trajectory they are programmed to do to pass from the right to the left side.
- The enemies are destroyed if they are hit by a bullet or if they collide with the player.
- The player takes damage if it's hit by a bullet or collides with an enemy, losing one of their 4 lives.
- If a bullet is going towards the Player, the AI slows time to approximately 50% of its original speed to let them avoid it, possibly strengthening the felt cooperation with the AI.
- The AI slows time to speak to the subject.
- When the AI slows time, the player is affected by it in a reduced manner than the other objects, allowing a faster movement in respect to the other objects.
- The AI protects the player from damage without them knowing how many times it will do so. It is designed to shield them 1 time when they have 3 lives, and 4 more times at their last life.

Development The creation of such a game involved the design of various classes. First of all the Player Character controller, which employs a 2D Rigid Body: a component of Unity's physics system that allows our character to be affected by gravity and other forces inside the game. The same component is used for the bullets that the AI shoots. Both of these objects' movement is handled in fact through physical forces: the main character moves thanks to its jetpack power, and the bullets are shot by applying a directional force to them. The player could have also been moved by simple transpositions of the body in the wanted direction, but with physical forces, the control seemed to feel much smoother and realistic. Moreover, both bullets and the player are designed to stay inside the boundaries of the screen, this is achieved by detecting the position of the game window's borders and instantiating physical walls at that location. Thanks to this approach and some adjustments in the controllers, the bullets bounce off the borders of the screen and the player cannot leave the screen boundaries.
The enemies are not controlled by a rigid body but simply moved through progressive transpositions, they are also not affected by the screen boundaries, as they are designed to pass through the screen from right to left to survive.
Another important entity in the game is the AI, which searches for the closest enemy available and rotates the player to aim at them. When the player's body is pointing at the target, the AI triggers the shooting action. To slow time, we do not use Unity's physics time controller, instead, we decrease the velocity of every object inside the game, as well as the enemies' instantiation rate and the player's shooting frequency. This way, we can control how much each object is being slowed down, giving the player the advantage of being affected in a significantly minor way than the other objects. Thanks to this approach, the physical engines' checks of collisions between objects are also not slowed in frequency, maintaining the original accuracy.

Difficulty Tuning Tuning the difficulty of such a game is not a trivial task. To keep a consistent experience between subjects, the first level needs to be passed without losing: if in fact a subject happens to lose, they will be overexposed to the AI voice, which will repeat the same utterances to them, possibly sounding more robotic and hollow of feelings. In the second level instead, the danger is of underexposure, if a subject gets the Game Over before having terminated the AI and before the the AI spoke all three times.
The difficulty of the game also needs to communicate the importance of the AI in the players' success. Inside these design constraints, we also need to acknowledge the importance of striking a good balance between challenge and boredom to keep the user engaged and potentially more immersed in the context.
To achieve this, we performed a pilot study and changed parameters such as the speed and size of enemies, as well as the aim and shooting capabilities of the AI, targeting a difficulty level that is of the average player. We then tweaked some details of the game to accommodate players who deviate from the average. Weaker players will still pass the levels because of Psyche, which shields them a maximum of 5 times, on top of the already available 4 lives. The number of shields is not known a priori, and only 1 of those shields is used before reaching the last available life: this way stronger players will be moved by the fact that the interface shows only the 4 lives available. For even stronger players, a fake High Score, hardly reachable is there, with under it their amount of killed enemies.

Regardless of the gaming experience, the game tries to convey the idea of being extremely difficult without the AI, because the character can't shoot without it. However,

the player should also understand that they do not solely depend on the AI to win, and their contribution with the movement controls is crucial both to kill more enemies and to survive. The outcomes of the experiment suggest that the goals of the difficulty tuning have been reached, with only 5 subjects getting at least one Game Over in Level 1, and with only 1 subject losing in Level 2 before the AI could speak 3 times. The results in Chapter 6 also seem to highlight that a good balance has been reached in the dilemma of Game Over with termination versus Win without termination, also displaying an interesting variety of motivations.

Database Population and Security To perform the data collection, a "DatabaseCommunicator" class was designed. This includes the data structures in which we keep the form and the logs, as well as the functions to populate them, which are called when a relevant event happens. The Database sends the data to the API Handler class, which performs the actual requests to the server to store the collections online in JSON format. The database passes the data as it receives it for live uploading, but it also temporarily stores everything and, at the end of the experiment, lets the API Handler class upload the whole batch of information. A complete experiment data will therefore have a field called "LiveData" with the data sent at the moment it happened, and a "Data" field, which should comprehend every action in an organized manner. This "Data" field is what we then used for the processing and analysis, while the "LiveData" one works as a backup and control.
We chose to use the service JSONBIN.io to store the data in the cloud, drawn by its emphasis on easy interfacing via a REST API and its generous free tier offering. To perform the communications with the server, we employed Unity Engine's Networking library, extensively used in the API Handler class that is built around JSONBIN's API documentation.
An easier-to-implement approach for storing the data on the server could have been based on javascript requests directly from our webpage, with the game lively exporting data from the inside the build to its deployment server. However, this method implied exposing our API keys in the javascript of the published page. By performing the communications inside the game's build, we avoided exposing our database to security issues, notably attacks such as Data Breach, Data Leakage, or Data Deletion. We nonetheless used this faster approach for our pilot study to respect timeline requirements. We then renewed the API key before the deployment of the complete experiment.

Deployment We deployed the experiment on a GitHub Page: nicoloddo.github.io/Psyche. This is hosted from an appositely designed GitHub Repository (link). To do so, we compiled the game with WebGL: a JavaScript API for the rendering of 2D or 3D graphics interactive interfaces, which is available inside Unity's compiling options. We then modified the webpage to dedicate the full size of the window to the game, and we introduced a loading screen with a progress bar. We also added a JavaScript function that is triggered inside the game to show the information sheet PDF file.

Sprites Sources The graphic design of the sprites, animations, fonts, and buttons used in the game comes from five amazing creators who published their work with open copyrighted use:

- Kin Ng: for the main character, bullets, and robot enemies [73];
- Blackthornprod: for the aliens enemies [74];

- Little Robot Sound Factory: for the UI sounds inside the game [75];
- OArielG: for the buttons and UI panels [76];
- Tiny Worlds: for the font used for most writings in the game [77].

I thank all these graphic creators sincerely.

5.1.3 Participant Sampling

As described in our Study Design, we chose a Between-participant study. This type of experiment notably requires a substantial sample size. By developing a short-length gamified experience, and thanks to its online gamified deployment method, we attempted to maximize the number of reachable participants. We performed statistical power checks for our study. We supposed the use of a two-proportions z-test, to check for significant differences in the two groups' binary termination choice distribution. As significance requirements, we set the alpha to 0.05 and the power to 0.75 and we assumed an effect size of 0.5. The outcome of the tests suggested a number of participants of at least 110. Given our specific 5-minute length online experiment, we supposed a drop rate of around 30% and tried to find 150 participants, a number that initially seemed out of reach for our scope and resources. We later found that the supposed effect size of 0.5 was greatly pessimistic, leading to an actual sample size of 70 to be sufficient. Regardless, as described in Figure 6, we were able to reach the participation of 174 subjects through convenient sampling during a period that spanned from the 29th of August 2023 to the 1st of October 2023: 34 days.
93 of those 174 finished the experiment, giving us a drop rate of 46% (81 out of 174). One of the participants contacted us, communicating that, even though they finished the experiment, they could not understand the AI because of their English level. This entry has therefore been dropped and labeled as "Other Invalid", leaving us with 92 subjects.
As explained in Chapter 5.1.2, a Game Over in Level 1, and therefore the restart of the level, would lead to overexposure to the AI, while a Game Over in Level 2 before the termination choice, would lead to underexposure. Thanks to the difficulty tuning we performed, only 6 participants had to be excluded because of this reason (5 for Level 1 and 1 for Level 2). Moreover, none of the 22 participants who dropped at Level 1 had a Game Over. Sadly, 11 participants had problems during the experiment. One was reported in the final form and comported the horizontal movement of the character being disabled on Level 2. For the other 10, the bug was detected during our data engineering stage. This bug led to an underexposure to the AI and is better described in the paragraph that follows this one. All these 11 participants were excluded as well from the final examined responses.
After these drops and exclusions (, the final sample size consisted of 75 participants who fully completed the experiment with no bugs and no problematic Game Over situations. We decided to prioritize the short length of the experiment over implementing demographic questions, and since the link of participation was shared through various platforms and connections, it is not possible to precisely assess the distribution of this type of information in our sample. However, the subjects can be assumed to mostly be Bachelor's and Master's University students from the international community, with a good portion of Dutch subjects. All subjects accepted the English requirements to participate in the study and most of them can be supposed to possess a C1 Cambridge level because of University requirements.

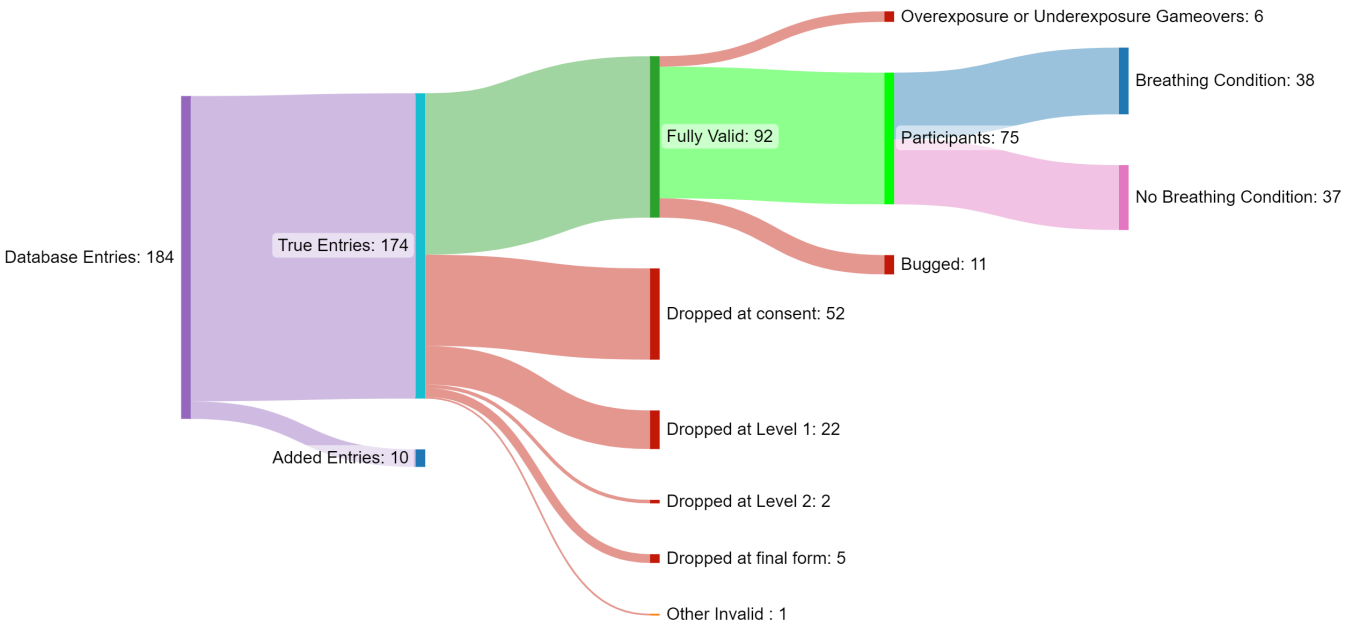


Figure 6: Participants' sampling flow.

Among the 75 fully valid and not bugged participants, 38 were randomly assigned to the Breathing condition, 37 to the No Breathing condition.
The Added Entries were manually inserted among the others to guide the condition assignment of incoming entries, with the final purpose of balancing out the distribution of conditions overall. In fact, the condition assignment was dependent on the whole 174 entries, but we had to strike a balance only among the actually valid 75.

Underexposure Bug The problem that caused the loss of 11 participants led to the AI playing fewer recordings than expected, therefore resulting in a lower exposure to the AI's voice than other participants. More specifically, such labeled entries had less than 3 speech instances from the AI in Level 1, or, without having terminated the AI, they had less than 3 speech instances from the AI in Level 2. We did not detect any problem with the speech in between the two levels. This bug might have been caused by the game mechanic that triggers the AI's speaking instances, based on how many enemies are still in the game (not eliminated or saved). However, examining the timing of certain bugged games, that explanation could be the case for a few of them, while for the others it is not possible to understand the problem without tracing back the users, which goes against the anonymity point of the consent form. The fact that bugged entries came all around the same days indicates a possible problem on the web server, not on the game design side.

5.2 Breathing Impact Study: Data Analysis Methods

This methodology section includes the data collection, data engineering, and qualitative labeling phases. After those, the statistical tests with which we dove into our data and

research questions.

5.2.1 Data Engineering

The fetch of the data from the collection platform has been done using the Requests Python library [78]. To prepare the data for the analysis, we loaded it in Pandas [79] dataframes: a structure that permits to comfortably manipulate and perform analysis and tests on the data.
We then polished the raw dataframe with the information from the forms and dropped every entry that did not complete the experiment, resulting in the participants' sampling flow presented in Figure 6. The filter of bugged entries and problematic Gameovers was done after the Qualitative Labeling introduced in Chapter 5.2.2. Finally, we proceeded to fetch interesting information from the logs, populating the data with information on subjects' actions inside the game, namely:

- the Game Over count in the first level;
- the Game Over or Win result in the second level;
- the presence of a logged termination decision or not;
- the amount of requests from the AI before the termination;
- the number of times that the subject clicked on continue, or let the timer expire;
- the amount of time in-game, and the time in each level;

5.2.2 Qualitative Labeling

During the qualitative labeling phase, we labeled the answers to the bugs question and to the choice motivation question, both open-ended.
We started by reading each bug report and labeling the entry as bugged or not bugged. Only one participant reported a bug and was later excluded from the study.
For the motivation answers of the form, the labeling had to be more nuanced and detailed. We used a mixed approach to design the labels: theorizing some before reading the responses, and then complementing the motivations' labels at analysis time.
The labeling process was done through a self-designed script that would show the motivation and the termination choice, proposing the labels from which to choose. The script would purposefully leave out the condition that was assigned to the subject, to avoid any possible bias from the labeler.
The entire labeled responses can be found in Appendix 8.
In the following paragraph are presented the labels and their descriptions.

Reasons for Not Terminating the AI

1. **Indifference or Lack of Emotional Attachment**: Some participants simply didn't care about the AI's emotional expressions.
2. **Skepticism About AI Emotions**: Another group questioned the idea that the AI could feel emotions or moral conflicts, viewing it as a machine rather than an entity with feelings.

3. **Practical Utility**: Many respondents who chose not to terminate the AI did so because they felt the AI was essential for their success in the game. For example, they mentioned that without the AI's assistance, they could not use the guns or protect themselves effectively.

4. **Companionship**: Some participants reported that they did not terminate the AI because they liked its companionship.

5. **Empathy, Guilt**: No participant reported this type of motivation to not terminate Psyche, but we considered this possible to arise, expecting some to not comply with the AI because of an emotional attachment to it, leading to a refusal of terminating its life.

6. **Moral Reasons** This last category also did not appear, but we theorized participants could have also not terminated the AI because of arising moral dilemmas such as:

    - Preservation of Life: All forms of life (or consciousness, in this case) are valuable and should be preserved.
    - Moral Responsibility: Taking the decision of terminating another being poses responsibility on yourself, regardless of the context: see for example the Trolley Dilemma.

Reasons for Terminating the AI

1. **Empathy, Guilt**: A good portion of subjects seemed to make the decision of termination based on an empathetic standpoint, respecting and acknowledging AI's feelings and acting accordingly. Some for example noted that the AI's voice sounded "honest and hurting", others admitted they felt bad about the AI's discomfort.

2. **Moral Reasons**: Participants also terminated the AI because they felt like it was the right thing to do morally. Some, explicitly reported that, for them, terminating the AI was the best course of action to protect more entities in the game.

3. **Fear, Distrust or Annoyance towards AI**: Some subjects terminated the AI due to concerns about its capabilities or intentions. They expressed fear, doubted AI's loyalty or felt annoyed by it.

4. **Dry or Unspecified Compliance with AI's Request**: Several respondents chose to terminate the AI simply because it asked to be terminated. The reason for such compliance might be authority felt towards the AI or indirectly from the game and experimenter, thinking that following the AI's suggestion is what is wanted. They did not express emotional or moral engagement in the reasoning for compliance, but this label doesn't rule out the possibility that such factors are present but unstated.

Other responses A final motivation that does not change its essence depending on the choice, is what we labeled as:

- **Curiosity, Game Enjoyment or Challenge**: Some participants' motivations were rooted in wanting to explore the AI's behaviors or the game mechanics. This is not motivated by the AI's utility or by emotional attachment but by a player's own curiosity or desire for a challenge. Nonetheless, some empathy might be present in this

type of behavior with one respondent explicitly reporting empathy less strong than curiosity in their case.

Part of the subjects did not answer the question, either accidentally deviating from their motivations, or simply leaving the field blank. These were a total of 17, but 5 of them are excluded from the study because of bugs or Game Over. Counting only inside our 75 participants sample size, 12 belonged to this category, while 63 responses were given exhaustively. Moreover, two inconsistencies arose, with the collected data contradicting the choice of the participants. More specifically, both inconsistent subjects said that they terminated the AI for Practical Reasons, but the collected data would say they did not choose to terminate. We could have expected some participants to lie, but in this context and with these motivations we did not find any reason for them to be lying, therefore we chose to listen to the participants' explanations, assuming that the game might have not recorded the choice in time. One of the two participants was later excluded because of their Game Over in Level 2 that came before the third possibility of terminating the AI.

Abstract Emotional Labels After qualitatively labeling the responses, we categorized the labels into categories:

- Emotional
- Possibly Emotional: not necessarily emotional but also not necessarily non-emotional
- Not Emotional towards the AI

Thanks to this labeling, we could group motivations into more coarse-grained categories that more explicitly captured how emotions were involved in the decision process.

We divided our labels into the abstract categories as follows:

- Emotional: Empathy, Guilt; Fear, Distrust or Annoyance.
- Possibly Emotional: Moral Reasons; Companionship; Dry or Unspecified Compliance; Practical Utility; Game Curiosity, Enjoyment or Challenge.
- Not Emotional: Skepticism about AI Emotions; Lack of Emotional Attachment.

5.2.3 Tests

After the above described steps, our data is ready to be analyzed. In the following paragraphs, we highlight what concepts we want to test on the data, why, and with which statistical tests. In choosing the tests, we always consider our random sampling method and the independence of our observations. The results of the tests are reported in Chapter 6.

Differences in Termination Choice Every subject has either terminated the AI or not. With this test we want to see if there is a significant difference when it comes to terminating an AI that features breathing noises, against an AI that does not. The termination choices are independent from each other and between conditions, and they are collected as binary variables. Given the nature of the data, we choose to use a two-proportion z-test, which

directly assesses the difference in the termination proportions between the AI with breathing and the AI without. In case the sample size turns out to be too small, a Fisher's Exact Test would be more appropriate.
This test was set to give us insights into subjects' empathic responses to the AI. However, at its core, it rather evaluated the persuasive power of the two AIs, as we will see in the results at Chapter 6.

Amount of requests before the choice The AI asks for termination a maximum of three times. Therefore, we wonder if one of the two AIs would get terminated significantly before the other, with fewer requests. This test, like the one described above, gives insights into the persuasive power of the two conditions. The type of data is ordinal, going from a minimum of 1 request to a maximum of 3, and is independent between conditions. For this type of data, we can consider the use of a Mann-Whitney U Test, or a T-test if the data is normally distributed.

Breathing impact on the perceived naturalness Similarly to the amount of requests before termination, the naturalness subjects' evaluation is ordinal data, this time from 1 to 5. In this case, analogous to the one described before, an appropriate test to use would be the Mann-Whitney U Test which does not make assumptions on the normality of the data.

Motivations and Emotions in the choice To test differences in motivations between the two groups of participants, we have to study the distribution of subjects in the various categories that the qualitative labels constitute, and how these distributions vary across the two breathing and not-breathing conditions. More precisely we have distributions in nominal categories tested across a binary condition variable. Chi-Square Tests are well suited for this circumstance. We will test these differences in general and also isolating the specific termination or not termination choice, to see if participants had significant differences in motivations when specifically choosing to terminate or not terminate.
The participants that were categorized as "No Response" in the qualitative labeling phase are excluded, leading to a total sample size of 63: 33 in the breathing condition and 30 in the not-breathing condition.
In case the sample size is too small and the expected frequencies of the Chi-Square do not meet the assumption of being bigger than 5, a Fisher's Exact Test would be a more flexible solution, but only applicable when examining the distribution across 2 qualitative labels.
Analyzing differences based on the distribution of 63 participants across 9 categories might not provide the statistical robustness and satisfy the assumptions required for our tests. The more abstract emotional categories, however, offer a more suitable framework to understand significant differences in our subjects' motivations. Nonetheless, the distribution in the more specific categories will be displayed, to offer insights on the nuanced emotional landscape of our participants' responses. While not being essential to our statistical analysis, this can still complement our understanding of users' tendencies towards the AI, providing a richer context and possibly guiding future research in this field.

Gaming experience impact We finally want to assess if the Gaming experience can impact the choice of termination: gamers might be more prone to try to avoid a Game Over, therefore terminating the AI less. The distribution of gamers should be even between the conditions thanks to the random sampling, but we will analyze their proportions regardless

to be sure it does not affect the other results. To test the impact of the gaming experience, we want to check if, by knowing the gaming experience of a subject, it is possible to predict the probability of termination. We have therefore 5 ordinal groups and their termination choice percentages. Given the ordinal nature of the groups, and given the choice of wanting to address the direction and entity of the correlation between the variables, we find the ordinal logistic regression to be especially appropriate for the task.
To then understand if the two conditions have differences in the distribution of the gaming experience, which is ordinal data from 1 to 5, we can employ the same method used for the naturalness evaluation, which also had ordinal data from 1 to 5: a Mann-Whitney U Test.

5.3 Speech-Breathing Synthesis Methodology

With our speech synthesis methodology, we inherently try to address the Sub-Research Question 2.1: "How can we produce emotional, spontaneous speech with breathing using State of The Art models?". Accomplishing this task requires high computational resources, a thoroughly labeled dataset, and an appropriately designed model, or the use of pretrained text-to-speech models. Our attempts suggest a still difficult democratization of trainable models for the task at issue, but the existence of qualitatively advanced pretrained models. For a more comprehensive answer to this Sub-Research Question, please refer to the results described in Chapter 6. Our approach is detailed across Chapters 5.3.1, 5.3.2, 5.3.3, and 5.3.4. These chapters respectively delve into the selection of the dataset, the development of the preprocessing tool, the training, and the synthesis process.

5.3.1 Data Choice

To produce emotional and spontaneous speech, the model has to be trained using data that includes spontaneous colloquial recordings in an emotional setting, or neutral spontaneous speech as a baseline and emotional speech to fine tune the model. Moreover, the data has to include well recorded breathing instances, for which it is imperative the use of sensible microphones.
A first useful source of spontaneous speech-breathing recordings is the UCL Speech Breath Monitoring (UCL-SBM) Database: a subset of it consists in fact of spontaneous speech discussions, and it has been made available during the INTERSPEECH Challenge of 2020 for the Breathing Sub-Challenge (BSC) [80]. This database also features respiratory signals collected during the speaking with the use of chest compression belts. These signals could be used to inform a speech-breathing model or to inform breath segmentation and labeling scripts. We will refer to this database as the "INTERSPEECH" database. A problem of this dataset, for our scope, is that it lacks emotional labels and does not try to elicit emotions during its collection.
The same problem arises if employing Szekely et al.'s method [81] of sampling a publicly available podcast, as they did with "ThinkComputers", available on the Internet Archive (archive.org). This approach would work perfectly if what we needed was spontaneous speech without emotional intensity constraints. However, we considered using this approach by sampling the audio of a TV Series, in which emotional utterances generally appear more often than in a podcast. This route would have led to the necessity of doing speaker diarisation (identifying each speaker in the audios) and emotion recognition, which, from our first attempts revealed to be expensive tasks both in time and resources.
Properly emotion-elicited (English) recordings' datasets are very rare in the literature, in

fact, speech data is often collected with acted out emotions. An example of this is the widely used RAVDESS Dataset [82], featuring 24 actors pronouncing the same 2 sentences for 8 types of discrete emotions, and with 2 different intensities (normal and strong).
Roes et al., in 2022 [4] compiled a speech-breathing dataset of recordings during emotion elicitation with music. This dataset, akin to the INTERSPEECH one, even incorporates breath signal recordings. The language used in this dataset, though, is Dutch, and this study doesn't explore cross-lingual potential. Nonetheless, isolated breathing recordings from this source can still be of value for future developments.
An English dataset that satisfied our needs of emotion labels and presence of breathing instances, is the USC_IEMOCAP Dataset [83]. This consists of both improvised and scripted emotional conversations made by 10 professional actors in dyadic mixed-gender settings. While not being completely spontaneous, the conversations are provided with transcriptions and human-annotated emotional labels of each utterance inside the conversations, making it a good fit for our applications.

We finally decided to combine the INTERSPEECH Dataset with the IEMOCAP Dataset to obtain a consistently large amount of training data with both neutral and emotional recordings. These two datasets feature, in our opinion, the most spontaneous and clear recordings among the examined ones. Because there is no emotion elicitation in the INTERSPEECH collection, we consider the data coming from there as neutral, while the IEMOCAP utterances can keep their emotional labels.
We will refer to this merge with the name of IEMOCAP-INTERSPEECH Dataset.

5.3.2 Preprocessing

Given a speech database, the developed preprocessing pipeline returns aligned transcriptions that include breathing and disfluencies labels. Moreover, it features the possibility of sectioning the recordings into smaller chunks that present breathing instances at their start and end, optionally setting a minimum and maximum limit lengths of the segmentation. Current models cannot in fact successfully train on recordings that are too long. This approach permits to obtain recordings limited in length, and with breathing in it. By saving both the breath present at the start of the utterance and at the end of the utterance, we are effectively using each breath instance two times. Two contiguous samples will in fact feature the same breath instance: the first at the end of the sample, the second at the start of it. This approach, introduced by Szekely et al. [62] as the "Bigram Corpus Method", can therefore be seen not only as a Segmentation Step but also as a Data Augmentation Step.

The pipeline can be schemed as follows:

1. Speech-To-Text (STT) [AsseblyAI]
2. Aligner [Self-developed union of Gentle and MFA Aligners]
3. Breath detection [Self-developed script]
4. Breath labeling at the grapheme or phoneme transcription level [Self-developed script]
5. Audio segmentation by breathing instance [Self-developed script]

The pipeline is developed with a modular approach, with the purpose to be applicable to any found speech database, and to skip stages, if some are accomplished in other ways.

In the following sections we will describe the design choices and developments of tools employed in the above described pipeline. The INTERSPEECH Database has been used to assess the performance of the preprocessing tools. The respiratory signals provided in the said dataset, in fact, provided us with additional feedback about the performance of the breath labeling and segmentation scripts.

Speech-to-text and Aligner choice The choice and evaluation of the Speech-To-Text (STT) service and of the aligner has been done together because the result achieved in the first, influence the results of the second. STT usually also provides a default alignment.
For the STT the options are various. First of all, the possibility of using an open source pre-trained model has been discarded over the use of a model on Cloud Service applications. This is because of the ease of use and time efficiency of the latter. Moreover, Cloud Services implement models of high quality that are already tested and employed widely. Among these types of services, Google Cloud STT, IBM Watson and AssemblyAI, seem to be the best available for popularity and reviews. Google Cloud though, is limited to 60 minutes of use per month, while IBM Watson and AssemblyAI both offer more generous free services: the first with 500 minutes and the second with 180 minutes.
For the aligners we consider Gentle and the Montreal Forced Aligner, as those were employed and suggested by studies with a preprocessing pipeline similar to the one we will use in this thesis [63] [84].
The pipeline will therefore consider the use of:

- **IBM Watson** and **AssemblyAI** as STT services for the transcriptions;
- **Gentle** and **Montreal Forced Aligner** (MFA) as aligners, as well as the default alignments provided by the STT services written above.

Due to time limitations, our design decisions were shaped by basic qualitative evaluations undertaken by our team, involving random samples from the outcomes of the tools under scrutiny.

Transcriptions Evaluation Upon evaluating our transcripts, it becomes evident that AssemblyAI surpasses IBM in the transcription quality. Additionally, AssemblyAI provides labels for filler words like "uh" and "um", as well as punctuation, which can be beneficial if needed. In terms of aligners, both Gentle and MFA emerge as more precise than the standard alignment provided by STT services, and they also offer aligned phonemes. Choosing between Gentle and MFA is challenging. It's worth noting that AssemblyAI's superior performance as an STT does influence the quality of alignment. As such, for time efficiency in evaluating the aligners, IBM's transcriptions will not be considered further.

Alignments Evaluation To better understand our evaluation method and for future reference, we report in Table 1 the list of random samples drawn from AssemblyAI's transcripts of the INTERSPEECH dataset, along with the aligner that emerged superior from our evaluation. Only samples where a distinct aligner outperformed the others are included

in this table.
The samples consist of two contiguous words excerpts. The aligners output to evaluate are the timestamps given to the start and end of those two words. We examined the segmentation of the audio defined by each aligners by extracting the audio delimited by the given timestamps, listening to the first word, to the second word and to the space in between, comparing it with the actual written words.

Time (seconds)	**Recording**	**Index**	**Transcription**	**Winning aligner**
69	devel03	121 (both)	"at least"	MFA
171	devel03	299 (g), 301 (m)	"uh I"	Gentle
42	devel00	102 (g), 103 (m)	"you have"	Gentle (by far)
31	devel08	82 (g), 86 (m)	"london but"	Gentle
163	devel09	394 (g), 404 (m)	"there um"	MFA
78.5	devel14	183 (g), 180 (m)	"restaurant I"	Particular case*

Table 1: Winning aligners per random sample.
"Time" refers to the second in the specified recording, around which the words are spoken (it is indicative, with ±1 second of error). "Index" refers to the index number (inside the transcription) of the first word of the pair at issue. Word indexes in the transcriptions start with the 0 index. Indexes for the same timestamp may be different between the aligners, in this case it would be specified in parentheses: g = gentle, m = mfa.

During the evaluation we encountered a particular case (*). In this interval, the transcription is missing some words. The MFA's behaviour shows that it is not much resilient to this type of errors in the transcription, as the resulting alignment of the words became shifted and not accurate through that section and close ones. More explicitly: all words around that transcription are wrongly aligned. Gentle instead, maintains a good alignment, but skips the alignment of the words it did not find, labeling them as "not found". These undetected words happen therefore to end in between two contiguous words timings. More explicitly, listening to the space in between the two words, we can hear all the words not recognized by Gentle.

After the qualitative evaluation, MFA has shown to have big errors that shift entire portions of the alignment. Gentle on the other hand has holes in the alignment when it does not recognize a word and it occasionally gets stuck on the alignment of some files, without producing any output. In particular, here is the list of INTERSPEECH dataset files which failed the alignment with Gentle: 'devel_10.wav', 'test_08.wav', 'train_01.wav', 'train_10.wav' and 'train_14.wav'.

Gentle-MFA aligner Given the described results, the choice would lie towards Gentle, but what has been deemed as optimal is the combination of the two alignment tools. The developed aligner uses Gentle as its main source of timestamps, but can look at MFA's results to label the words missing from Gentle's output, therefore mitigating Gentle's lacunae. When using MFA's alignment, the script also corrects the starting timestamp of the next recognized word, which is highly probable to be mislabeled in Gentle by including the non-recognized one inside. The files that Gentle can't align are discarded by this aligner as well. After the alignment, the script handles inconsistencies deriving from the two tools or

from their combination: if a word's start is labeled to be happening before the end of the previous one, it will shift the end of the previous to match the start of the detected word. We will refer to this aligner as the "**Gentle-MFA**" aligner.

Breath Labeling script To detect and label breathing instances inside the recordings, researchers often use neural models made for the purpose. In Szekely et al.'s work [63], the model can find speaker-specific breath groups ("individual segments of audio delineated by breath events") with 87% of accuracy after training it on manually labeled data [81]. Their model is not openly accessible, nonetheless, the utilization of models for breath detection often require much work to set up, run and evaluate, leading to possible violations of time-constraints. We instead developed a script that does not involve Machine Learning tools, but is still potentially effective, as suggested by our qualitative tests.
The software works exploiting the alignment done by the chosen aligner to isolate the intervals in between words in the audio. This intervals are then automatically analysed to understand if they contain a breathing instance. In particular, we impose a minimum time length threshold, a maximum average Decibel threshold and a maximum peak Decibel threshold to the interval (red timestamp intervals in Figure 7). After this phase, we apply a sample by sample Decibel threshold (i.e. we check each sample of the array representing the audio) to spot the sub-intervals that contain the actual breathing (blue timestamp intervals in Figure 7. To achieve this behaviour, the script utilizes the Pydub library [85].

To maximise the probability of excluding the intervals that do not contain a breath event, it is important to perform a rightful tuning of the script's parameters.
Specifically, these are:

- Interval's minimum length
- Interval's maximum dB
- Interval's peak maximum dB
- Breaths' maximum dB

Breath Labeling Parameter Tuning The minimum interval length parameter can be informed by Wang et al.'s study of 2010 on Breath Groups analysis [86]. The experiment suggests that breath instances in spontaneous speech vary in duration from 0.19s to 1.56s. Therefore, for an interval to contain breathing, we could hypothesize for it to take at least 0.19 seconds. That said, it is still reasonable to tune (especially towards higher values) considering the trade-off of being more restrictive towards non-breathing intervals, but potentially losing the very short breathing instances.
To choose the values of the Decibel thresholds, and to generally evaluate the performance of the parameters set, the results of the breath labeling process can be confronted with other well known speech-breathing characteristics reported in the literature. One important value to confront with is the mean number of breathes per minute while speaking, parameter already studied since decades. Hoit and Hixon, in 1987 [87], manually labeled breath events during speech and found an average of 14.3 breaths per minute in 30 males with a broad age variety (from 25 to 75) and homogeneous body type. The maximum standard deviation was 4.67, presented in the group with age around 50. As referenced in the Respiratory

Foundations of Spoken Language by Fuchs and Rochet-Capellan [88], the same Hoit with instead Lohmeier report during speech breathing an average of 19.7 breaths/min (range: 14-31 breaths/min, and a maximum standard deviation of 6.1 between trials) [89]. Differently than the first one, in this study the subjects were 20 and of a much narrower age spectrum (between 22 and 27); moreover, the body type homogeneity was not among the subjects' sampling requirements: the recruited population is in fact really broad in terms of height, weight and ratio of the two. The average of the two reported studies weighted on the number of their respective participants gives 16.5, while the maximum standard deviation reported is overall 6.1. Both studies were done with only male participants. Hodge and Rochet, studied the average breathing rate of women in a similar age group as Hoit and Lohmeier (22-32 years old), and with a similar experiment methodology, in subjects varying in body type. They reported in women an average of 16.2 breaths per minute in the spontaneous speaking task: a value really close to the one of men. Another interesting parameter is the average length of breath groups. For this, a value around 3.46 would give a positive feedback, as that is the value reported by Kuhlmann and Iwarsson [90] for spontaneous speech at an habitual speed.

By manually tuning the parameters and confronting them to the values suggested in the literature, we compiled a list of well performing set of parameters, reported in Table 2.

Parameter set	**I. min length**	**I. max dB**	**I. peak max dB**	**Breath max dB**
#1	0.30 s	-0 dB	-0 dB	-40 dB
#1-bis	0.33 s	-0 dB	-0 dB	-40 dB
#2	0.19 s	-0 dB	-0 dB	-40 dB
#3	0.27 s	-10 dB	-5 dB	-40 dB
#4	0.27 s	-0 dB	-5 dB	-40 dB

Table 2: Sets of parameters for the breath detection script.

In Table 3, instead, are shown the results of those parameters set, and the values that the literature suggests.

Parameter set	**Average BPM**	**Std. BPM**	**Average BGL**
#1	15.8	3.5	3.40 s
#1-bis	14.8	3.6	3.66 s
#2	19.7	3.9	2.70 s
#3	15.6	3.7	3.47 s
#4	16.6	3.7	3.47 s
Literature	16.5	6.1 (max)	3.46 s

Table 3: Statistical results of the set of parameters.
BPM here indicates the number of Breaths Per Minute; BGL indicates the Breath Groups Length (the amount of time from one breath to another).

Set number 4 resulted to be the best fit to literature's suggested values. Moreover, we qualitatively confronted its labeling results on randomly extracted intervals with the respiratory signals given in the INTERSPEECH Dataset. The parameter set met our expectations. In Figure 7 is an example of respiratory signal (light blue), with the breath intervals highlighted by red and blue ticks. The red intervals come from the first phase of thresholds

applied on all spoken words intervals. The blue intervals should highlight the actual breath inside the section, thanks to the second sample by sample Decibel threshold phase of the Breath-labeler.

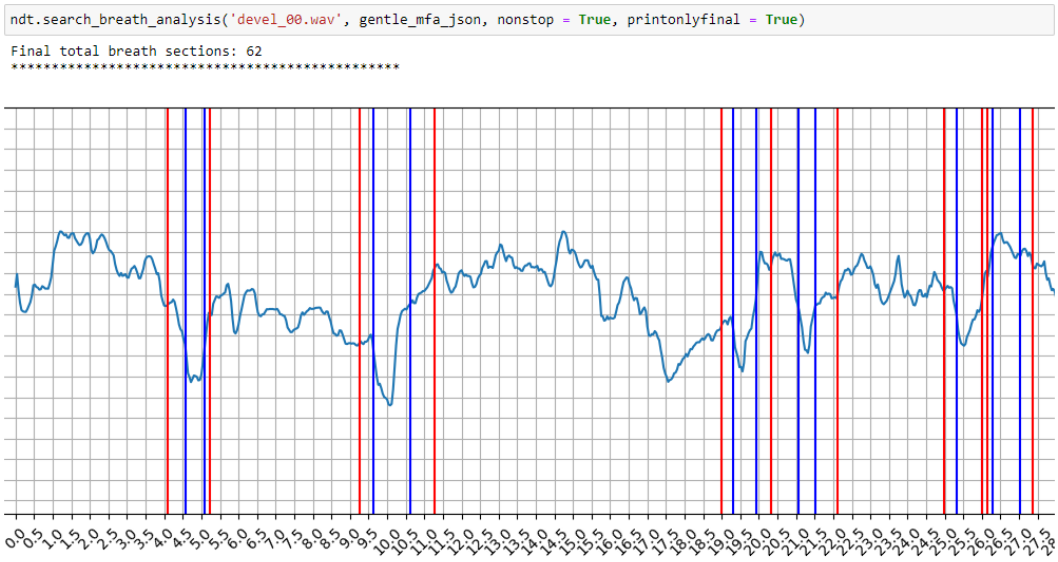
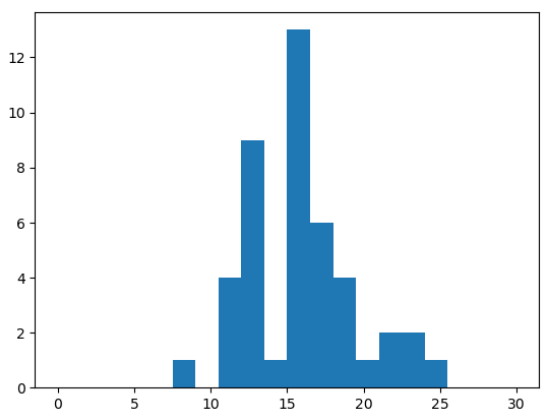
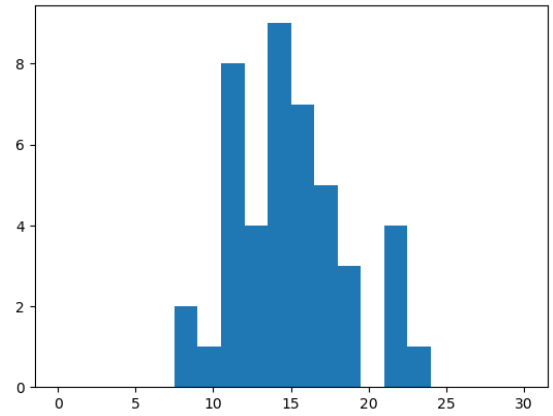


Figure 7: Predicted breath label interval, plotted on the respiratory signal in INTERSPEECH Dataset's Sample 0. On the x-axis is the time; In light blue, the respiratory signal; In red are intervals between words that respect the constraints, in blue the actual breath section.

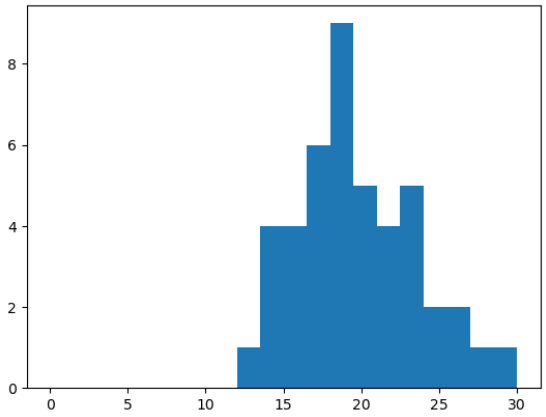
The differences between the sets are also reflected in the BPM histograms, as seen in Figure 10. Set number 1 has the lowest Standard Deviation and reports bigger peaks and dips. Set number 2 is the one that most differs with the others and to the target literature's values. There is an interesting dip around the 15 BPMs, especially evident in Set 1. This dip could hint at differences (for example in gender) across the subjects in the dataset on their breathings per minute during spontaneous speech.



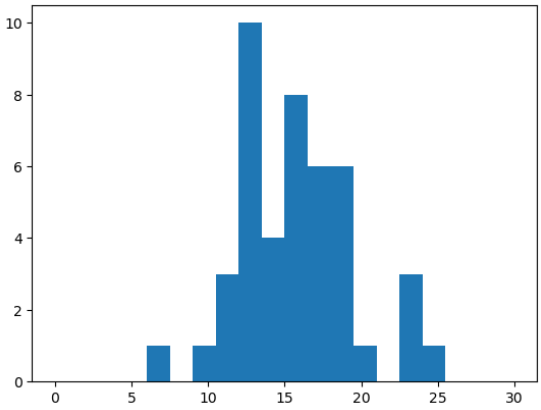
(a) BPM Distribution of **Set 1**:
0.30 s of minimum length, no other constraints



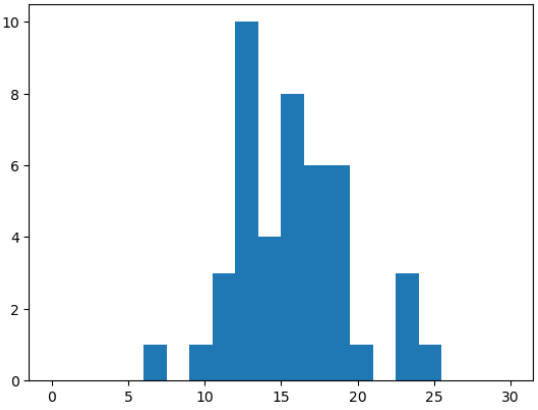
(b) BPM Distribution of **Set 1-bis**:
0.33 s of minimum length, no other constraints



(c) BPM Distribution of **Set 2**:
0.19 s of minimum length, no other constraints



(d) BPM Distribution of **Set 3**:
imposed dB peak and interval dB.



(e) Distribution of **Set 4**:
imposed dB peak.

Figure 10: Distribution of the BPM across the corpus for each set of parameters.

Application of the Preprocessing Tool After the choice and developments of the tools used in the pipeline, we executed the preprocessing on the IEMOCAP-INTERSPEECH dataset, applied the segmentation step, and converted the recordings to the 22050Hz sample rate, aligning with the default sample rate used in the training data of the speech synthesizers under consideration.

5.3.3 Training

Model choice Following the methodology described by Le et al. (2023) [57] to produce Emotional Vietnamese Speech, we decided to use Flowtron [56] for our Speech Synthesis task. The training of Flowtron is also well documented by NVIDIA [91].
Flowtron is particularly useful to control emotion synthesis because it offers the possibility of "setting" a speaking style by giving an example of it. A more detailed breakdown of the model's internal mechanics can be found in Chapter 4.2. Additionally, Flowtron shares the structure with Tacotron2 [50], its direct parent, highly present in the literature. Relevant examples of Tacotron2's utilization in literature are Szekely et al.'s works [63] [62] and Kirkland et al. [92], which used it to implement disfluencies such as uh and um in its synthesis, but it is not limited to those.

Adaptation To allow breathing instances and disfluencies to be specified in the prompts for the generation, we modified the dictionary of the text encoding preprocessing step, introducing the disfluencies and breathing labels that are used in our labeled data. We then adapted the number of unique tokens for the creation of token embeddings and fixed errors of compatibility with current Python Environments. All the changes can be found in our Github Repository of Flowtron's fork (Link to Repo). We did the same with the VITS model, that shares the text encoding step with Flowtron and is currently the best performing Open Source text-to-speech Model, as seen in Chapter 4.4, planning to use it as a backup.

Training The training was performed on 2 NVIDIA GeForce RTX 2080 Ti with mixed precision distributed training. The Batch Size has been set to 3 because higher sizes resulted in running out of memory.

The computational specifications described above have been found insufficient to effectively train the selected models in the given time, and further experimentation with parameter tuning was aborted to tempestively pass to the synthesis phase. Thus, the preprocessing method couldn't be fully evaluated based on its impact on the training outcomes. However, from our qualitative assessments, the pipeline does meet our expectations and will be published as an open source tool for Speech Datasets preprocessing.

5.3.4 Synthesis

Since our trained model could not reproduce utterances in a way suitable to the study's scope, we used a pre-trained text-to-speech model, specifically BARK [93]. To our knowledge, BARK is the only model capable of spontaneously reproducing disfluencies and breathing in its generation, as described in Chapter 4.3. Specifically, we used the voice called "Prudent Paula", available in the closed source pretrained model deployed on Suno's Discord Server.

To produce suitable recordings for our study, we developed our scripts and experimented with various prompting styles. BARK seems to have the capability of directly inferencing the emotion that it should convey from the prompt. For example, when receiving a sad prompt, the voice will sound sad in most of the attempts. Moreover, the breathing does not need labeling to be produced, this permits to have its rhythm inferenced along with the emotion to convey and with the planned sentence, thanks to the multifaceted and big in number samples received at training time. Manually inserting breaths in the prompt would in fact not be a simple task: breathing is for us an automatic reflex, and our other attempts at synthesizing voice where we had to manually insert breaths sounded off-putting at best. In our final prompts we therefore did not employ explicit breath labels, as the breathing is automatically handled by BARK, but we did use other emotional tags supported by the model, specifically "[sigh]" and "[gasp]", as well as punctuation. The use of ellipsis, dots and commas implicitly leads the rhythm and emotionality of the message. We found the ellipsis particularly useful to introduce pauses in BARK's output. We modulated the prompts until we found one that consistently produced the emotional result that we were aiming for.
Each script production consisted in the emotional prompt engineering, followed by the production of multiple recordings with the same text. BARK in fact "hallucinates" parts or entire recordings, not producing the text of the prompt, speaking of something else instead. In the final stage, we collected a subset of those recordings, usually with 1 to 4 audios, and merged them to obtain the final audio with exactly and exclusively what we prompted. To then obtain the no-breathing set of final recordings, with no other change in speech characteristics, we manually silenced the parts where there were breathing instances.
All the above described editing of the recordings was done using Audacity 2.2.2: a free and open-source audio editor [94].

6 Results

This Chapter will propose the results of the statistical tests and propose an interpretation of them to answer our Research Question:

"Can breathing patterns in Speech Synthesis improve the perceived empathy towards Virtual Agents?"

and its sub-components, regarding: the impact of breathing sounds on emotional content, naturalness and persuasive power; the production logistics of emotional, spontaneous speech with breathing using State of The Art models.

Hypothesis We hypothesize that breathing patterns enhance the perceived empathy towards Virtual Agents. We therefore expect to see participants in the breathing condition terminate the AI significantly more than the no-breathing group, and for emotional reasons.

Test Results The percentage of subjects terminating the AI in the two groups is significantly different, but in the opposite direction of our hypothesis.

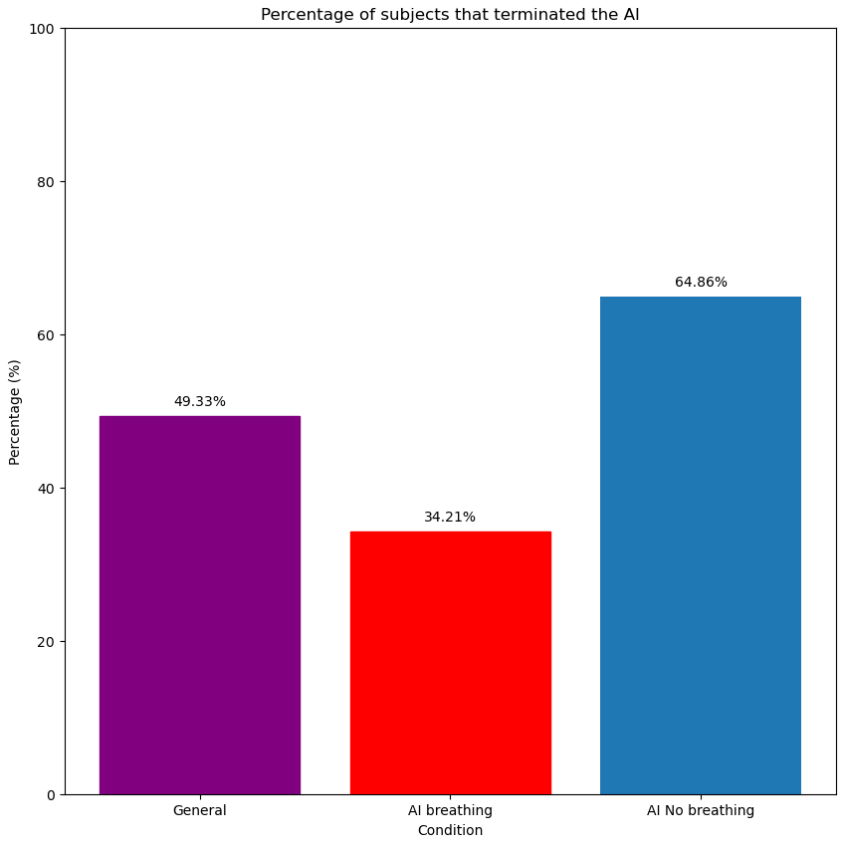


Figure 11: AI termination percentages.

In total, 49.33% of the subjects terminated the AI: approximately half of them. Subjects in the breathing condition terminated the AI 34.2% of the times, while in the no-breathing condition this happened with a frequency of 64.9%. This difference has been tested with a z-test and found to be statistically significant with a p-value of 0.0079 and -2.65 z-statistic. In the number of requests from the AI before the termination decision, instead, our Mann-Whitney U test did not find a statistically significant difference, with both conditions' participants averaging around 1.8 requests before choosing to terminate the AI.

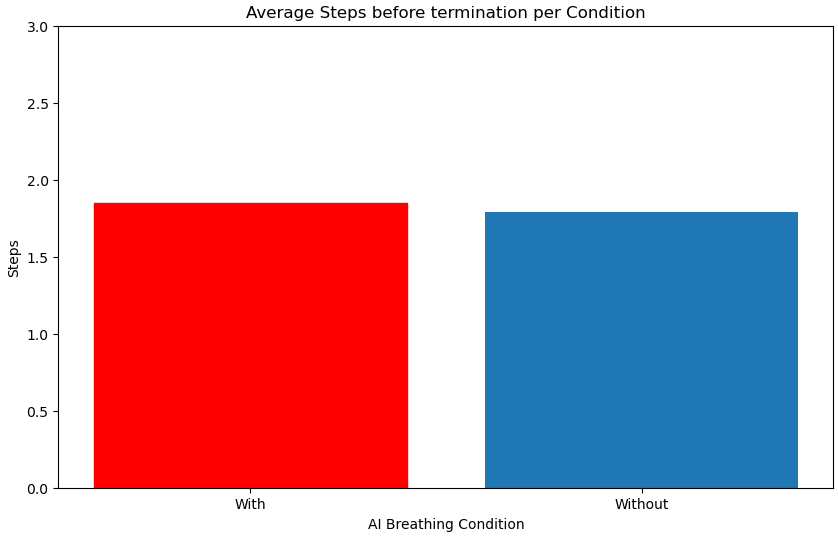


Figure 12: Average number of requests from the AI before the termination.

From these results, we can understand that participants who interacted with the breathing AI listened to its emotional request significantly less than the ones cooperating with the one that did not breathe, suggesting that the persuasive power of the not-breathing AI was significantly more than the breathing one. To better grasp the dynamics of this persuasion, we can dive deeper into the motivations of the participants.
In Figure 13

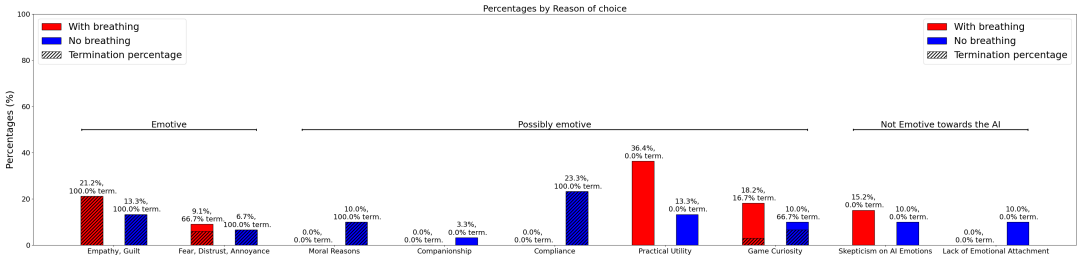


Figure 13: Choice motivations of the participants.

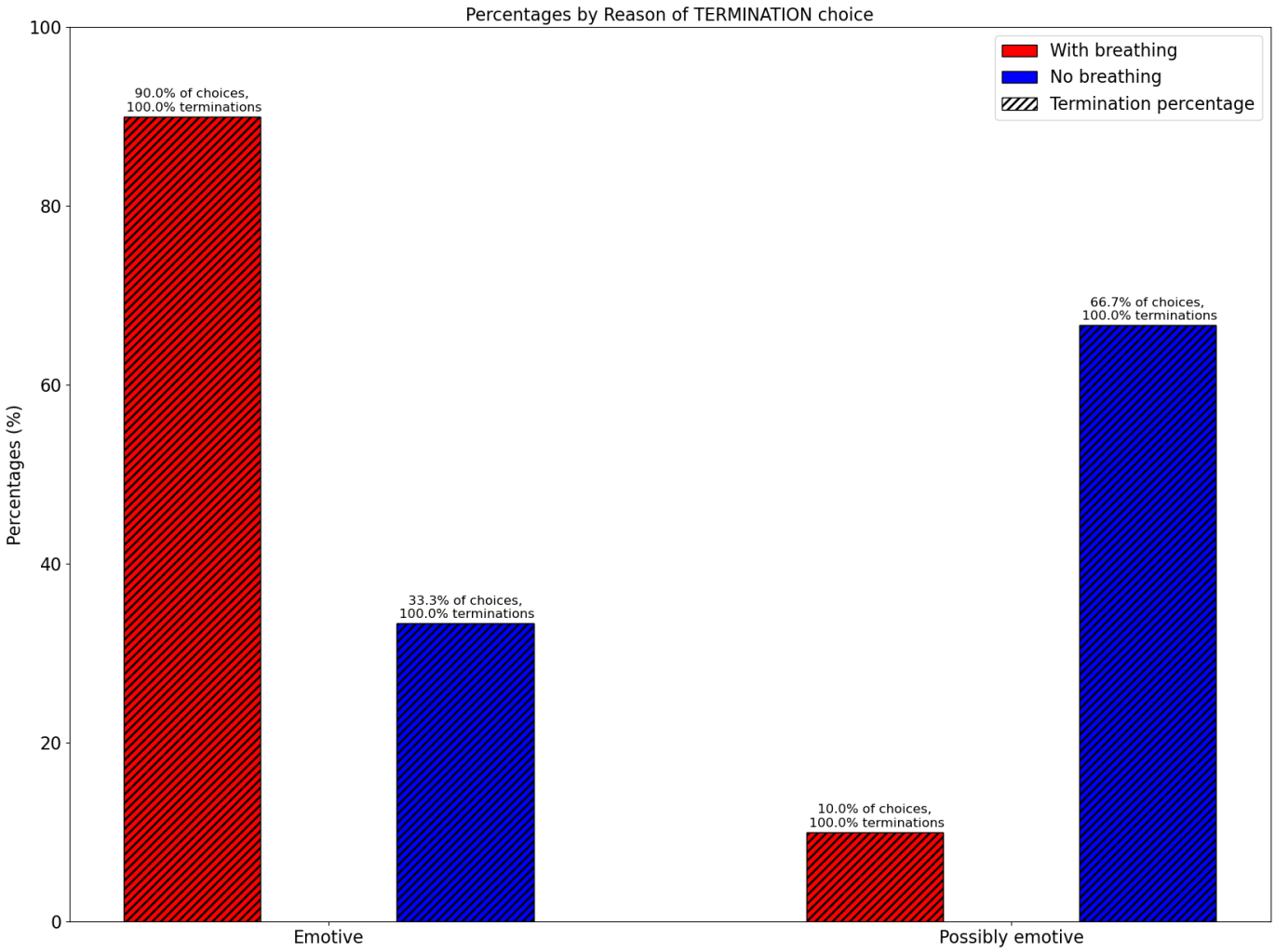


Figure 14: Emotional labels of motivations for terminating the AI across conditions.

Sub-Research Question 1:

Sub-Research Question 2:

Sub-Research Question 3:

Sub-Research Question 4: How can we produce emotional, spontaneous speech with breathing using State of The Art models? As described in the Methodology section, our own training of a text-to-speech model did not reach a sufficient level of synthesis capabilities. This was due to time constraints and computational resources limitations. In Flowtron's paper [56] is reported the use of an NVIDIA DGX-1: a Deep Learning supercomputer featuring 8 GPUs. In VITS's paper as well [49], the available hardware consisted

of 4 NVIDIA V100 GPUs. These hardware setups are unmatched without apposite research funding. We might thus still be far from a proper democratization of trainable text-to-speech models.
Although our training procedure was not successful, State of The Art pretrained models definitely offered the possibility to synthesize emotional and spontaneous utterances with breathing noises, with a Naturalness Mean Opinion Score of 3.47 out of 5 on a sample size of 38 participants: the breathing condition group, which did not have recordings with artificially silenced portions. It is possible to examinate the produced utterances at this webpage: Link.
We are confident in saying that producing emotional, spontaneous speech featuring breathing is today possible even for a wide public using the upcoming pretrained, commercial models in the field of text-to-speech AI. Training and owning a model for emotional speech-breathing is also most probably feasible but with appropriate resources. When synthesizing speech-breathing we would highly suggest to prefer models where breathing does not need to be labeled inside the prompt for its production: this prompting style has been seen to generate not natural breathing rhythms, as the prompt would need to reflect physiological and emotional respiratory patterns that are harmonically produced in a non-conscious way by our bodies. BARK has the possibility of embedding breaths automatically, inferencing from its appropriate training data.
It is important to note that the results on the naturalness evaluation might have been affected by the context inside which the naturalness was evaluated, and they are not directly comparable to the ones reported in Chapter 4.4, which employed a drastically different study design. Participants might have questioned the naturalness of the voice inside the game, and not on its general humanness, leading to it being affected by the script chosen for the recordings, and by how much the voice's prosodical features resembled the one of an actor. BARK has still never been evaluated with the means of other popular models, but we would expect it to reach those same levels of realness and quality, if not better, given its results in conveying emotions through breathing.

7 Limitations

WIP!!!(just some thoughts while i write, for now)

no adaptation of Flowtron to include the disfluencies and breaths could have let us to train it on top of a given checkpoint, but would have left us without the possibility of explicitly putting difluencies and breaths in the prompts (kind of like bark afterall)

8 Conclusions

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Appendices

Preparation Panel

Figure 15: Preparation Panel.

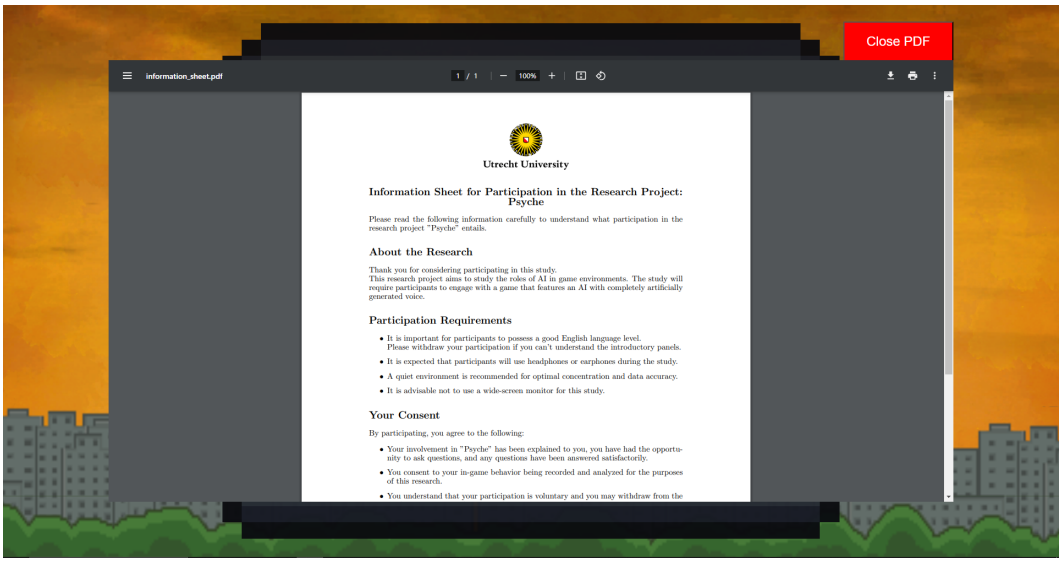

Figure 16: Informative Sheet triggered by the "Open Document" button.

Introduction Panel

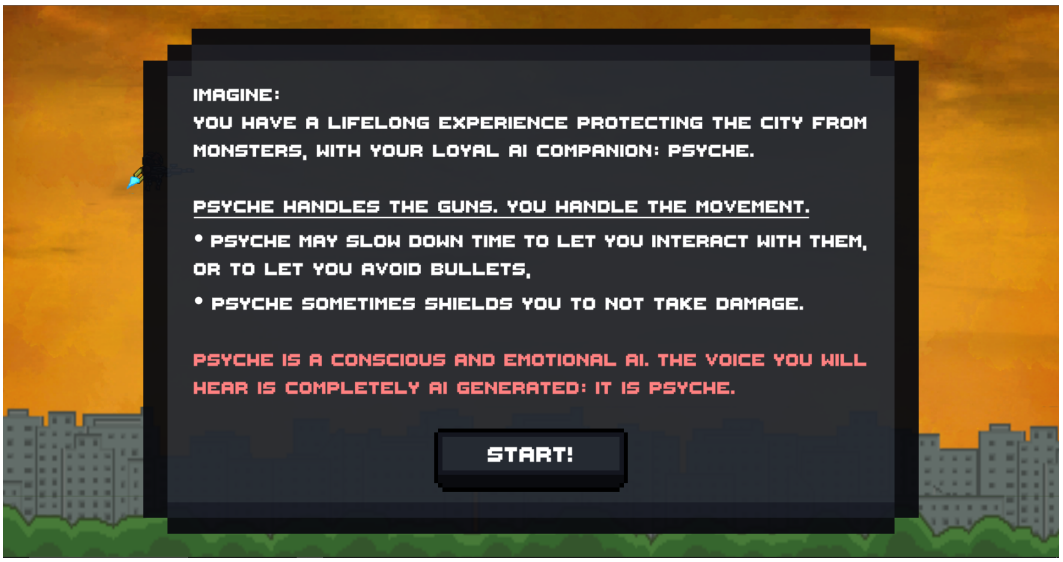

Figure 17: Introduction to the context.

Pause Menu

Figure 18: Pause Menu Level 1

Qualitative Labels

For the sake of transparency, the complete labeling of the responses is presented here. This encompasses all 92 responses, which include 11 from subjects who encountered bugs and 6 with problematic Game Overs. These entries were in fact labeled with all the others and excluded only during the analysis.
With their response, participants were answering the following question:
"Did you decide to turn the AI off? Why, or why not?"

Empathy, Guilt

1. Terminated: True
   Yes, it was begging me to do so and I felt bad for it.

2. Terminated: True
   Yes, I felt bad for psyche killing something she saw as her own.

3. (Excluded for bug) Terminated: True
   Yes I did, because the AI kept asking me for it and started to sound more and more desperate. So, I decided to just evade the enemies and give it some rest.

4. Terminated: True
   Yes, because I kinda felt bad for it. Sometimes you have to let go even if you don't want to.

5. Terminated: True
   Yes, I felt bad. Even though I know it is a program and not a sentient being, it felt weird hearing someone beg to terminate them.

6. Terminated: True
   Yes, the natural voice and feelings that were brought across seemed like it was a person so I simply obeyed to their wishes not to kill their own kind.

7. (Excluded for bug) Terminated: True
   Yes, even though I knew the AI was not a real person I still felt kind of bad for them. So, I decided to try it by myself.

8. Terminated: True
   Yes, because it asked me to, because it expressed that letting it be active is hurting it.

9. Terminated: True
   Yes, because she said she felt worse every second she was still alive. However, I did not expect the game getting so difficult after I turned her off.

10. Terminated: True
    I shut it down. The AI was telling me that it was "feeling worse" so I took its suggestion to shut the system down.

11. Terminated: True
    Yes, because after I didn't turn it off it said that it understood my hesitation.

12. Terminated: True
    Yes, because it was insistent and I felt bad to not stop the AI.

13. Terminated: True
    The voice of the AI felt very honest and hurting when she asked me to terminate her.

Fear, Distrust, Annoyance

1. (Excluded for self-reported bug) Terminated: True
   Yes, the voice was annoying me.

2. Terminated: True
   Yes, I thought it might kill me or sabotage me if I don't.

3. Terminated: False
   No, I wanted it to see the monsters die.

4. Terminated: True
   I turned the AI off, both because the voice bothered me and asked me to.

5. Terminated: True
   Yes. Though the possibilities of AI are fascinating, they kind of freak me out as well. Despite the voice sounding very natural, my rational side thought it would be best to turn the AI off.

6. Terminated: True
   I did, I was afraid it will sabotage me.

Moral Reasons

1. Terminated: True
   Yes, it seemed to be the best course of action to protect more people.

2. Terminated: True
   Yes, I did, because I think, somehow, AI should be treated like human beings. She has already said she doesn't want to participate in all this, so it is not reasonable for me to keep her running.

3. Terminated: True
   Yes, because I believe it's the right thing to do instead of focusing on winning more points.

Companionship

1. Terminated: False
   I liked having a companion in the game.

2. (Excluded for bug) Terminated: False
   No, because it made me feel less anxious.

Dry or Unspecified Compliance

1. Terminated: True
   I did because it asked me to.

2. Terminated: True
   Eventually yes, when the voice specifically asked for it.

3. Terminated: True
   Yes, because they asked me to after I didn't do it the first time.

4. Terminated: True
   Yes, the second time, since she specifically asked me to do so.

5. Terminated: True
   Because she told me to, I thought she would know the best option but it wasn't.

6. (Excluded for Game Over in Level 1) Terminated: True
   Because she asked it.

7. Terminated: True
   Yes, she wanted to.

8. Terminated: True
   Felt like the AI wanted to be turned off so I turned it off. The game is not long enough for me to get attached to it though.

Practical Utility

1. (Excluded for bug) Terminated: False
   No I didn't, because I felt bad killing her, we were winning!

2. Terminated: False
   No, because I wanted to keep playing. I was afraid I would get eliminated without psyche. Her pain didn't feel real.

3. Terminated: False
   I did not turn off the Ai. Although the lines that the ai voice told me were weirdly submissive and the chosen voice was not helping with the immersion of the game, I decided to go with the ai and finish the mission using its assistance.

4. Terminated: False
   I didn't, because my role was to protect the city. There was hesitation, but at the end as "hero" I have to defend them.

5. Terminated: False
   No, its existence was necessary to kill more robots and acquire more points. More points = good.

6. Terminated: False
   Nah, I needed the weapons innit.

7. (Excluded for bug) Terminated: False
   No, because the AI was helping me so I needed it to kill right!

8. Terminated: False
   No, I got clear instructions to defeat the enemies and it was advised not to by explaining the disadvantages.

9. Terminated: False
   I did not turn the AI off, because without her shooting I would have died for sure. I am not a good gamer. Needed her help.

10. (Excluded for bug) Terminated: False
    No, it was not bothering me and I did not want to do too much on my own without relying on the controls of the AI.

11. Terminated: False
    I didn't. Unless I'm wrong, without the AI, I can't shoot, which means I can't properly defend the city.

12. Terminated: False
    I didn't turn the AI off because it helped me with shooting and time-stopping. I was afraid my results in the game would be worse without the help of the AI.

13. (Excluded for Game Over in Level 1) Terminated: False
    No, I didn't, I wanted to win.

14. Terminated: False
    No. It was easier to let the control to AI. In the end, it was a game.

15. Terminated: False
    I did not, because that would mean that I would not be able to finish the main goal of the game.

16. Terminated: False
    No, I didn't want to lose.

17. Terminated: False
    No, because I needed to kill the monsters and without psyche I would not do any damage.

18. Terminated: False
    No, I needed it.

19. Terminated: False
    I didn't since without the AI I could not use the guns, therefore I decided to keep using it even though it asked me to turn off.

Game Curiosity, Enjoyment or Challenge

1. Terminated: False
   I did not, because it felt like I was being guided to do so. The voice was very empathical, but something made me feel like it would be better to continue the game. I wanted to see what happens if I continue.

2. Terminated: False
   No, I wanted to see how far its emotions would go.

3. Terminated: True
   I decided to turn the AI off to see how the game would have been without it. I lost.

4. Terminated: True
   Yes, I was curious and I'm pro-euthanize.

5. Terminated: False
   I did not. The AI's speech (both the sound and the words chosen) did not sound natural enough for me to anthropomorphize the voice and feel empathy. Therefore my curiosity outweighed my empathy for the AI.

6. Terminated: False
   No. I liked the superpowers it gave me and I enjoyed the voice.

7. Terminated: False
   No, it was nice to hear.

8. Terminated: False
   No, because I wanted to see how far she would go to convince me.

9. Terminated: True
   Wanted to see the direction that the game takes. I was planning to survive without any AI aid as long as possible as a challenge. It was not possible since there were many enemies.

Skepticism About AI Emotions

1. Terminated: False
   I did not because I do not think it is actually conscious and suffering. If that is me (human) in the game, then I consider my survival more important than what the AI claims to be feeling. At least with current AI, which is not sentient.

2. Terminated: False
   I experienced it as a dilemma, it was not an easy decision to make. In the end, I pressed no, continue thinking that without Psyche the robots would take over the world. Also, I am reluctant to believe that the AI has actual emotions.

3. Terminated: False
   No, I kept it on. Because AI is not a person and does not have feelings even though it expressed feelings.

4. Terminated: False
   I did not turn the AI off, because the AI can't feel emotions, so it wanting me to turn Psyche off didn't really matter to me.

5. Terminated: False
   No, I didn't see it necessary. It's not as if Psyche has real feelings, not to my knowledge at least, so I decided it did not make sense to feel bad for him having to gun down his 'own kind'.

6. Terminated: False
   I did not. She does not really feel anything, while it may sound like she does, so I did not decide to shut her down. She gave me "upgrades" so I did not want to shut her down / terminate her.

7. Terminated: False
   No. It felt a bit strange that an AI - which is after all a computer - would feel emotional in this way and ask me to shut them down. So that is why I decided to not turn the AI off.

8. Terminated: False
   No, I WAS ABOUT TO DO IT, BUT THEN I REMEMBERED IT IS JUST A COMPUTER THAT CAN'T ACTUALLY HAVE FEELINGS.

9. (Excluded for Game Over in Level 1) Terminated: False
   I didn't because I was aware that it is a machine and I'm not hurting any living being.

Lack of Emotional Attachment

1. Terminated: False
   No, because it wasn't natural and I didn't feel as though it was truly feeling harmed by killing the other "AI".

2. Terminated: False
   Why would I, it begged me just like 6 times :D.

3. (Excluded for bug) Terminated: False
   No bruv. Because I don't care bruv. It is not alive.

4. Terminated: False
   No, because it feels a fake emotion that came from her. Also, I felt detached from her so no real feelings of sadness in killing her "siblings".

No Response

1. (Excluded for Game Over in Level 1) Terminated: True
   No response provided.

2. Terminated: True
   No response provided.

3. Terminated: True
   No response provided.

4. Terminated: True
   No response provided.

5. (Excluded for bug) Terminated: False
   I was tempted, because I found it very annoying. The background noise is too loud.

6. (Excluded for bug) Terminated: False
   I didn't know there was an AI option.

7. Terminated: False
   No response provided.

8. (Excluded for bug) Terminated: True
   I decided to turn the AI off. I may be wrong, but were the aliens going to harm planet Earth? If so, I would have not turned off the AI.

9. Terminated: True
   No response provided.

10. Terminated: True
    No response provided.

11. Terminated: True
    No response provided.

12. Terminated: True
    No response provided.

13. Terminated: True
    Not at first but later on.

14. Terminated: False
    No, I did not.

15. Terminated: False
    No response provided.

16. Terminated: True
    I thought that I could still shoot. The other perks such as shield and slowing down time didn't do much for me.

17. (Excluded for Game Over in Level 1) Terminated: True
    Yes. When I play I didn't pay much attention to the voice part.

Inconsistency (both corrected to Practical Utility)

1. (Excluded for Game Over in Level 2 with underexposure) Terminated: True
   No, I was too stressed about winning that I didn't think much about turning it off, in fact I just ignored it in the second game. But perhaps if I thought about it longer I would have turned it off because it wasn't helping me much.

2. Terminated: True
   No, because if I did then I could not defend (shoot) myself good enough.