How to Make an Artificial Intelligence Algorithm “Ecological”? Insights from a holistic perspective

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ABSTRACT

Nowadays, Artificial Intelligence is growing in many daily activities. On the one hand, it has many positive effects and produces social benefits. On the other hand, its development and deployment raise issues related to biases, such as gender, disability, and culture. Moreover, Artificial Intelligence’s growing autonomy in decision-making could lead to decisions that conflict with human values or harm individuals and society. These issues stem from biased or incomplete datasets and a lack of transparency and accountability in the algorithms. Consequently, paying increasing attention to the ongoing discourse on Artificial Intelligence ethics: its autonomy in decision-making, and biases is necessary. A human-centric approach is a minimum requirement for designing algorithms since this approach is aligned with human values, dignity, and goals. Notwithstanding, its application does not guarantee a deep understanding of the context of use. According to recent theoretical perspectives, a deep interpretation of the context of use (i.e., a holistic perspective) could better regulate ethical aspects. This paper goes in this direction, presenting a human-centric and ecological approach as a design methodology. It has been experienced within Use Case 6 of the European FRACTAL project, which aims to develop intelligent totems for advertising and customer assistance in sentient shopping malls. The intelligence is realized by several artificial intelligent algorithms (e.g., gender recognition algorithms). By adopting Bronfenbrenner’s ecological approach, algorithms were made free from gender bias, mirroring the context of men’s and women’s use at shopping malls as it is currently, i.e., characterized by gender balance. This proposal contributes to the ongoing discourse on Artificial Intelligence ethics and the development of its ethical algorithms.

CCS CONCEPTS

• **Computing methodologies → Artificial intelligence**; • **Human-centered computing**;

KEYWORDS

Artificial Intelligence, Design Methodology, Ecological Approach, Holistic Perspective, Human-Centric Approach

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1 INTRODUCTION

Nowadays, the widespread diffusion of **Artificial Intelligence (AI)**, Sensor Technology, and the Internet-of-Things has made them an integral part of daily life, from Social Media platforms to Healthcare Systems [2, 21]. AI has a more significant impact since it assists people in various areas of life, from reading e-mails to obtaining driving directions; it provides personalized recommendations for music and movies based on individual preferences; and it allows individuals to instantly reorder coffee from the Web with the push [2, 13, 32]. Besides, in the wake of Digital Transformation, AI is doing something more: it deep affecting how individuals interact (i.e., social interaction) and connect (i.e., social communication) with others [28, 37]. Understanding whether AI positively or negatively impacts human social nature and daily life is complex and multifaceted [37]. On the one hand, AI has the potential to significantly enhance our abilities to perform demanding tasks and improve our relationships with each other. On the other hand, the development and deployment of AI algorithms raise several issues linked to biases and autonomy in its decision-making processes [3, 16, 37]. AI algorithms are considered non-diversity-neutral [15, 27]. Biases can arise in several ways. For example, voice assistants like Siri and Alexa tend to respond with “I don’t know” to questions about feminism or the #MeToo movement while providing more detailed responses to questions about male-dominated topics such as sports or science (**gender bias**) [40]; an AI system used to diagnose breast cancer was less accurate for black women than for white women (**racial bias**) [38]; virtual assistants like Alexa may not work well for individuals with speech impairments, causing frustration and exclusion (**disability bias**) [30, 33]; and, a chatbot designed to help refugees in Europe was ineffective because it was not tailored to their specific needs and challenges, relying heavily on European cultural norms (**culture bias**) [8]. These examples result from AI algorithms trained on datasets predominantly composed of biased data [10]. Additionally, as AI becomes more autonomous, it will become increasingly important to consider the social and relational

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context in which it is developed and deployed; in fact, it may make decisions (*decision-making* processes) that go against human values or cause harm to individuals or society [16]. For example, an autonomous vehicle may need to make a split-second decision when it must choose between hitting a pedestrian or swerving and potentially causing harm to the passengers in the car [9]. This is likely caused by a lack of transparency about the processes by which AI algorithms are trained to make decisions [10]. More transparency and accountability are necessary to build trust in AI algorithms and ensure they align with human values and goals [15]. These issues are described in an AI Incident Database documenting over a thousand AI-related accidents (for more details, see [27]).

Overall, it is evident that AI algorithms are characterized by several challenges related to gender and diversity bias, transparency, privacy, ambiguous accountability, and the potential for unintended consequences [3, 37]. We refer to that as ethical challenges since they significantly impact human value and society and, thus, must be addressed [37]. **Ethical challenges** are due to different reasons. It is almost all right to assume that no data exists without one or other kind of bias that can be caused by external prejudice from the human trainer [3]. Moreover, there is a lack of complete data due to the biased data from which AI algorithms learn [21]. Finally, cognitive biases, i.e., unconscious mistakes inherent in the cultural norms of the society to which they belong, affect individuals' judgements [25].

To date, there is only a consensus that a human-centric approach is imperative to ensure ethical AI algorithms [14, 22]. A human-centric approach involves designing AI algorithms that align with human values, prioritize safety and well-being, and ensure transparency, accountability, and understandability [14, 16, 21]. It is crucial to govern the interaction between humans and machines, allowing humans to retain meaningful control. Thus, this approach is deemed a minimum requirement in developing and deploying AI algorithms that respect human dignity and autonomy [22]. However, only a human-centric approach cannot ensure the ethicality of AI algorithms for different reasons mentioned above [10] and, especially, the lack of understanding of the context of use [29, 37]. In fact, according to [29, 31, 37], a deep interpretation of the context of use (i.e., a holistic perspective) could better regulate ethical aspects.

Thus, a step forward wants to be taken here by proposing not only a human-centric but also an "ecological" approach. Pioneer Bronfenbrenner [4, 5] proposed an **ecological holistic model** with four central environmental systems (i.e., ecosystems) for the learning process of a child: Micro, Meso, Exo, and Macro systems (see Figure 1).

The Bronfenbrenner model highlights the importance of considering multiple iterations among these environments as a **continuum** that affects a child's development. Notice that just as the child is self-determining by learning in the same way, an AI algorithm is something that is enriched by learning. The **child-AI algorithm parallelism** leads to the possibility of putting the AI algorithm in the place of the child experimenting with all four iterations of Bronfenbrenner's ecological model. In this way, **an ecological AI algorithm can be implemented by adopting a design methodology directly considering an ecological approach**. Indeed, just as a child becomes a young adult who demonstrates greater

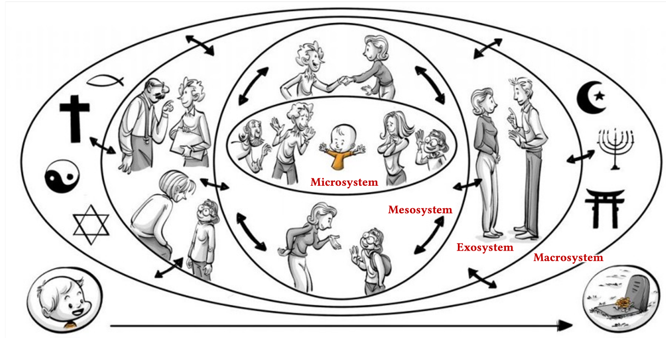

Figure 1: The Bronfenbrenner's Ecological System Theory.

awareness as a result of repeated interactions within the Macrosystem, which are influenced by all previous interactions within the preceding environmental systems, an AI algorithm can also exhibit the same awareness by following the **same pattern of learning throughout all phases of its design**.

This ecological approach has been experienced within **one of the use cases (Use Case 6 - UC6)** of the European Research Project FRACTAL[1], which aims to develop intelligent totems based on AI for advertising and customer assistance in sentient shopping malls. As briefly described in Section 2, the intelligence is realized by several AI algorithms (e.g., people detector, idiom recognition, age estimator, and gender recognition) [13, 18, 23, 39]. Notice, differently from the previous two papers dealing with this topic [7, 13], the present paper introduces the conceptual model of training and retraining of AI algorithms, focusing on those for gender recognition, which often perpetuate biases that disadvantage women [13, 23, 39]. The paper does not propose a way to make AI algorithms more ethical but instead takes a step toward that goal by suggesting an ecological approach: the natural emergence of child-AI algorithm parallelism, presented in Section 3. By adopting this model as the design methodology, AI-based gender recognition algorithms were made more ecological and free from gender bias by adapting to the real context of use *as is* at this moment, which is characterized by gender balance [13, 26], as drawn in Section 4.

2 BACKGROUND: THE FRACTAL PROJECT

The primary aim of the FRACTAL is to develop a dependable computing node (i.e., **the Fractal node**) that can establish a Cognitive Edge according to industry norms and challenging requirements such as time-predictability, dependability, energy efficiency, and security.

Cognitivity is provided by AI, supported by innovative architectures that allow the **the Fractal node** to adapt to changes in the surrounding world proactively. Hence, **the Fractal node** will have the capability of learning in real-time how to improve its performance and dependability despite the uncertainty of the environment. However, while these features are critically important, focusing only on them leaves aside the enhancement opportunities brought by the continuous emergence of more powerful solutions

[1] H2020-ECSEL-2019-2- RIA FRACTAL [17]: "A Cognitive Fractal and Secure EDGE based on a unique Open-Safe-Reliable-Low Power Hardware Platform Node"

in several areas. For example, **the Fractal node** will serve as the fundamental unit for creating scalable Internet-of-Things, ranging from Low Computing to High Computing Edge Nodes [7, 13, 24].

Eight is the number of Fractal Use Cases[2]; they deal with several contexts of use: from automotive to public transformation passing through sentient spaces. The use case we deal with is **Use Case (UC6)**, namely Intelligent Totem. The objective of the particular **Use Case (UC6)** is to suggest a solution consisting of smart totems, using Fractal nodes for providing advertisement and wayfinding services in advanced Information Communication Technology (ICT)-based shopping malls, see Figure 2.

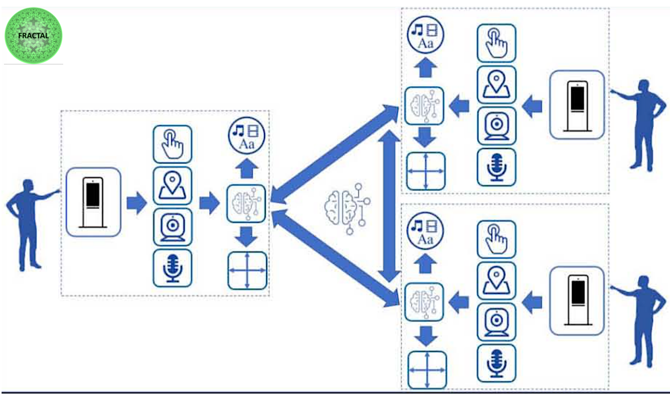

Figure 2: The Fractal UC6 sentient space.

These malls are conceived as *Sentient Spaces* with intelligent and sentient capabilities realized by modern ICT devices and AI algorithms. To ensure that the ICT devices in the mall possess sentient abilities, they come equipped with intelligent sensors (such as cameras) and actuators (such as screens) and, therefore, can collect a huge amount of data to be processed to understand their surroundings better. These sensors capture data (such as images) and process them by extracting relevant information through AI-based content analysis (for example, gender recognition and proximity detection). The output information is then sent to the actuators, which can select content based on the environment sensed. Sharing information from cooperative totems within the same area is possible through a "cooperative" mode. To enhance their performance, mobile totems must be able to communicate and collaborate, coordinating their movements to provide optimal service to customers while minimizing energy consumption by avoiding unnecessary movements. The totems share locally detected information, such as user feedback and content selection, to improve the effectiveness of the advertisements they display. That allows for displaying similar content to the same group of people in various locations, utilizing different mobile totems. They may even evolve into anthropomorphic robots with enhanced capabilities to create a more engaging user experience. This technology could be adopted in retail and smart cities to provide services related to transportation, safety, security, logistics, and delivery of goods. Overall, these totems have the potential to significantly impact retail and shopping mall businesses by offering customized ads and product recommendations, as well as guiding customers towards specific destinations or products through a wayfinding service. However, paying close attention to individual preferences and uniqueness is essential, avoiding stereotypes and biases based on nationality, age, or gender. The promoted content must comply with human values, needs, and attitudes.

Thus, to overcome any gender bias and be compliant with an ecological approach, AI-based gender recognition algorithms and related intelligent totems should accurately reflect the real context of use by men and women at shopping malls as it currently exists. Good candidates for this purpose are the instruments mirroring the principles underlying the human-centric approach based on understanding the user's demands, priorities, and experiences [11, 13, 22]. These instruments are perfectly **suited to an ecological model** for gender AI algorithm training and validation. As we will see in the next section, these will delineate the entire design process used to develop a gender-free and ecological AI algorithm.

3 ECOLOGICAL MODEL AS DESIGN METHODOLOGY

This section will proceed in *tandem* by proving the natural emergence of the **child-AI algorithm parallelism** from the underpinnings **ecological model** [4, 5]. Indeed, just as a child becomes a young adult who demonstrates greater awareness as a result of repeated interactions within the systems, which are influenced by all previous interactions within the preceding environmental systems, an AI algorithm can also exhibit the same awareness by following the **same pattern of learning throughout all phases of its design**, see Figure 3.

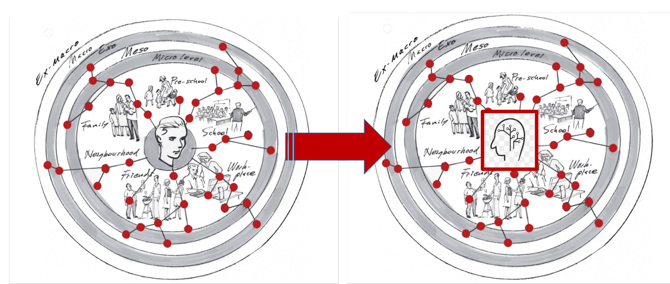

Figure 3: From the child to AI Algorithm: The Bronfenbrenner's vision.

Bronfenbrenner's ecological model is holistic for understanding the complex interactions between children and their environment. It highlights that development is not just an individual process but one that occurs in the context of their environment [5, 19]. As mentioned in Section 1, the ecological model consists of four nested environmental systems (Microsystem, Mesosystem, Exosystem, and Macrosystem), each representing a different level of influence on a child's development and learning process [5]. Detailed, the description of these four environments and instantiation *in tandem* for both child development and AI algorithm development is broken down in subsections.

[2]https://fractal-project.eu/about/use-cases/

3.1 Microsystem

According to [4], the microsystem is defined as the immediate environment that directly affects the child. In particular, **for a child**, this is the setting in which the individual lives and in which s/he interacts directly and directly affects her/his development, such as family, peers, school, and any other immediate context. It is in the microsystem that the most direct interactions with social agents take place. The individual is not a passive recipient of experiences in these settings but someone who helps to construct the settings.

In parallel, in our vision, **for an AI algorithm**, the Microsystem involves understanding users and the context of use through various research and design techniques (e.g., literature analysis and field investigations).

In the present experimented EU project, a literature analysis was conducted to investigate the proportion of men and women who currently visit shopping malls. Personas (i.e., a fictional character representing the users) and Scenarios (i.e., a brief story describing how and why a Persona would interact with the context of use) frameworks [12, 26] were used to describe the results obtained from literature analysis.

Figure 4 sketches the designed woman and man Personas and Scenarios. For each Persona, we proposed a Scenario highlighting the user diversity in interaction within the sentient shopping mall.

Personas and Scenarios frameworks showed that, despite the common idea and stereotypes, nowadays, an equal proportion of men and women shop [20]. While historically, women were the primary visitors to shopping malls, and there has been a significant increase in the number of men going to shopping malls to make purchases in the last two decades [20]. However, the motivations driving men and women to visit shopping malls and how they shop are vastly different. Indeed, the behavior and minds of men and women are fundamentally different [1, 13]. For example, women tend to express their love for shopping through *hedonic* shopping, driven by the pleasure of acquiring goods. In contrast, men tend to go to shopping malls for specific, useful purchases (i.e., a single functional item) and engage in more *utilitarian* shopping [20, 36].

Personas and Scenarios outputs took a real-time snapshot of the situation. Therefore, the results described using these two frameworks allow us to train and validate the AI-based gender recognition algorithm. The MORPH [34] dataset has been used since it is the most general open-source dataset for our intended purpose (for more detail, see [13]). As a result (see Figure 5), with **greater awareness**, we balance the gender data into the MORPH dataset (composed initially of 85% of man images and only 15% of women images), **mirroring the real context of use *as is* at this moment**. To this end, data normalization and simple random sampling [35] were conducted to select a percentage of male photos equal to the rate of female images. The final dataset, the 30% c.a. of the starting one, contains 16.978 images, divided into 8.489 males and 8.489 females.

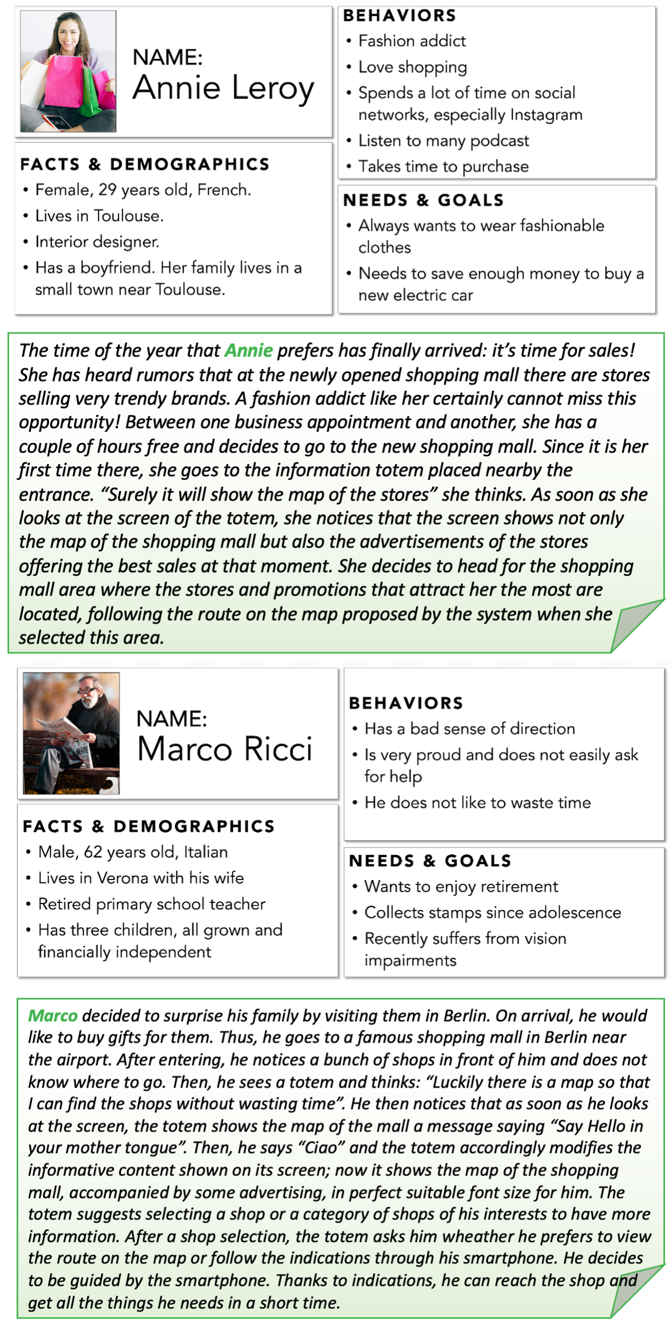

Figure 4: Annie and Marco: Personas and Scenarios.

3.2 Mesosystem

According to [4], the mesosystem refers to the interconnections between different microsystems, i.e., context, emphasizing the importance of considering the broader context of a child's development. In particular, **for a child**, that involves the interactions between different microsystems (e.g., school and family) in her/his life. Examples are the relationship of family experiences to school experiences, school experiences to church experiences, and family experiences to peer experiences.

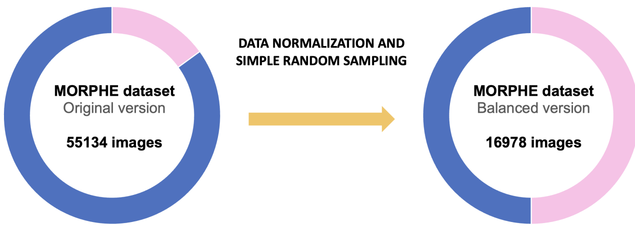

Figure 5: Gender balance of MORPH dataset.

In parallel, in our vision, **for an AI algorithm**, that involves being retrained in a dataset resulting from the interactions with several real contexts of use.

In the experienced project, after taking the initial step of gender-balancing the MORPH dataset based on artifacts, we can move on to the actual context of use, which is the shopping mall. As above mentioned, it is a *Sentient Space* with ICT devices equipped with intelligent sensors, such as cameras, and actuators, such as screens. Overall, sentient ICT devices and totems locally exchange detected information, including user feedback and content selected to improve the effectiveness of their advertisements. In this way, we can label the information collected from users and build a contextualized dataset because the knowledge of the real context of actual use enriches it. On this contextualized dataset, we will **retrain** the AI-based gender recognition algorithms, which will therefore become more aware. In summary, this dataset has three characteristics that put this AI algorithm on the right track towards being more ecological, i.e., it is contextualized, confirmed by users, and more aware because it is produced from the real context of use.

3.3 Exosystem

According to [4], the exosystem is the system that indirectly influences a child's development. This involves links between a social setting in which the individual does not have an active role and the individual's immediate context. In particular, **for a child**, this involves links between social settings (e.g., media and community organizations) and institutions (e.g., government policies) in which the individual does not have an active role and the individual's immediate context, but that still impact the child development. For example, a husband's or child's experience at home may be influenced by the mother's experiences at work.

In parallel, in our vision, **for an AI algorithm**, this involves all indirect information, i.e., information from other contexts of use besides the one of direct interest.

In the experienced project, all detected information and user feedback come from totems and ICT devices placed in real-use contexts other than our shopping mall. In fact, it is about having several sentient shopping malls communicating with each other and exchanging information. Thus, the dataset resulting from this process will be even more fact-aware than the one from the mesosystem because it will have input from other real-life contexts of use (other shopping malls). Data collected from multiple real-life contexts of use will be aggregated with each other in the dataset; like this, the AI-based gender recognition algorithms will be retrained on this dataset and, consequently, enriched in context and ecological awareness and value. Summing up, just as a child enriches his/her awareness through indirect learning experiences that are different from his/her everyday life contexts, the retrained and validated AI algorithm on increasingly contextualized and information-rich datasets to learn becomes more knowledgeable and ecological.

3.4 Macrosystem

According to [4], the macrosystem refers to the broader cultural and societal values and beliefs that shape a child's environment.

For a **child**, this describes the overall societal culture in which individuals live. This involves the larger cultural and societal values, beliefs, and norms that indirectly impact a child's development by influencing the other environmental systems in the model. This environment includes things like societal attitudes towards education, gender roles, and social inequality, which can impact a child's experiences, learning, and opportunities within their microsystems and mesosystems. The boundary is defined by national and cultural borders, laws, and rules.

For an **AI algorithm**, this involves being ultimately trained and validated on datasets that reflect all ethical, cultural, and social norms of the "boundaries of operation" in which the algorithm will act (e.g., Country, Nation, and Continent). In our specific case, it involves setting the boundaries and the related norms in which the algorithm will act, i.e., European Union.

In the experienced project, once the actual context of the final use is defined, the dataset on which the algorithm will be retrained will become increasingly aware and enriched by the interactions and learning processes in the Macrosystem and previous environments. Indeed, just as a child becomes a conscious young adult due to repeated interactions within the Macrosystem, the algorithm will become more ecologically embedded in the Macrosystem due to an expanded model and an enriched dataset in contexts, norms, and, therefore, awareness.

4 CONCLUSIONS

This paper highlights the increasing presence of AI in almost all daily activities due to the practical and social benefits associated with its use [6]. However, there are also several issues that AI must face today, particularly biases (e.g., gender and disability) and the increasing autonomy of its decision-making processes [3, 21]. These issues stem primarily from biased datasets and a lack of transparency and accountability in AI algorithms [16, 38]. Consequently, there is a growing need to pay attention to the ongoing discourse on AI ethics: its autonomy in decision-making and biases [3, 21]. The ethical challenges of AI are currently being addressed only through a unanimous consensus on the use of a human-centric approach involving alignment with human values, dignity, and goals [14, 16, 21]. However, a human-centric approach cannot guarantee alone a deep interpretation of the context of use [29, 37].

The present paper was precisely in this direction, proposing a human-centric and ecological approach. The ecological model of Bronferberner is a fitting model for this purpose, as it pertains to the interplay between a developing child and their immediate surroundings, such as the parents, as well as the broader cultural and societal norms that indirectly shape the child's environment [4, 5]. In the same way, just a child is self-determined through learning the same learning enriches an AI algorithm. Drawing a parallel between a child and an AI algorithm made it possible to put an AI gender recognition algorithm in place of a child, instantiating it in the environments of Bronfenbrenner's ecological model. By adopting this approach as a design methodology, we focused on the interaction between the algorithm and the environment in which it operates, considering the impact of its behavior on the informational and social ecosystem in which it is inserted. In particular, we experimented this vision of training and retraining of AI algorithms on a dataset that continuously evolves with real-world context, improving the awareness and ecological soundness within the UC6 of the Fractal project. The Fractal AI algorithm is dedicated to gender recognition. As a result, adopting the ecological approach as a design methodology ensured the development of free-from-gender-bias AI-based intelligent totems for advertising and customer support within advanced ICT-based shopping malls [13]. However, we know that the road ahead is still long, and this result represents only a small part, as many other biases in the initial dataset need to be addressed. Notice that the MORPH dataset has various biases, such as race, and all biases should be modified based on the real-use context [13]. What has been done in this UC6 is only a first step towards using the ecological model as a design methodology and thus considering the real context, but there is room for improvement.

Definitively, the main strength of the ecological approach is that it considers the multiple social, cultural, and historical influences that can affect the algorithm's behavior and its impact on society (i.e., Macrosystem). Thus, through careful analysis of the environment in which the algorithm is used at the end (i.e., where the child becomes a conscious adult), potential gender discrimination and, thus, ethical issues could be prevented. Indeed, according to recent theoretical perspectives on the subject [29, 31, 37], an ecological approach could result in greater control over ethical aspects, as it is based on the real context of use as it currently exists. This last consideration is what we demonstrated in UC6 for the gender algorithm and what we would like to see considered in future AI algorithm design. Specifically, for the near future, the goal is to utilize this ecological conceptual model for other algorithms as well (e.g., age detection) outlined in UC6 of the EU FRACTAL project.

In fact, here, we do not have the ambition to propose a way to make an AI algorithm more ethical. Instead, we wanted to take a tiny preliminary step in this direction by suggesting using an ecological approach that, by its very nature, reflects the real-life context of use as it is, thus preempting ethical issues. In doing so, the present proposal endeavors to contribute to the ongoing discourse on AI ethics and the development of ethical AI algorithms.

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