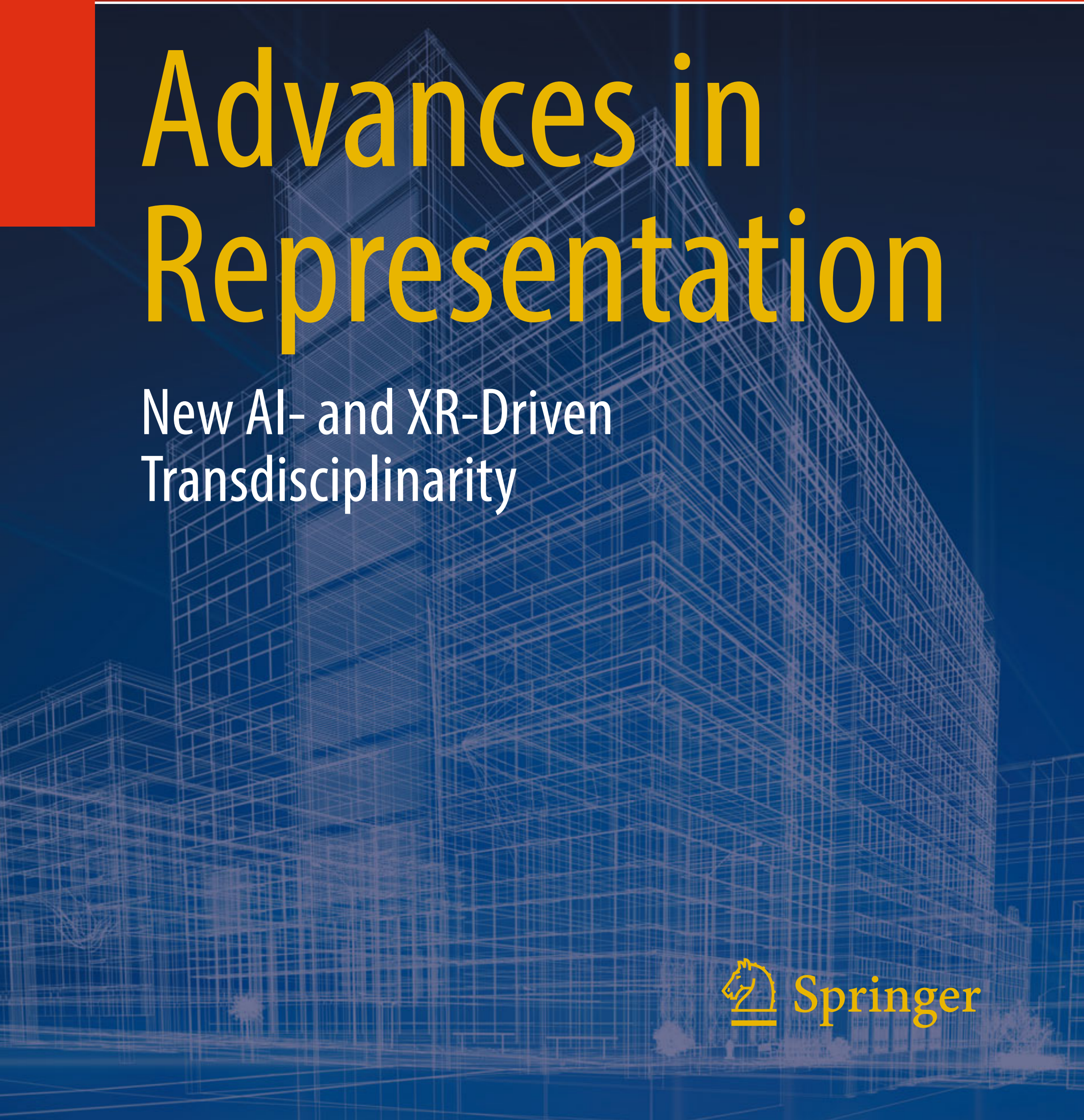
Digital Innovations in Architecture,
Engineering and Construction

Andrea Giordano
Michele Russo
Roberta Spallone *Editors*

Advances in Representation

New AI- and XR-Driven Transdisciplinarity



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Digital Innovations in Architecture, Engineering and Construction

Series Editors

The Architecture, Engineering and Construction (AEC) industry is experiencing an unprecedented transformation from conventional labor-intensive activities to automation using innovative digital technologies and processes. This new paradigm also requires systemic changes focused on social, economic and sustainability aspects. Within the scope of Industry 4.0, digital technologies are a key factor in interconnecting information between the physical built environment and the digital virtual ecosystem. The most advanced virtual ecosystems allow to simulate the built to enable a real-time data-driven decision-making. This Book Series promotes and expedites the dissemination of recent research, advances, and applications in the field of digital innovations in the AEC industry. Topics of interest include but are not limited to:

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- Risk and disaster management.

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Editors

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Foreword

The volume that Andrea Giordano, Michele Russo, and Roberta Spallone are publishing today collects the results of research conducted, as the editors testify, by some 180 scholars from five continents, who collectively or individually present 57 papers, plus two invited papers.

The collection of books dedicated to the advances and challenges of representation disciplines, now in its fourth volume, demonstrates the consolidation of the REAACH association's role as antennae for the extent to which digital methodologies and technologies affecting the discipline in its relations with the design, the built environment, and the heritage appear, disappear, evolve, and transform.

Connected to these developments, different fields of knowledge converge and intertwine from time to time, seamlessly between humanities and hard sciences. It is precisely the dual humanistic and scientific nature of the drawing discipline that acts as a catalyst in this new phase of knowledge reconfiguration around the artificial intelligence revolution. The latter, central to the interests featured in the research presented in this volume, takes the form of an opportunity to see, to borrow Pierluigi Contucci's words, the most fascinating humanistic questions dialoguing amiably with scientific ones (P. Contucci, Rivoluzione Intelligenza Artificiale, 2023, Edizioni Dedalo, Bari, p. 7).

In this sense, the REAACH association's objective of fostering the mutual exchange of knowledge and multidisciplinary research, increasing the network of research interconnections, is continually being updated and attracting new partnerships.

The book offers this varied panorama of knowledge, viewpoints, and internationally relevant case studies, looking ahead to new developments in which the future is already present.

April 2024

Francesca Fatta
UID President

Preface

The volume *Advances in Representation. New AI- and XR-Driven Transdisciplinarity* collects the outcomes of experimental transdisciplinary research carried out by international teams. The discipline of representation emerges as an explorer, inventor, and creator of new methodologies, technologies, and fields of application, catalyzing and promoting unprecedented connections with other knowledge.

The volume we are about to release results from a year-long work. It was a matter of selecting international research that would show the most up-to-date panorama of innovative and experimental research in the field of artificial intelligence (AI) and extended reality (XR) and guiding them through the different stages of double-blind review to the achievement of scientifically validated results.

The contributions have been collected according to eight topics, in which the AI&XR binomial, through the mediation of representation, is experimented in the different fields of heritage, design, and education, articulated in the focus on Historical Sources, Archaeological/Museum Heritage, Heritage Routes, Classification/3D Analysis, Building Information Modeling, Building/City Monitoring, Education, Shape Representation.

Our thanks go to Francesca Fatta, president of the Unione Italiana Disegno (UID), for her advice and constant support during all phases of our work, to Alessandro Luigini, president of the IMG Network, for sharing ideas and insights, to the scientific and review committee, consisting of Marco Giorgio Bevilacqua (University of Pisa), Stefano Brusaporci (University of L'Aquila), Valeria Cera (University of Naples Federico II), Francesca Fatta (Mediterranea University of Reggio Calabria), Alessandro Luigini (Free University of Bozen-Bolzano), Federica Maietti (University of Ferrara), Barbara Ester Adele Piga (Politecnico di Milano), Cettina Santagati (University of Catania), for their proactive proposals, hard work, and continuous support. Special thanks go to Giulia Flenghi and Enrico Pupi for carefully editing this volume.

Finally, our heartfelt thanks go to the scholars who responded to the call rigorously and skillfully, with high-quality contributions that exceeded our expectations.

We hope that their papers will stimulate interest and inspiration for innovative research in readers.

Padua, Italy Andrea Giordano
Rome, Italy Michele Russo
Turin, Italy Roberta Spallone
April 2024

Preface: Introducing the Relationships Between Digital Representation and AR/AI Advanced Experiences

Keywords Digital Representation · AI · XR · Cultural Heritage · Building Design

Introduction

The breadth of interests that emerges around the discipline of Digital Representation linked with Artificial Intelligence (AI) and extended reality (XR) experiences, offering new ways of interacting with the real, coupled with the very rapid development of technologies, tools, and devices, as well as careful monitoring of the disciplines that can be involved, are in the center of the interests for this book. In this sense, the fields of application open to the worlds of tangible and intangible cultural heritage, architectural, environmental, infrastructural, and product design, and education as a place for advanced training and as a tool for educational enhancement.

This collective volume intends to explore, through the lens of the Representation discipline, the research areas that gravitate around AI-XR, opening up new transdisciplinary thinking.

Digital Representation, AI, and XR in Cultural Heritage Domain

In recent years, the intertwining of digital representation with artificial intelligence (AI) and extended reality (XR) advanced experiences is finding a fertile field of application in Cultural Heritage (CH).

The broad concept of Cultural Heritage encompasses those declinations of heritage, tangible and intangible, that comprise the objects of the applications of interest for this volume:

The historical building and artistic goods—mainly referring to the statuary, paintings, artifacts, and tools that populate the anthropized spaces—in their different states of conservation;

The sources documenting the design of the built heritage and artworks, their realization, and transformations;

The routes, connecting the different assets through relationships of meaning that include material and immaterial aspects of heritage.

It is on these thematic bases that the contributions in the three sections mentioned above are articulated, sometimes interweaving AI and XR, some others employing only one or the other, bringing novel and original results to the attention of the international scientific community. The research displayed dialogues with the built environment, whether existing or disappeared; it confronts the historical and archival documentation of the design process and the transformations of artifacts and the urban fabric; it seeks answers to the complex relationships between the remains of settlements and individual monuments of the past and the works and products of man preserved in the collections; and it creates new spatial connections between places, buildings, objects, and documents.

In the field of digital representation for heritage, methodologies of graphic analysis, reconstructive, regressive, interpretative modeling and techniques of geometric, parametric, informative, and algorithmic modeling are relatively well established in terms of theoretical statutes, operating methods, and available hardware and software tools. Conversely, as is well known, the discipline of artificial intelligence is developing rapidly and continuously in application to all fields of knowledge and everyday life. In particular, AI has seen new opportunities offered in the field of cultural heritage aimed at documentation and protection [1], accessibility [2], semantic enrichment of CH images [3], artifact recognition [4], up to the most recent developments of generative AI [5, 6] to feed the field of reconstructive hypotheses in a creative sense.

AI's challenges in analyzing and classifying archaeological heritage [1] can be usefully extended to the broader field of the historical built environment. Indeed, the uses of artificial intelligence in archaeology, i.e., machine learning (ML) and deep learning (DL) algorithms, convolutional neural networks (CNN), and deep learning (DL) models, aimed at distinguishing archaeological remains and detecting changes in them over time to make decisions on appropriate strategies for conservation and protection, are matched by various strategy for monitoring the built environment.

Concerning the issues of cognitive accessibility to heritage, technologies to create and deliver in situ, i.e., in museums and cultural sites, and online experiences can use AI to broaden the scope of enjoyment. One of the most exciting perspectives is the idea expressed in [2] of employing eXplainable AI (or XAI) and Human-Computer Interaction (HCI) as enabling technologies with richer interfaces that adapt to the target audience dynamically. Such developments can be made possible by an interdisciplinary approach involving other disciplines, such as interaction design and pedagogical and participatory design, in the creation of a cultural offer suitable for all.

The semantic enrichment of CH images [3], through the concrete and abstract values, often left unexploited that they include in the cultural, social, economic, and political spheres can profitably make use of AI technologies, such as Computer Vision (CV) and semantic web technologies. With the emergence of new technologies and the availability of cultural heritage images in digital format, methodologies to semantically enrich and utilize these resources provide a new information apparatus, feed knowledge, and generate new connections between artworks and assets that are far apart in space and time.

The use of convolutional neural networks (CNNs) to recognize architectural textures and monuments [4] represents one of the most recent developments in AI that can also be used on mobile devices thanks to the spread of machine learning technologies on them. The use of personal tablets and smartphones for the enjoyment of cultural content, undoubtedly fuelled by the restrictions of the pandemic period, can change the experience of visiting cultural sites by making vast digital collections of text, models, images, and other data accessible in situ.

Similarly, the extended reality (XR) domain—i.e., virtual (VR), augmented (AR), and mixed reality (MR)—in the spatial sciences [7] and, more specifically cultural heritage [8] is rapidly changing the interactions between the real and the virtual, allowing for increasingly articulate and engaging interactions for the public.

As noted, in recent years, the term extended reality (XR) has been used as an umbrella term to encapsulate the entire spectrum of VR, AR, and MR [7], and in some sense, is similar to the well-known reality–virtuality continuum proposed in the seminal work by Milgram e Kishino (1994) [9].

AI and XR are not simply engaged as the last step, that of communication, in the process of analysis, interpretation, modeling, and presentation that constitutes the established workflow of the disciplines of representation with respect to heritage, but shape and transform its methodologies and outcomes at every stage.

Digital Representation, AI, and XR in Shape Analysis and Representation, and Education

AI&XR and Classification/3D Analysis

The subject of AI/XR for data classification and analysis mainly involves digital information obtained from an active or passive 3D survey process. On the acquisition side, research focuses on NeRF-based algorithms that can extract geometric information from images under complex environment conditions and optically uncooperative materials. Besides, applying ML and DL algorithms for semantic classification and segmentation of massive 3D data in terms of logical and hierarchical systematization is aimed at improving data understanding, management, and utilization [10].

Supervised ML machine learning involves increasingly complex datasets, and it will evaluate not only the compositional and textural aspects of the architecture but also the level of uncertainty of the process in both training and results. On the other hand, image datasets allow experimenting with DL algorithms for semantic segmentation [11], providing increasingly articulated answers that can be organized according to knowledge graphs. A final relevant aspect relates to constructing 3D models and communicating surveyed data, mainly based on XR applications. It is fascinating to highlight how such advanced visualization and communication tools are functional in making 3D content interactive and explorable, starting from point clouds at the spatial scale to textured polygonal models at the architectural scale. These digital twins become not only the result of a critical interpretation process but also ground for simulation through virtual sensors for training and monitoring urban areas, extracting predictive data valuable for their management.

AI&XR and Shape Representation

The use of AI and XR for shape representation is not just a tool but a gateway to innovation. Given the breadth of the topic, it leads to general and specific reflections in different application areas. The aspect that disruptively connotes this area is the construction of new content. At the methodological level, great attention is focused on text-to-image generative processes [14]. The emergence and development of increasingly high-performance programs in creating images from text descriptions makes it cogent to understand generative models in depth in order to critically evaluate their use in the different stages of creating and representing a form. Neural networks show great potential, introducing new paradigms in architecture design. The reversal between description and representation opens up scenarios that affect both creative aspects and interpretation, opening up new connections between the existing and the digital imaginary. The application of predictive algorithms to represent architectural shapes that no longer exist stands as a tool to support the iterative process of understanding and interpreting vanished architecture traces. In addition, the same tools can be applied to generating new 3D spaces, unlocking unpredictable spatial relationships, and stimulating design creativity [15]. The connection between the physical and digital realms is found in AI-generated images, which are a valuable opportunity for constructing exhibitions and evolving spaces, fueling the construction of scenarios to support the performing arts. Alongside AI, applying XR techniques for visualization and interaction remains an established practice that is increasingly leaning toward interaction and immersion. In this sense, VR and AR have become fundamental tools for realistic shape prefiguration, feedback collection, and content fruition at industrial, cultural, and museum scales.

AI&XR and Education

The use of AI and XR for educational purposes is not just a trend, but a transformative force finding more and more space within experiments. It highlights the marked propensity for both users and content creators to use new technologies but leaves many questions open [12]. The construction of multimedia itineraries based on augmented and interactive content to unveil the complexity of cultural heritage remains entrenched, offering increasingly engaging and adaptable visit routes to an increasingly heterogeneous audience regarding digital skills. The construction of such content requires combining knowledge in terms of optimized content creation and visual and multimedia communication processes. The rapid development of XR tools to support such pathways also critically reflects their role in heritage communication, considering that teaching applied and serious games are increasingly essential for enhancing Cultural Heritage [13]. From the point of view of architect and engineer curriculum training, AI may increasingly enter disruptively within the flow of parametric modeling and representation, imposing some critical reflections on the conscious use of these tools within a rapidly transforming learning process. In its declinations and ramifications versus AI and XR, this process is inescapable to address the new challenges imposed by intelligent architecture that directs us toward sustainable and on-demand production of building systems, using cutting-edge technologies supported by algorithms with energy-efficient criteria.

Digital Representation, AI, and XR in Innovative Design and Monitoring

The core prominence of the contributions of this section intends to testify how AI/XR linked to new interoperable technologies have the capacity to transform research and communication by implementing collaborative theory and practice in the creation of new assets with the production of dynamic Digital Twin for buildings [16], heritage, and infrastructures, also related to urban/landscape contests [17]. The initiative also demonstrates the current need to interpret, represent, and promote the information of assets as dynamic in space and time through digital methods and tools, focusing on the innovative and effective BIM and Scan-to-BIM processes [18]. The notion of the digital and the material is of current relevance in the field, especially as related to 3D models as repositories of data. Consequently—referring to the various examples of contribution—the proposed methodologies have interesting articulations involving four distinct phases for this type of investigation:

- Data acquisition: archival research, laser scans, and photogrammetric surveys processed and organized through 3D modeling implemented between interoperable platforms;
- Data communication: the information collected with the proposed methods conveyed through the design of apps and interactive systems for multimedia devices and web platforms. This process involves the design and testing of Augmented Reality and 3D models for multimedia devices and the implementation of Immersive Reality;

- Integration of AI/XR-based image management systems aimed at versatile simultaneous data acquisition and communication in the same workspace;
- Enabling XR visualizations for task assistance and providing contextual information linked to the inertial sensors;
- Integration of models as means of analysis in multiple processes, such as architectural/engineering design, conservation of architectural heritage with the virtual reconstruction of architectural features, management/communication of buildings and infrastructures, and urban/landscape studies for multiple opportunities.

Then the submissions are in a range of multidisciplinary skills fundamental for this project: History of art, History of architecture and of the city, Representation (in particular architectural survey, Building Information Modeling—BIM, Geographic Information System—GIS, Perspective and Photographic restitutions, Structural Engineering, Design, Conservation and Management of buildings, Information and Communications Technology—ICT to link AR/XR to BIM. Then this section of the book testifies how new technologies have the ability to "revolutionize" research and teaching by implementing collaborative theory and practice in the field of Digital, to interpret, represent, teach, and promote the knowledge, management, design, interpretation of buildings, infrastructures, cities also related to space and time connections. More of these are processed for an appropriate and fluid imaging/visualization on mobile devices and, in parallel, serve as the reference for the creation of the BIM model incorporated with all data acquired during the proposed processes. The implemented AR app, supported by the GIS geo-localization, allows the user to easily reach the hotspot on buildings—if realized—as a reference point and identifies new paths and exploration opportunities within the urban space.

The "fruitage" then is perseverance that ensures flexible workflows, which can be adapted to various case studies. Exploiting the resources developed thanks to these new technologies encourages scientific and cultural dissemination and enables new stimulus and motivations for research, exploration, and assessment for:

- Visual Studies, highlighting the reasons why we turn to the Visual to investigate subjects inherent in new architecture/engineering design, history of constructive transformations, degradation monitoring;
- Digital Visualization, concerning the theoretical/instrumental/digital contribution of Representation/Visualization, specifying the importance of the measure to understand spatial/formal data to generate interoperable 3D models (BIM) that allow experimental interpretations and punctual analysis of architecture/engineering in relation to the urban sites and landscape.

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Contents

Is a Picture Worth a Thousand Words? Comparative Evaluation of Generative AI for Drawing and Representation

Giorgio Buratti and Michela Rossi

Keywords Artificial intelligence · Generative neural networks · Prompt design · Visual storytelling · Text to image

1 Introduction

Generative Artificial Intelligence defines machine learning and deep learning technologies capable of creating new content based on prior data. Today, the application domains of these tools range from obtaining text, images, and videos to musical motif creation from simple textual input. The possibilities of real or imaginary elements' representation expressed by these computer systems trigger the debate on the possible implications and evolution of drawing and representation discipline. The paper analyses the most widely used image-generative intelligence in search of common patterns and potential differences. The aim is to define a use protocol that, starting with a fundamental analysis of the operating principles, outlines a theory of informed use in drawing, design and research purposes.

The development of AI, today widely discussed, is a meandering process covering nearly seven decades of highly purposeful moments, alternated with stasis periods. Ever since the conference at Dartmouth College in 1956, where McCarthy [1] introduced the suggestive definition of Artificial Intelligence, sanctioning the actual birth of the discipline, the evolution of software capable of reproducing capabilities typical of human cognition, such as interaction with environment and people, learning,

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adaptation, understanding and planning, has been closely linked to technological, scientific and/or contextual advances [2].

It is, therefore, not surprising that the past decade of computing acceleration produced numerous tools capable of realising an image from natural language text descriptions. Only in the year 2022, a dozen AI applications quickly emerged from research environments to project themselves onto the market, becoming pervasive realities. The potential expressed by these tools is reminiscent of the transformative impact of CAD applications between the 1980s and the 1990s. This revolution profoundly changed how we think about and design objects, spaces, and cities and how we represent them. Compared to the by-now traditional modelling software, the advent of AI poses an inevitable and far more destabilising question: are these new technologies capable of generating formal solutions autonomously? And if so, what role will humans have in the new paradigm? Will it be necessary to understand creativity no longer as the ineffability that characterises artistic intuition but as linked to Machine Learning and probabilistic reasoning techniques?

These questions highlight the need for a deeper understanding of AI operating principles to understand their characteristics and anticipate their possible or desirable uses. Therefore, starting with a survey and theoretical analysis of the relevant technology, this paper frames, in the possibilities offered by the impressive speed of development, the main AIs capable of converting text inputs into images. Each of these systems, in fact, employs different algorithms based on similar operational models. Starting from textual input, sequences of words obtained through weak and/or solid conjunctions and separations, one indicates the subject one wishes to visualise, its context, qualities, proportions, desired lighting, but also a particular style with which to make the image and whatever else may come to mind. The following will explain the operating principles and algorithms that lead to the generation of the image, a necessary step in investigating the potential and anticipating the challenges, with particular attention to ethics, posed by its eventual use.

2 Natural and Artificial Neural Networks

The applications studied in this paper all belong to the Artificial Neural Networks class (abbreviated as ANN), an algorithmic structure consisting of artificial neuron interconnections which use a connectionist approach to computation. Since the 1940s, it has been known that intelligence and learning are the result of signals transmitted between neurons in the human brain [3]. The basic theory, still valid today, is that connections among specific neurons are strengthened by communication frequency. It follows that uncertainty in trying a new activity and confidence due to experience gained result from a more or less strong connection among the neurons involved in a specific action.

The wide variety of ANNs existing today descends from this model. The neuron biophysical representation, proposed by McCulloch and Pitts [4], was fundamental to developing neural networks. According to the two researchers, once a certain amount of stored energy has passed in biological neurons, the impulse from the dendrites is transmitted to an adjacent neuron via an axon. Each neuron crossed thus corresponds to a specific instance that modifies the electrical impulse, determining the response to a particular stimulus. The crucial aspect of this theory is that for the same stimulus (incoming impulse), the same neuron can block, transform or allow transmission to the next neuron, depending on contingency.

In human beings, the instances that modify the stimulus–response path are related to those emotional, experiential, kinaesthetic and value factors, summarised in the term learning. Through experience and study, by making trials and mistakes, we strengthen or weaken connections among neurons that lead to the correct behaviour, intending as the one having the most success for a given action.

The process is so effective that it can be mutated as conditions change. Modifying the synaptic weight attributed to a specific stimulus changes the neural pathway and, consequently, our behaviour or action. This characteristic allows us, driving in traffic toward a particular destination, to identify a new road if we meet unexpected obstacles along the predetermined way.

In artificial neural networks, neuron nodes are mathematical functions that operate on simple binary data that, processed by each node, result in an output more or less consistent with the request submitted (Fig. 1). As with the biological neuron, each node has a threshold value above which the received information is passed to the next layer of nodes. It is thus possible to weight the incoming data, strengthening the artificial neuronal pathways that performed best for a specific purpose while weakening the less efficient ones. The higher the number of nodes (layers), the more pathways are available, improving the neural network resolution and adaptive capacity. The assignment of different values to the nodes and the higher articulation, in fact, allows the algorithm to overcome the sequential linear scheme, selecting the most correct among the multiple trajectories permitted by the network. Indeed, the rhizomatic structure implies variability in the data path, the network being an acentric, non-hierarchical and nonlinear system. It follows, however, that the outputs will be, to a more or less variable extent, always different.

In particular cases, a stimulus, impulse or message is structured as a feedback loop, a configuration in which variables propagate across different nodes in a circular trajectory, changing with each pass in the loop.

The consequence is self-regulation of the whole system, as the retraction loop acts as a controller capable of responding to context-related variations to maintain a balanced situation. The action of a temperature controller well exemplifies the principle: if the water of a boiler is too hot, the thermostat will turn off, allowing the optimal temperature to be reached, and then turn on again the moment it gets too low, continuously changing the system and keeping it in equilibrium at the set temperature.

McCulloch and Pitts' model, now universally recognised, did not convince most coeval researchers. The proposed neural network's simplification and the hardware's limited computational availability affected the capacity and accuracy of these structures, which were deemed unsuitable for performing complex operations [5]. Most scientists at the time were convinced that proper artificial intelligence should use

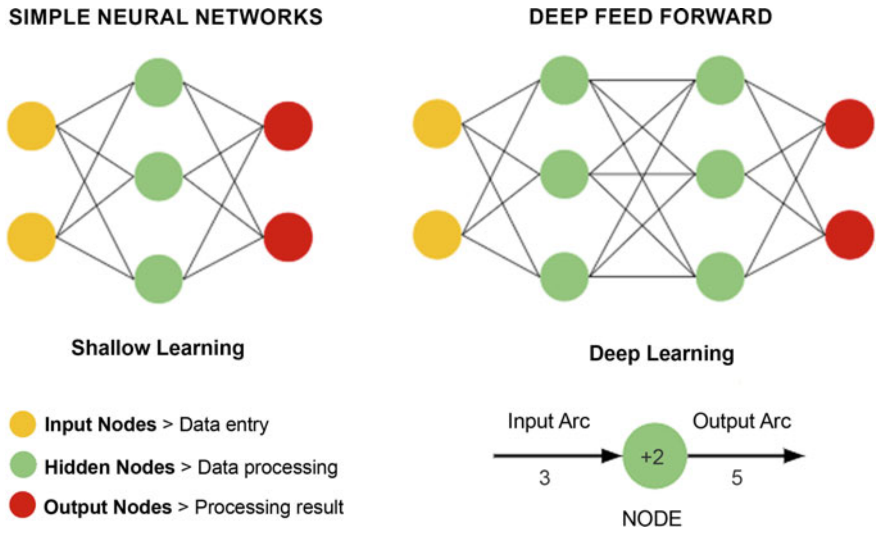

Fig. 1 Graphical representation of a neural network. Nodes perform operations (from addition to complex algorithms). Arcs transmit information. The more layers of hidden nodes the network has, the higher its performance will be (editing: G. Buratti)

symbolic logic, indoctrinating the computer with all the rules necessary to deduce possible effects from a set of knowledge, statements or assertions.

It was not until 1958, when Frank Rosenblatt, a psychologist at Cornell University, conceived Perceptron Mark 1, that it became clear that a fundamental moment necessary to improve the performance of a neural network was missing: the training [6, 7]. Perceptron was a colossal machine capable of simulating the behaviour of (only) eight neurons. Each neuron received a portion of the signals emitted by light detectors, combined them, and, depending on the result, emitted binary data that, combined with the outputs obtained from the seven homologous nodes, described the displayed object. Initially, the results were terrible, but Rosenblatt remedied this by resorting to a method called supervised learning: memorisation was obtained stochastically thanks to a human supervisor who adjusted the nodes' neural weights until Perceptron could correctly recognise a triangle or a square. From that moment, the system could act correctly on its own (Fig. 2).

Rosenblatt's work aroused keen interest and considerable expectation in the scientific community of the time, giving great impulse to research on neural networks, which was significantly curtailed when, in 1969 M. Minsky and Papert [8] pointed out the operational limitations of the Perceptron, mathematically demonstrating the impossibility for these structures to solve numerous classes of problems. Once again, research on neural networks has to be abandoned, stagnating for several decades.

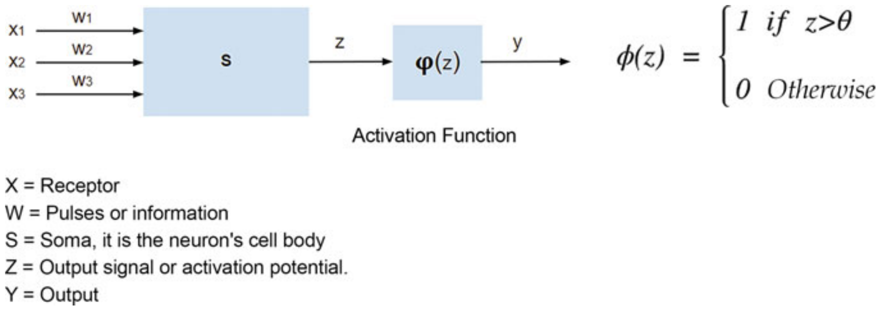

Fig. 2 Schematic of Rosenblatt's perceptron learning algorithm, based on the work of McCulloch and Pitts. In the MCP model, the neuron transmits a signal when the accumulated signal exceeds a certain threshold, allowing it to assign a specific value to the considered phenomena and classify them. The neural networks used today are the evolution of this model (editing: G. Buratti)

Yet, today, although AI platforms exploit complex algorithms to simulate the behaviour of millions of neurons, the essential operation remains the same as Perceptron: analysis of incoming data and training sets, often requiring no human supervision, to teach the models to produce the desired output, trials and corrections until the error has been sufficiently minimised. Although based on different algorithm families, the generative AI described below descends from these experiences. How modern neural networks generate images will be explained below.

3 From Text to Image

Text-to-image artificial intelligences share many operating principles (Fig. 3). Usually, the primary interface tool is a prompt in which you type words or simple phrases describing the image you wish to obtain. Using a source image in many applications is also possible, although integration with written text is often necessary to achieve interesting results.

The next step involves linking the typed lemma to the signified image. In most cases, this is done through a device called Prior, which relates the written word to a database of taxonomized images. All pictures that refer to the terms used will then be selected from the database the algorithm draws on.

The development of datasets has been facilitated over time by the uninterrupted Internet growth: in fact, millions of images are already available online, associated with their respective textual descriptions, thanks to HTML (Hyper Text Markup Language), which allows web pages to be laid out and formatted, labelling and recognising the different elements of a multimedia page.

Through the <Img> and <Alt> Tags, which respectively identify an image and the textual part that explains its content, it is possible to reconstruct massive data sets quickly. The data collection construction plays a crucial role in the training and

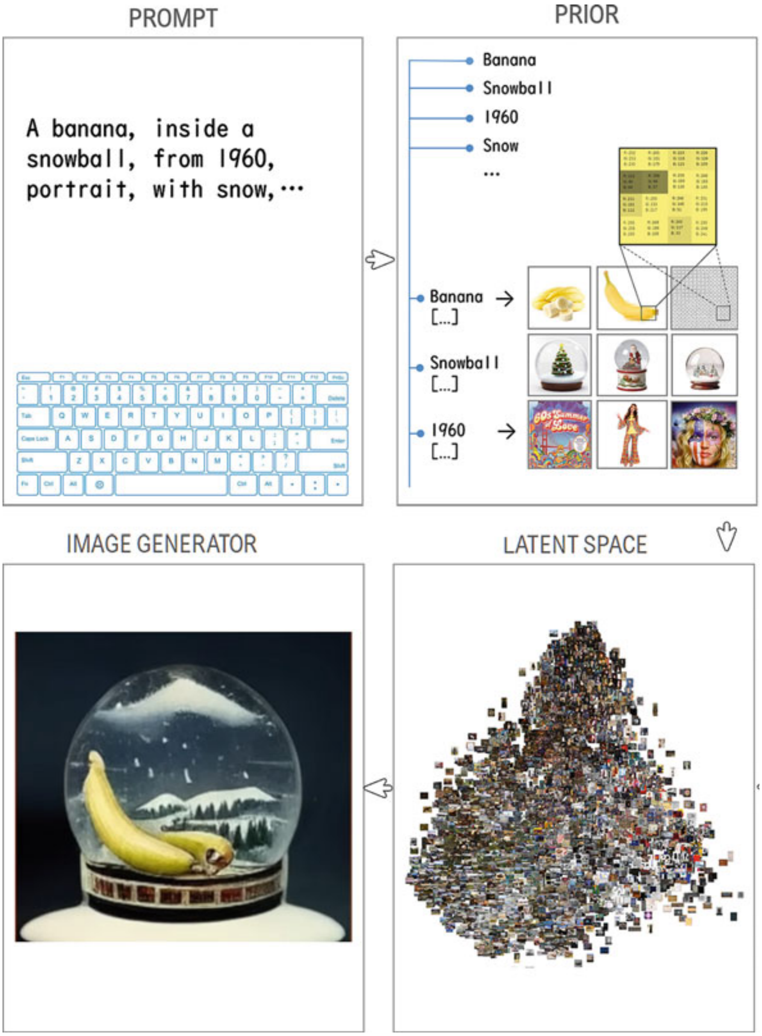

Fig. 3 General overview of artificial intelligence text-to-image functioning (editing: Giorgio Buratti.)

operation of these applications. If the inputs are missing, are of poor quality or are biased, the results will be accordingly. During training, the neural network associates textual definitions with images by comparing the colour triads of single pixels. The computer cannot recognise the symbolic content of an image but interprets it using discrete data such as RGB triads, histograms (the statistical distribution of pixels), or a vector description. It then compares millions of alphanumeric characters with billions of numbers until it statistically recognises those patterns that allow it to identify, for example, a banana. At this point, the collected data must be processed and transformed into a new image that meets the specifications provided by the user via a prompt. This is the most technologically complex moment: in fact, it is not enough to compose a patchwork of images to obtain innovative reprocessing, but it is necessary to introduce a Latent Space. Latent Space is the device that provides the computer with structured and quantified information on the image's qualitative parameters. Assume we are asking the AI to represent a banana in a 1960s glass bowl, like in Fig. 3.

The latent space connects the database to the part of the algorithm that generates the image and can be imagined as a multidimensional space containing characteristic values that cannot be interpreted directly but are encoded in a meaningful internal representation, such as, for example, the banana colour.

The latent space connects the database to the part of the algorithm that generates the image and can be imagined as a multidimensional space containing characteristic values that cannot be interpreted directly but are encoded in a meaningful internal representation, such as, for example, the banana colour. In one-dimensional space, it is relatively simple to measure by deriving it from the pixel colour triplet, the amount of yellow needed to distinguish the banana from another object such as, for example, a red balloon (Fig. 4a). If, however, we want the machine to distinguish a banana from the same balloon, this time a yellow one, the colour will not be sufficient; we will need to include a new dimension that can be identified and measured by the computer, such as, for example, curvature. We will thus obtain a two-dimensional space defined by the amount of yellow (X) and the curvature values (Y) that structure the banana and the yellow balloon at different coordinates, distinguishing them (Fig. 4b).

However, a slice of the same banana would be enough to undermine the model categorisation: the slice is yellow and has a higher curvature than the balloon, so that it would be placed in the wrong region of the reference system (Fig. 4c). Therefore, an additional dimension (Z) corresponding to a new descriptor parameter is needed. Balloons usually have more obvious reflection zones than bananas, so including the reflection dimension to create a three-dimensional vector space will allow the processor to distinguish balloons from bananas correctly (Fig. 4d) [9].

While effective in describing balloons and bananas, it is evident that the measurements of yellow, curvature, and reflection are utterly insufficient to represent billions of other possible daily combinations required of generative AIs. Current neural networks, therefore, have multidimensional latent spaces that go as far as considering 500 or more variables (Fig. 4e), among those found to be most effective in generating images during training. The greater the number of variables considered, the better the results will be, although as the number of parameters increases, there is a significant computational resource overhead.

Within these spaces are parameters that a human would hardly distinguish, but when interpolated by computer, they create meaningful regions and clusters that can capture the image's essence. Hence, there is a definition area for bananas, one for glass balls, snow, and 60 s. The coordinates that control the points are the words typed into the prompt. Each point in the latent space defined by the words can be considered the ingredient in the recipe that generates a possible image.

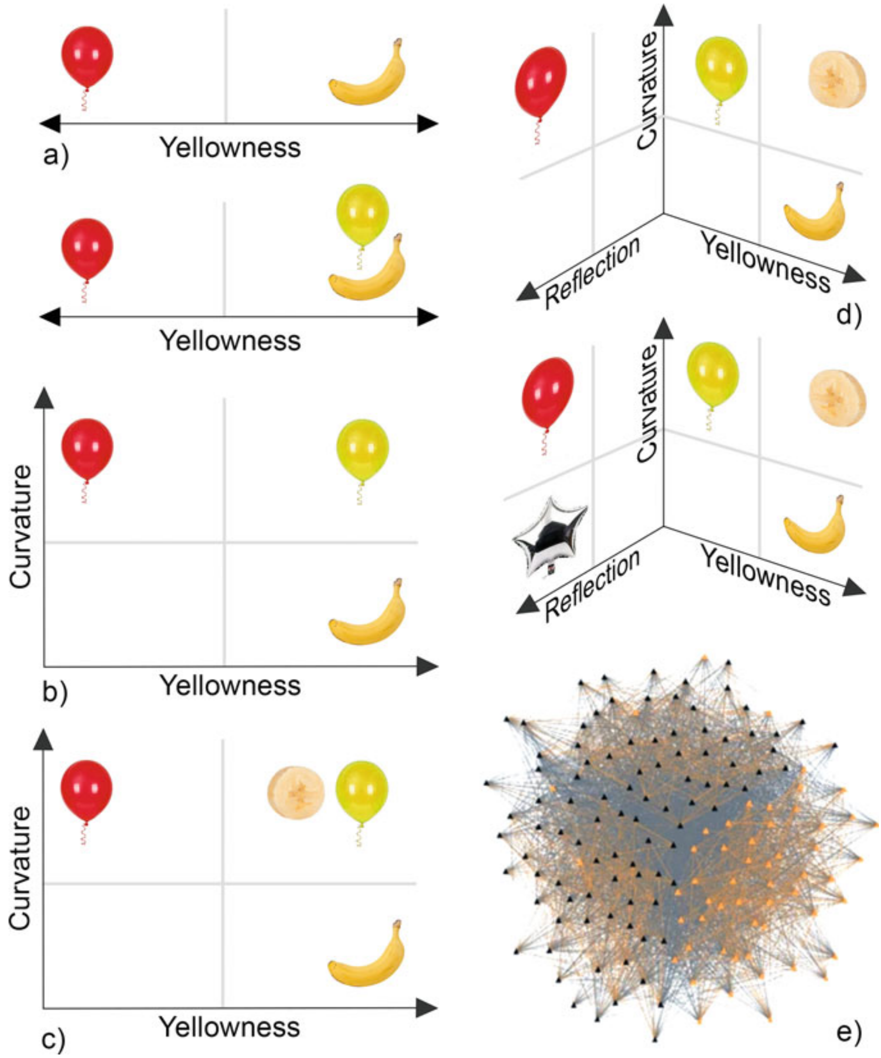

Fig. 4 Conceptual scheme of latent space functioning (editing: G. Buratti)

The next step is translating these points into a new image, a process that distinguishes today's applications into the following groups.

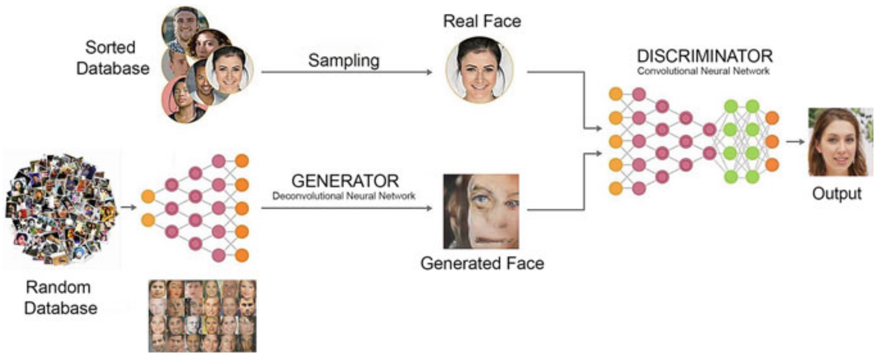

Fig. 5 Generative adversarial networks incorporate two separate networks, generator and discriminator, which enable it to produce highly realistic images (editing: G. Buratti)

3.1 Generative Adversarial Networks

This is a machine learning class in which two neural networks are trained competitively in the context of a zero-sum game. The first network, called the Generator, produces new data, while the second, the Discriminator, compares the data obtained from the processing with the existing data collected in the database (Fig. 4).

Suppose we use the prompt to obtain a face. The Generator extracts the latent space points related to the face cluster and recomposes them randomly, getting thousands of more or less satisfactory results. The Discriminator verifies the Generator's results, comparing them with its database built only from real-face photographs.

If the Generator output meets the tolerances set by the Discriminator, one obtains the final synthetic face image. Usually, the outputs gotten are reconnected to the generator's database in a retraction loop that continuously improves the performance of the generative network (Fig. 5).

3.2 Autoregressive Models

These are image generators based on well-established statistical models that define the variables of a given phenomenon according to their past values. The more stable the rules governing the historical behaviour of a system, the more correct the result of a predictive model based on these rules. This is the type most commonly used in applications related to interpreting or producing written texts. Since the syntactic rules of a language tend to be stable, the algorithm can determine the probability of assigning the next word relying on the previous one (Fig. 6). In image production, the same principle is applied to pixels. Based on training, the adjacent pixel is assigned on a probabilistic principle.

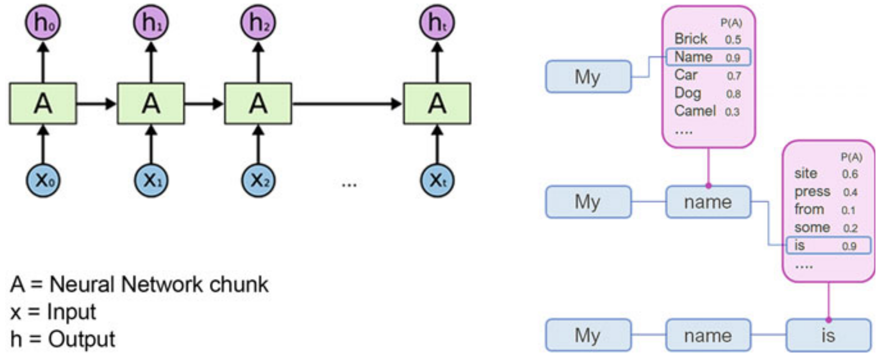

Fig. 6 The autoregressive model is a sequential model in which the output variable depends linearly on the previous outputs, so it is possible to predict the following output based on probabilities derived from the database sequence history (editing: G. Buratti)

3.3 Diffusion Probabilistic Model

A variant where the data in the latent space is compressed into a lower dimensional space, simplifying the image's semantic meaning. The number of vectors describing the latent space is reduced by leaving out some data in exchange for optimising computational performance. This allows applications based on this algorithm to operate on personal computers equipped with consumer GPUs, not depending on the more powerful proprietary servers. It is thus the only algorithm among existing AIs, available to anyone with a permissive license, that allows users to develop, modify, and use the original code at will.

The naming of this class is inspired by the diffusion physical principle whereby, if a drop of dye is placed in a glass of water, we will have areas of different colours depending on the two liquid concentrations. When the distribution balance is reached, the liquids will be thoroughly mixed, and the colour will be uniform. Similarly, the algorithm adds a progressive amount of random information from the images selected from the database, blending their pixels in successive steps into a single random agglomerate. The same neural network iteratively cleans the chaotic ensemble from Gaussian noise, checking its consistency against the latent space data retrieved from the prompt and generating the final image by successive steps (Fig. 7).

4 Experimentation and Use

The following generative AIs were used for comparative experimentation: Midjourney, Stable diffusion, and Dall-e 2 (Table 1) [10, 11].

The exact words entered, in different moments, (Fig. 8) to generate the image in the various tools prompts were: "Generative AI, artificial intelligence drawing, a

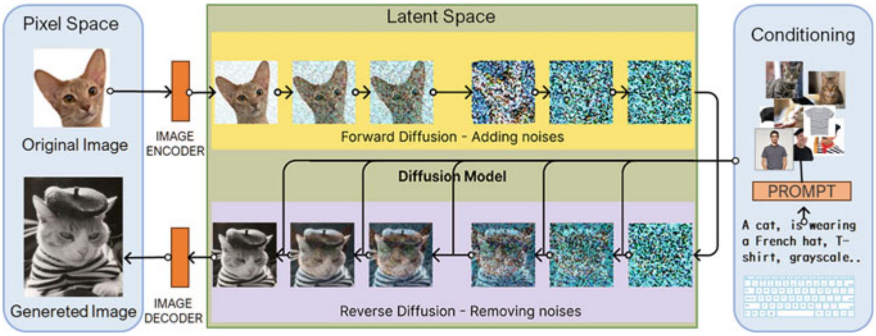

Fig. 7 The Diffusion model defines a chain of diffusion steps to add random noise to data and then learns to reverse the diffusion process to construct desired data samples from the noise (editing: G. Buratti)

paintbrush, a beach at sunset, and a calm sea". Although stylistically differentiated according to the peculiarities of the different applications, the results are surprisingly homogeneous in content. (Fig. 8). All the tools polarise in representing an AI as a more or less friendly-looking robot. The paintbrush and easel were even more problematic, as none of the objects handled by the robots refer to such a tool. After several unsatisfactory trials, since, as already mentioned, the results with the exact linguistic coordinates are different; it was decided to indulge AI by accepting the robot as an artificial intelligence symbol, although it was not our initial idea.

The new description was: "a humanoid robot, painting on a beach at sunset, painter's ease, calm mediterranean sea, no photorealistic". Adding more words did not lead to significant improvements, moving the result away from the authors' intentions.

Of the obtained results, the one judged most satisfactory, or somehow closest to the authors' sensibility, is the one generated by Stable Diffusion (Figs. 8 and 9). It should be noted that Stable Diffusion allows intervention on the seed compared to other software. The seeds are the numerical coordinates corresponding to the points in latent space and, thus, to the final image structure. Slight variations of the seed allow the same region of latent space to be navigated, resulting in minor variations in the image. This way of modifying the prompt to browse the latent space in search of the right image features is now known as prompt engineering. According to some [12], it is already a profession, which may be a premature consideration since all AI intended for the public is rapidly developing in intuitive and more user-friendly graphical interfaces.

The resulting image was then treated with Firefly Adobe for an Outpainting operation. This new feature appeared with the advent of generative AI, creating an image beyond its original limits. In practice, the AI algorithm generates another portion of an image using the pre-existing data within the picture in continuity with the image's semantic content. Inpainting, conversely, is the symmetrical process that completes or transforms portions of an existing image, keeping the image's contents.

Table 1 The main features of the three text-to-image applications used for the comparative experimental test

DALL-E 2	Midjourney	Stable diffusion
Initial release		
April 2022	July 2022	August 2022
Developer(s)		
Open AI	Midjourney, Inc	Runway, CompVis, and Stability AI
Algorithms		
Diffusion model conditioned on CLIP image embeddings	Generative Adversarial Network	Latent diffusion model
Use		
Usable exclusively online. Direct sign-up at the OpenIA site	Usable exclusively online. It is only accessible through the Discord bot on the Discord server	Stable diffusion is the only text-to-image application to be downloaded to one's computer. This mode can be used free of charge online and on one's machine
Payment		
50 free credits at registration and then 15 free credits each following month or paid credits subscription plans	It's necessary to pay subscription plans based on the calculation you request from the server. It works on a GPU time system, that is, the minutes it takes to generate an image	Stable diffusion is open-source and free to use. However, it does offer monthly subscription plans for developers and businesses that need more from the tool
Max resolution		
1024 × 1024 pixel	1024 × 1024 (square) 1456 × 816 (widescreen 16:9)	1024 × 1024
Copyright		
All images produced are distributed under a Creative Commons license to be used freely but not commercially	All images produced are distributed under a Creative Commons license to be used freely but not commercially	Stable Diffusion makes its source code available, along with the model (pre-trained weights). The images created are open source and fall under the CC0 1.0 license. They can then be marketed

Outpainting was used here to resize the image obtained from Stable Diffusion (Fig. 9). For reasons of computational workload, currently available tools tend to work on small, low-resolution images, requiring the handling of fewer pixels, although these limitations are fast disappearing. The Outpainting and Inpainting tools also allow different graphic configurations, leaving the user to choose the best one.

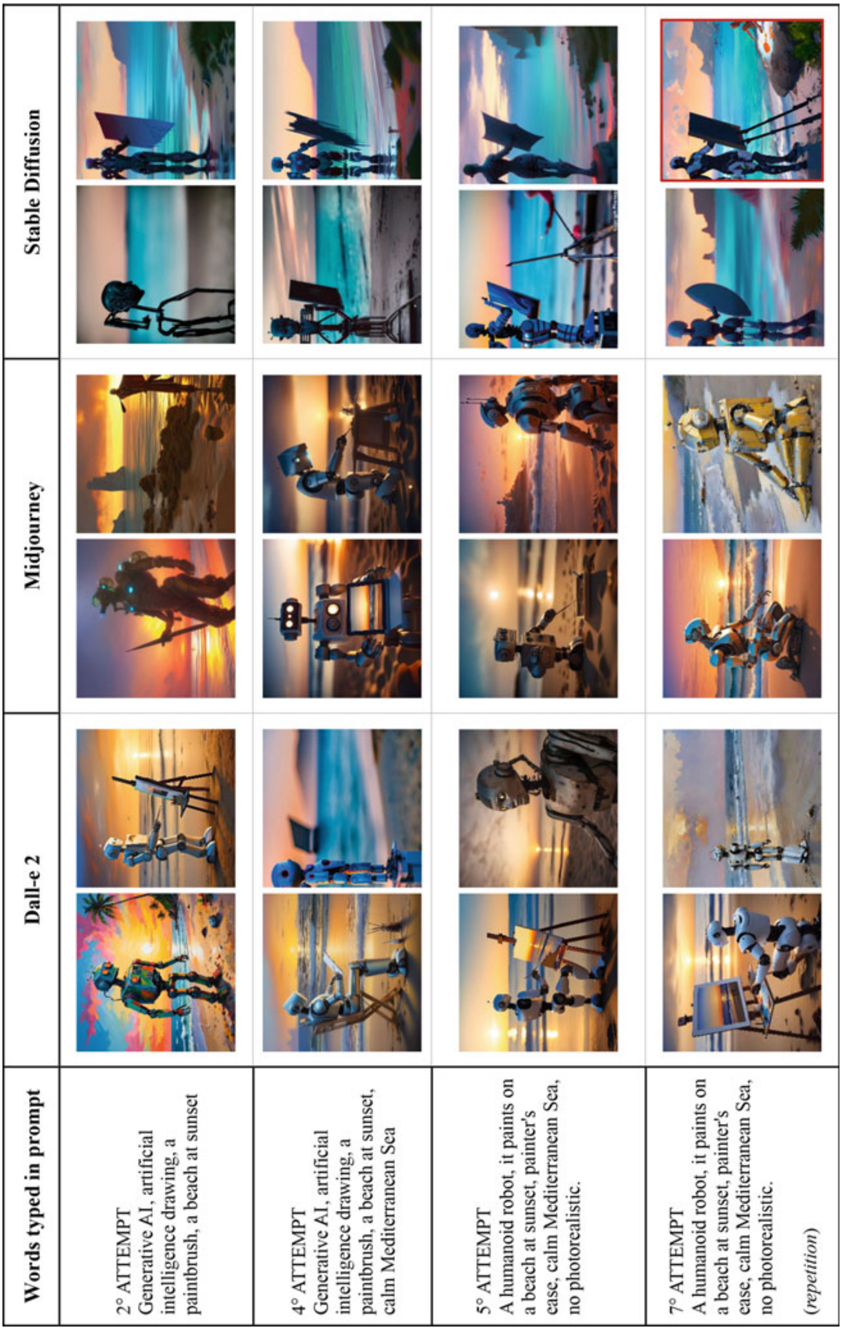

Fig. 8 Comparative table of the outcome summary obtained with the different tools. The image outlined by the red border, closest to the authors' wishes, was chosen for the outpainting operation (editing: G. Buratti)

Fig. 9 Two examples of how, starting from the same image and keeping the same settings, it is possible to get different outpainting results with Adobe Firefly (editing: G. Buratti)

5 Conclusion

The experimentation demonstrates the interesting potential for figuration that these tools offer us. Over and above the general interest aroused and the hype created at a social level, the continuity of these tools with the software automation processes that have been in solid development in the visual and figurative arts field is evident. The innovative elements concern the poietic process, which has always been partly left to the technology used—from the pencil to the brush since the modelling software—and the availability of an unthinkable realism linked for the first time to the medium and not to the author. Rather than an authentic dialogue with the computer, it would be better to speak of an anthropological change in the human–machine relationship. It is not yet possible, in fact, to establish an actual conversation in the etymological sense of *cum-versare* (cum = with, versare = to turn around, to find oneself, to entertain oneself), which is a dialogical confrontation. Despite being a textual input, the prompt has little in common with the natural language we write and speak daily. It is a hybrid between natural language and programming codes.

With computers, there can be no real communicative relationship at this stage, hence the randomness—sometimes fruitful and surprising, sometimes frustrating and disappointing—of the results that can be obtained.

It is difficult for now to identify a correct methodology of use. The path leading to the image is characterised by a process of hermeneutic circularity based on repeated attempts and modifications in search of the best results. These may be surprising and unexpected in terms of effectiveness or graphic technique but are often far removed from the user's initial mental prefiguration.

In light of the experimentation conducted, it is also unattainable to identify or measure distinctive features of the different instruments. If, in the first phase of use (from 2022 to the half of 2023), it was possible to discern a trend in specialisation of the output quality, with some applications being more effective in portraying landscapes, rather than faces or in reproducing the style of famous painters, this is no longer the case today. This is probably because while generative neural networks were initially trained on a specific database, the daily use of thousands of users, which continues to teach them, has blurred the differences, broadening their capabilities in a process of continuous improvement proceeding at an impressive rate.

It seems possible to broadly optimise the functions of prompts through two descriptive lines:

- Terms and words related to the subject you are trying to create. (A cityscape, a tiger, an elf woman in armour).
- Terms and words related to the style of representation (photorealistic, manga style, wax crayon, Monet's style, etc.).

Good results are also obtained with terms related to historical periods or painters (1960s style, like Van Gogh style, etc.). This is not surprising once one understands how such applications work and the nature and labelling of the reference databases.

Although presented as polyglot, these tools offer better results using English, the most widely used language online, with which English-speaking companies have trained and developed them. It would be premature to give more precise guidelines: using the prompt is an iterative process. Experimenting with different ideas and testing artificial intelligence commands is essential to get results. There are no fixed rules for how AI outputs information, so flexibility and adaptability are crucial.

As is often the case in the age of computerisation, repositories that collect word collections associated with a graphical output are already available. Those can be copied and pasted to obtain stylistically similar results, although perhaps too uncritically way.

At present, the observable benefits are:

- A significant time saver, especially for correction operations and image cleaning. The time saving is considerable and allows the user to concentrate on creative processes.
- New features such as Outpainting and Inpainting. Excellent results can be achieved quickly for general or background images, whereas specific depictions may take time or effort.
- Image realism and graphic quality. The results obtained are often high-level visual solutions.

However, these positive aspects are accompanied by some fundamental critical elements:

- Lack of originality. The outputs created are based on the database and the training received. This leads to constantly dealing with the same data, endlessly repeating and recomposing existing models.
- Contents distortion. Generative AI depends on the training data used to generate new information. If the first contains biases, the latest data will reflect these distortions. The quality of the training data is essential to create plausible and realistic information. The ethical component related to what is produced with these tools is often misled by the term 'intelligence' with which these tools are classified.

Human beings are endowed with moral principles that discern right and wrong, based on cognitive concepts dictated by their upbringing and culture of reference. A generative AI follows the designer's programming and is not conscious of the intentions or consequences of what it generates. Some applications have already been criticised for generating images based on stereotypes that risk feeding misogynistic and racist tendencies. This is one of the reasons why the AI Safety Summit [13], held in London in November 2023, set itself the goal of outlining a common strategy for all stakeholders to establish the ethical criteria and moral challenges posed by this technology.

- The traditional concept of intellectual and/or artistic authorship is questioned: no longer a well-defined author, but a diffuse distribution of authorship, where both man and machine, including those who designed and trained it, participate in the result. On the one hand, the issue of protecting authorship rights about the content used to train the algorithms arises. On the other hand, the question is posed as to whether the works produced by generative AI can be protected by copyright.
- The first problem is the most complex, as it calls into question the basic operating principle of neural networks: the need to use big data for training purposes. As this paper is being written (January 2024), the World Intellectual Property Organisation is examining this issue to establish guiding principles. In the meantime, many copyright owners, ranging from image repository companies such as Getty Images, through prominent newspaper publications to graphic designers, artists and photographers, have taken legal steps to protect their works.

Concerning possible use for design purposes other than visual communication, so far, these applications are severely limited by being able to generate only two-dimensional content. As described above, the results are often random and not sufficiently controllable for a design use other than graphical representation except in the initial concept stages, more as suggestions than as actual technical/constructive drawings. Unlike algorithmic modelling, where large amounts of data are handled under designer control, generative AI applications hide the parameters in Latent Space. In both tools, the first result obtained often does not respond to the designer's mental foreshadowing. Still, while algorithmic modelling makes it easy to interpret and modify variables, with AIs, the process is too haphazard for the highly hierarchical and time-optimized path that any project implies. This does not detract from the fact that AI has enormous transformative potential, perhaps more significant than the impact of CAD applications in the last century. The incredible speed of development related to the peculiar workings of neural networks is not comparable to any other technology in human history (Fig. 10).

The challenge is understanding which design process operations can be delegated to machines, leaving designers to focus on highly creative activities. From this perspective, design becomes a matter of choice: machines produce countless variations, while humans choose according to their own visions and purposes. This involves a shift from tactics to strategy [14], from how to why, ushering in a new

Midjourney v.1 (February 2022) Midjourney v 5.2 (October 2023)

Fig. 10 The difference in outputs achieved by Midjourney in just over a year and a half (editing: G. Buratti) way of understanding the profession, more like the role of the curator rather than the craftsman.

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