The book discusses how to include artificial intelligence (AI) systems in the early stages of the design process. Today designers need new tools capable of supporting them in dealing with the increasing project's complexity and empowering their performances and capabilities. AI systems appear to be powerful means to enhance designers' creativity. This assumption was tested in a workshop where sixteen participants collaborated with three AI systems throughout the creative phases of research, sketching, and color selection. Results show that designers can access a broader level of variance and inspiration while reducing the risk of fossilization by triggering lateral thinking through AI-generated data. Therefore, AI could significantly impact the creative phases of the design process if applied consciously. Being AI systems intelligent agents, the book treats the Human-AI collaboration as a collaboration between human agents, proposing a set of guidelines helpful to achieving an efficient partnership with the machine.

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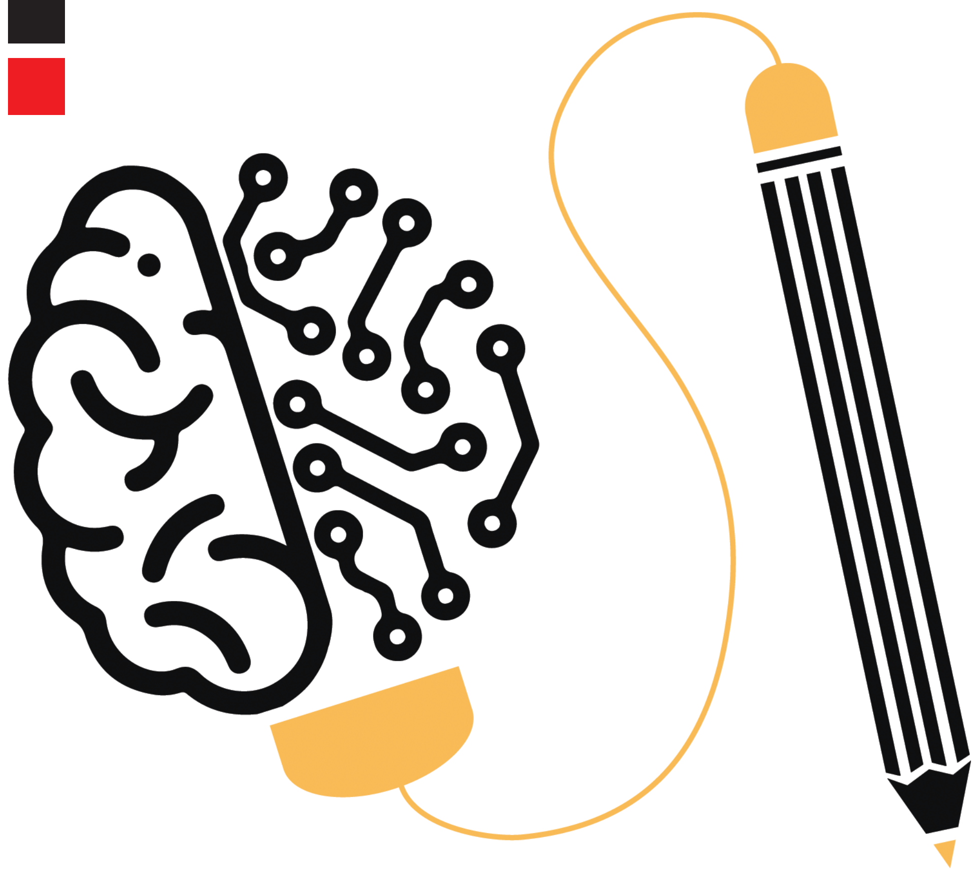
Artificial intelligence in the design process

The Impact on Creativity and Team Collaboration



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Contents

Introduction

This book intends to generate curiosity, stimulate debate, and provide a starting point or valuable progress for the studies around artificial intelligence concerning design. It is based on the degree thesis of Fabio Figoli, discussed in December 2021 at Politecnico di Milano, Master of Science in Design & Engineering. Lucia Rampino was the thesis supervisor, and Francesca Mattioli was the co-supervisor.

A triple focus conveys the research: the two-way relationship between artificial intelligence and design, the recognition of artificial intelligence as an emerging tool in the design process, and considering the idea development activities rather than the executive ones.

The main aim of Figoli's thesis was to clarify how artificial intelligence can be implemented in practice in the design process, exploiting its potential and helping designers understand how to cooperate efficiently with it. To this end, first, an extensive literature review on the new human-machine relationship was performed. Then, a workshop was organized, where sixteen participants were asked to design a simple object with the support of different tools based on artificial intelligence.

The book describes the results of this research activity. Firstly, it outlines the state-of-the-art of design, with a focus on collaboration, and describes artificial intelligence's main features. Then, it illustrates how this technology can impact the design process, particularly in the early stages. Finally, it focuses on the consequences of introducing artificial intelligence within human design teams, especially for human trust and creativity.

1. Why Design and Artificial Intelligence should join Forces

1. The Increasing Complexity of Wicked Problems

Design and artificial intelligence (AI) may seem like two distant fields, with the former focusing on the designer's creativity and sensitivity, and the latter on the rigorous calculation of the machine. Therefore, these two fields are often perceived as opposite: either human *or* machine, while the possibility of a human *and* machine collaboration is overlooked.

In order to understand why design and AI should join forces, it is essential to take a step back and recall the nature of the discipline. Since its conception as an academic subject, design has always had difficulties to find a common and shared definition. After over one-hundred years, scholars and practitioners still debate its nature. Although it may appear as a purely theoretical issue, this dispute brings several consequences for the entire discipline.

First of all, the absence of well-defined disciplinary boundaries sets the figure of the designer as a dynamic one, with a natural predisposition for change, adaptation, and flexibility. Such propensity allows the designer to address different problems and find a coherent and creative solution. A designer is trained to broaden the scope of her activity and cross the boundaries of other disciplines and research fields, making interdisciplinarity one of the profession's critical assets. Indeed, an experienced designer should assimilate knowledge from any valuable source, extracting it from its original context and employing it indirectly (e.g., for inspiration) or directly (e.g., for the shape definition) into her project.

This manner of addressing problems is at the base of the *lateral thinking* approach defined by De Bono (1967). In opposition to the predictable step-by-step vertical thinking, *lateral thinking* enables the designer to observe any problem from different perspectives, leading to creative, original, and out-of-the-box solutions (fig. 1).

As said, design often expands beyond its boundaries and draws knowledge and expertise from adjacent fields. Consequently, design thrives on *contaminations*, which may come from other disciplines towards design, but may also go from design towards other disciplines.

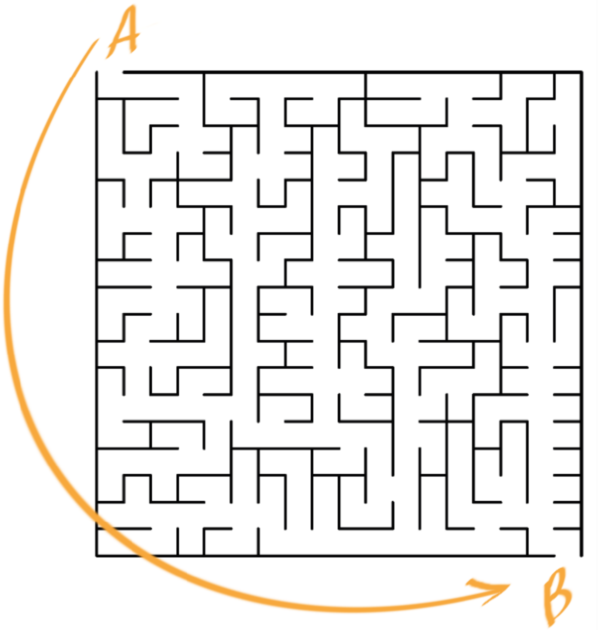

Fig. 1 - The image of the labyrinth is often used to visualise lateral thinking: a cognitive process guided by lateral thinking allows the designer to have a broader and external perspective, which is not constrained by the labyrinth's rules.

An example of design influencing other fields is *design thinking*, the design process heavily based on lateral thinking and brought to success by the U.S. design company IDEO (Brown, 2009). Design thinking encompasses several practises, which are often grouped into the five phases of empathising, defining, ideating, prototyping, and testing (Plattner et al., 2011). It helps to analyse any problem from different perspectives and develop a creative and effective solution (fig. 2).

Today, *design thinking* is regularly employed by professionals outside the design field to solve issues of diverse nature such as engineering, health, economics, and management.

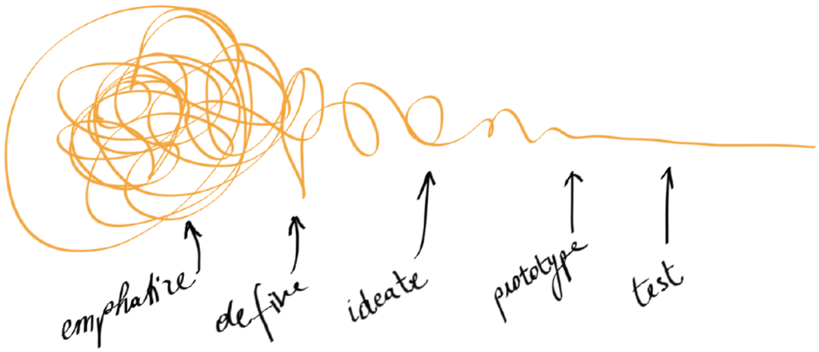

Fig. 2 - Design thinking. Adapted from Plattner et al. (2011).

What also makes design unique is the kind of problems faced by designers, defined as *wicked problems*, and described by Rittel as:

> a class of social system problems which are ill-formulated, where the information is confusing, where there are many clients and decision makers with conflicting values, and where the ramifications in the whole system are thoroughly confusing (Churchman, 1967, p. B-141).

In other words, a *wicked problem* is made up of countless relevant and heterogeneous factors, which make its definitive resolution impossible. Similarly, many possible variables influence the designer's work heavily and directly. Moreover, the characteristics of the *wicked problems* designers must face considerably evolved from the Industrial Revolution, acknowledged as the birth of the discipline of industrial design, to nowadays.

2. Design Collaborations under Different Perspectives

To understand the evolution of the nature of wicked problems addressed by industrial design, Rampino (2018) described contemporary design practice as a combination of four perspectives that evolved according to the diverse socio-cultural, socio-economic and technological developments: the *technical*, the *human*, the *digital*, and the *social* perspectives. The conceptualisation provides a practical framework for summarising the design discipline's evolution and highlighting the increasing complexity designers deal with in contemporary practice. Indeed, Rampino proposes that the perspectives do not substitute each other but instead sum to the previous perspective, creating a multifaceted perspective that is the current design practice (Rampino, 2018). As society evolved becoming increasingly complex, also design had to deal with an increasingly complex wicked problem. However, from the technical to the social perspective, the lowest common denominators unite all four perspectives: designers must collaborate in plural groups in order to solve wicked problems. This plurality ranges from the disciplinary plurality yet present in the technical perspective until the wide variety of plural social actors to be included in the design process under the social perspective, as it seeks to address global challenges. In the following sections, the four perspectives are briefly presented with regard to collaborations as a strategic asset for designers to face the specific challenges that each perspective entails.

2.1. Collaborations under the Technical Perspective

The *technical perspective* on industrial design is intertwined with the idea that artefacts development aims to respond to the need for mass production, typical of the industrial economy (Brand & Rocchi, 2011). Under this perspective, the modern idea of industrial design was initially conceived since industrial manufacturing and design were no longer done by the same person (Bürdek, 2015), distinguishing design from craftmanship. Therefore, design is primarily oriented toward standardisation, the paramount requirement to conceive artefact fast and profitable to be produced on a mass-scale. From the technical perspective, designers' work must rationally and efficiently provide a profitable solution within the new product development process undertaken by manufacturing companies (Rampino, 2018). To this extent, the designer focuses on the artefact itself and its physical characteristics, which are seen as the main feature to create value by rationalising the design manufacturing choices and minimising the cost-to-income ratio.

> Industrial design is a process of creation, invention and definition separated from the means of production, involving an eventual synthesis of contributory and often conflicting factors into a concept of three-dimensional form, and its material reality, capable of multiple reproductions by mechanical means (Heskett, 1980, p. 10).

Conceiving industrial design as the science of artificial (Simon, 2019), industrial designers are those professionals who take part in the new product development process with other specialists (e.g., managers, engineers, technicians) and can rationally synthesise multiple factors in one single concept that can be manufactured and produced. In terms of attitudes, skills and knowledge, the designer must be open to other approaches to new product development that emerge in the multifunctional team, be skilful in collaborating with multiple professionals, be flexible and creative, and combine all the above with sound technical knowledge. In the technical perspective the design profession is already conceptualised at the intersection of various knowledge domains, creating the opportunity (and the necessity) for designers to interact with different worldviews and synthesise them into one single artefact.

2.2. Collaborations under the Human Perspective

The *human perspective* is connected to the advent of the experience economy (Brand & Rocchi, 2011). By the ’80s, since markets were saturated with identical mass-produced goods, industrial design became more oriented toward developing artefacts that respond to individuals’ desires. Therefore, stakeholders were also included in the focus of the industrial design that expands from merely physical attributes to the meaning that those physical attributes convey to various stakeholders (Krippendorff, 2006).

> If design used to be a matter of physical form, its subject the material object, it now increasingly seems to be about the user and her experiences (Redström, 2006, p. 127).

This change in focus is connected to a shift in design culture from a positivistic to a pragmatic paradigm: the designer is not a «scientist of the artificial» anymore, but rather a «reflective practitioner» (Schön, 1983). Therefore, industrial design is no more conceived as a scientific procedure to apply, but rather a knowledge creation process associated with specific thinking models (Oxman, 2006). In fact, under the human perspective, the design discipline witnessed the development of the academic discourse around designerly ways of thinking and the associated managerial trend of design thinking (Johansson-Sköldberg et al., 2013) as a profitable approach to new product development, which effectively creates value for stakeholders.

Based on Rampino (2018), industrial designers in the human perspective are hence the professionals who, through their ways of thinking and doing, can create artefacts by considering the perspectives of multiple stakeholders. The designers' attitude is to understand how other people assign meaning to artefacts; they are skilful in creating meaningful artefacts and know how to embed products' immaterial attributes into the material ones. Since different stakeholders assign different meanings to the artefact, products differentiation becomes possible for designers by understanding stakeholders' expectations and behaviours (Krippendorff, 2006). Designers develop this understanding by considering and involving different stakeholders in various stages of the design process. The designer becomes the expert in understanding how people assign meaning to artefacts and a professional able to relate with different people.

2.3. Collaborations under the Digital Perspective

The *digital perspective* is related to industrial design in the knowledge economy (Brand & Rocchi, 2011), characterised by the advent of the internet and digital technologies that profoundly transformed the economy and society. These technologies fostered an increasing shift from analogical to digital and from material to dematerialised artefacts (Findeli, 2001; Tessier, 2021). With specific regard to products, they increasingly contain sensors, electronics, and intelligent materials, becoming more complex, dynamic and interconnected (Rampino, 2018).

> […] a domain which was once considered pure industrial design is faced with many interaction design challenges (Djajadiningrat et al., 2004, p. 294).

The traditional knowledge of manufacturing processes and technologies was also innovated by introducing digital fabrication, which opened the way to new geometries, design principles and possibilities. Moreover, the easiness to connect globally provided the possibility to relate with stakeholders in a worldwide network. In the digital perspective, the focus of industrial design becomes even more comprehensive, as it must consider a global interconnected network of artefacts and stakeholders. Under the digital perspective, industrial designers effectively navigate this complex worldwide network and envision new artefacts that dynamically exist within it. Also, digital technologies opened new possibilities for collaborations because it became possible to be connected and collaborate remotely on a global scale in a brief period. Designing became possible also with and for people very distant from each other. Communities of designers and other stakeholders started to gather in global communities, collaborating with a broader and complex network. Highly contextualised in the digital perspective, Fab Labs are a clear example of how the digital revolution created the opportunity to establish a worldwide community of situated maker spaces that, despite the distance, are strongly connected by the material attributes of products manufactured through digital technologies.

2.4. Collaborations under the Social Perspective

The *social perspective* is related to the transformation economy (Brand & Rocchi, 2011), in which the downsides of previous economies entered the focus: environmental decline, social inequality, and economic disparity start to be seen as systemic issues. A renewed interest and attention toward global issues influenced the economy (Brand & Rocchi, 2011) and industrial design, one of the disciplines that had to reconsider its impact on society. For this reason, the design focus expanded to include a systemic view of society.

> Designers no longer can hide behind the needs and wishes of the consumer; instead, they have to take responsibility as 'shapers' of society. Doing so entails a shift from a user-centred approach to a society-centred one (Tromp et al., 2011, p. 19).

Under the social perspective, industrial designers are aware of social actors, that through a critical understanding of society, can envision artefacts that address global challenges and contribute to systemic well-being. Raising awareness around the themes related to human rights, labour conditions, and environmental issues pushed designers to start collaborating with minorities and unprivileged groups and consider the planet, moving beyond human centeredness.

3. The Near Future: Collaborations Beyond Humans

To better understand the situation in which designers operate today, we must consider how the advent of the digital age caused significant social and cultural changes in short periods. Society is increasingly fragmented; minorities fight for their rights and demand protection; heterogeneous individuals replace homogeneous and well-defined groups. In short, wicked problems are becoming more and more complex.

Using a metaphor, we can affirm that in the first half of the last century the designer had to deal with wicked problems that could be either dark or light grey. Today, the level of complexity has risen to the point they can be any colour of the spectrum, blend and change abruptly.

Designers have always tried to adapt to change and have been pushed to renew their modus operandi several times. Many are indeed the issues that have called for the reassessment of the project's priorities: the skills required and the designer's role within the new product development team, the teams' composition, the teamwork dynamics, the users' and companies' needs, the individual's awareness, to mention the most relevant.

In addition to all this, we must also consider the fast technological changes of *Industry 4.0*: products integrate material and digital components in an increasingly inseparable manner; available materials are growing in numbers, and if treated properly, they can become *smart*, capable of receiving inputs, reacting and transforming them into outputs; manufacturing processes enable the production of shapes previously unfeasible, and so on.

Today's exceptionally dynamic and diverse society and fast technological advancement represent a challenge for design. The discipline appears to struggle to keep the pace, and designers seem overwhelmed by large amounts of information and expertise, making every project more demanding. Design's methodological tools and competencies run the risk of being insufficient to adequately reach the scope of new projects, consequently designing products that are misaligned with the user's needs.

It is here argued that we are approaching another moment of revolution in the design profession: designers need to engage in collaborations with more than human intelligence to support their work at every stage of a project. To address this challenge, Artificial Intelligence (AI), which is included among the so-called *disruptive technologies*, appears an intriguing future collaborator, able to provide many potentialities during the steps of the design process. Additionally, designers could adopt AI in their work relatively quickly, as AI is already well established in many other working sectors from which much can be learned.

For these reasons, the topic of AI has obtained an increasing interest from researchers and practitioners in the design community, as demonstrated by the numerous recent academic papers and conferences on the subject (see the reference list).

4. Our Focus

Artificial intelligence is a revolutionary technology that is in constant development and expansion. Therefore, companies and institutions invest significant resources in research and experimentation on it. The steep rise of the technology is unlikely to slow down soon, with almost every industry now regularly implementing AI into their workflows. The scope of AI research is vast and diverse, so it is crucial to frame the focus of our book.

First of all, in this work, artificial intelligence is considered exclusively through its two-way relationship with design, particularly product design. In this specific disciplinary area, AI is at the service of designers to improve designing mass-manufactured objects. However, given the blurred boundaries of design, our book also interests other related disciplinary areas, such as service design, fashion design, interior design, communication design, etc.

In product design, AI can have two main areas of application, both extensively debated: the product itself and the design process. Therefore, we can say that AI can be either *the material of design* or *a design tool*. In the first case, the final product is equipped with AI functionalities. In the second case, AI is applied to enhance and optimize the outputs of the design process. In this book, we focus on this second aspect, given the lack of academic publications on the subject and the centrality of the issue in today's design discipline that needs to find new design tools.

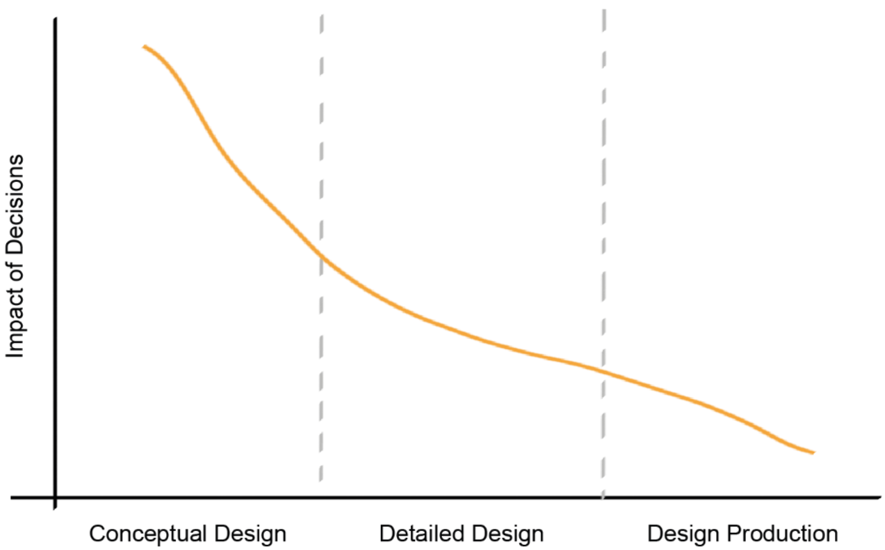

Fig. 3 - The impact of decisions in the early design stage. Adapted from the work of Wang et al. (2002).

Narrowing our scope even more, the book focuses on the initial phases of the design process, ranging from research to concept, thus excluding engineering, prototyping, and production. Indeed, in these later stages, the implementation of AI occurred naturally, given the technology's predisposition to solve purely analytical and technical problems. In contrast, the usefulness of AI in the early phases of the design process, which are the most creative ones, is still unexplored and opaque, thus leaving a research gap that needs to be filled.

As widely acknowledged, changes in the early design process are the most critical ones compared to the later stages, where the design choices are often reduced to details (Wang et al., 2002). Therefore, AI's impact on the process outputs can increase exponentially if applied in the early phases (fig. 3).

We chose to focus on the idea development activities rather than the executive ones for all these reasons.

2. What is Artificial Intelligence

1. An Overall View

It is now helpful to describe the main features of this technology to understand to which extent artificial intelligence can affect the design process. However, given our focus, it is not necessary to investigate the technical aspects of AI extensively: a basic idea of the subject will be enough to facilitate comprehension[1].

First, it is good to know which fields of science we are dealing with (fig. 1): moving from broad to specific, we first enter the almost boundless world of *computer science*, which includes any topics related to the design and use of computers. Next, within computer science, we encounter the field of *data science*, which provides for all the systems and models that can be used to extract relevant information from data. Finally, inside this area, we find AI that focuses on making machines perform cognitive and intelligent actions, similar to those performed by the human brain. In general, AI systems analyse large amounts of data, aiming to identify patterns and internal relationships that enable the generation of predictions. Today AI is a precious technology in many sectors because it allows machines to perform tasks typical of human operators, and often, thanks to the superior computing power of devices, even faster and with a lower error rate.

It is possible to break AI into two macro-categories: *weak* AI and *strong* AI. The first one focuses on systems trained to solve specific tasks, for example, virtual assistants, such as Amazon's Alexa. The

[1] Most of the information and images presented in the following paragraphs are based on the book *Machine Learning for Absolute Beginners* (Theobald, 2017).

second one is about systems that seek to emulate human reasoning and better solve complex and unknown problems autonomously.

In addition, it is worth reminding that the debate on AI is a technical-practical discourse and an ethical, social, and cultural one. In this book, we will barely approach ethical and social issues. Still, we are fully aware that they remain critical and fundamental topics, which must be addressed to ensure proper and healthy integration of the technology in our society. AI implementation requires great awareness and a sense of responsibility on behalf of researchers, professionals, but also national and international governmental institutions involved in its usage (Óhéigeartaigh & Liu, 2020).

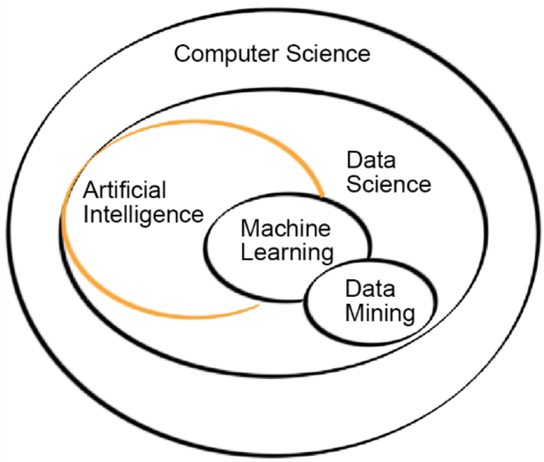

Fig. 1 - Artificial intelligence position in data-related fields.

2. Machine Learning

The topic of artificial intelligence is vast, and it includes a set of sub-branches. In terms of diffusion and potentialities, the most relevant is machine learning (ML), which enables devices to autonomously learn and improve their capabilities. In our research, most of the tools considered are machine learning applications. Therefore, it is worth paying attention to this specific sub-field of AI.

As said, machine learning is based on the concept of self-learning, which implies the use of statistical models based on data and empirical information to identify patterns and improve performances over time. This technology is so interesting because the learning process is not explicitly programmed. So, instead of an *input command*, a device is provided with *input data*, which are then processed through a model into an output (fig. 2). Therefore, thanks to machine learning, we can train a device to make autonomous decisions, adapt and modify assumptions based on provided data and on encountered errors, in the same manner human beings learn from their experience.

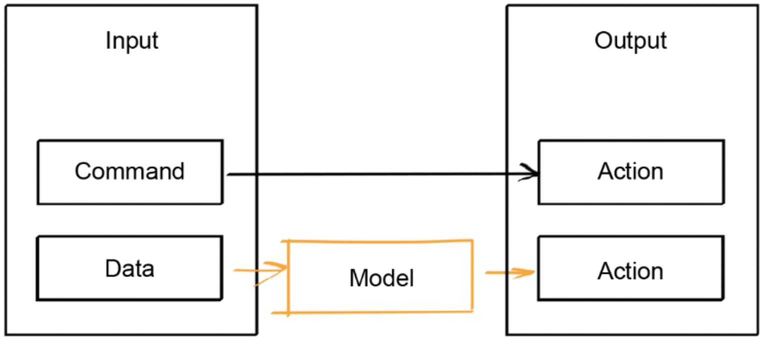

Fig. 2 - Input command vs Input data.

Data quality is vital for successful training, meaning that any deficiencies or errors in the information provided to the device would inevitably damage the final output. In machine learning, data is divided into *training data*, used to develop the model, and *test data*, used to verify whether the achieved model is reliable and valid. The model is ready when the result is considered satisfactory in both phases. To achieve the desired result, machine learning experts have at their disposal numerous methods and tools, more or less complex, which can be combined to obtain a lighter, less expensive, and better performing model.

Machine learning can be classified into three main types: *supervised*, *unsupervised*, and *reinforcement*.

Supervised learning works by relating the variables in the data and the outcomes, which are already known. For example, it is used for predicting house prices.

In unsupervised learning, the variables and the data patterns are not entirely classified, leaving the machine the task of finding hidden patterns and creating labels. As a result, the device is likely to identify patterns within data that were unknown, thus solving a problem autonomously and originally. For example, unsupervised learning is used for finding customer segments.

Reinforcement learning uses the most complex algorithms in machine learning, for example, applied in autonomous vehicle driving. In this case, the machine learns and constantly improves, not only through the pattern that relates data and outcome but also through feedback from previous iterations, in a sort of trial and error. Therefore, unlike supervised and unsupervised, reinforcement learning involves a constant evolution of its model and never reaches an endpoint.

Another branch of machine learning that is getting particular attention and surprises for its potentialities is the so-called *artificial neural network* (ANN), which is closely related to reinforcement learning. In this technology, data is processed through layers of analysis in a model close to the human brain.

Neural networks work best when dealing with highly complex patterns, which are difficult for machines to solve but simple for the human mind. A well-known example are CAPTCHAs (Completely Automated Public Turing test to tell Computers and Humans Apart), simple tests used by websites to differentiate between real and automated users. Identifying stretched letters or numbers or clicking in a specific area is relatively easy for humans but almost impossible for machines. The same applies to challenge-response tests and pedestrian path prediction in self-driving systems. Data with many diverse inputs, which are challenging to handle by standard models, can be exponentially simplified when analysed by a deep number of layers.

A typical neural network comprises three layers: an *input* layer, a *hidden* layer, and an *output* layer (fig. 3). The hidden layer – defined as such because it is not possible to see explicitly inside it – is where the input is transformed into output. The most relevant consequence is that, although it is possible to get outputs, it is often impossible to fully understand how these outputs have been achieved, possibly complicating the human-machine communication and the evaluation of the achieved result.

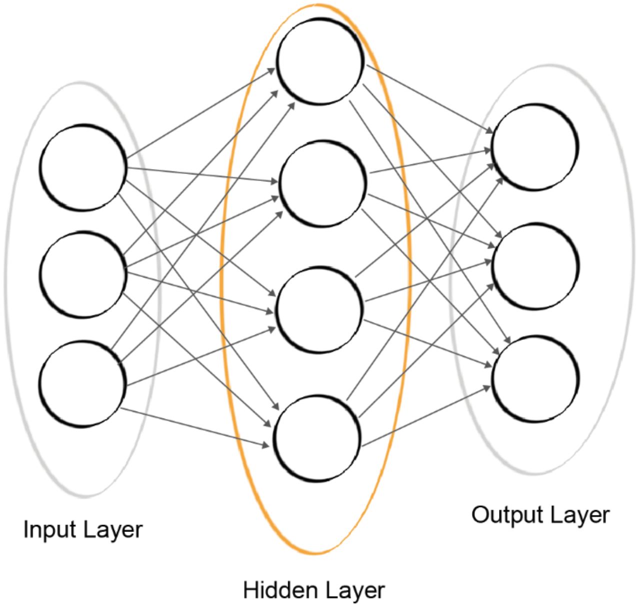

Fig. 3 - The three layers inside a neural network.

3. AI Applications

AI is an ever-growing and improving technology that can benefit several working sectors. Nowadays, it is not easy to find a field that has not integrated it. Hereafter, a list of the most common application of AI is presented.

- *Business*: AI is used for data analysis and management tasks, both internal to companies – such as personnel management and job automation –, and external – such as customer service.
- *Finance*: The excellent computing power of AI at the service of vast amounts of financial data allows us to generate accurate forecasts that translate into reliable financial pieces of advice. These recommendations can operate on tiny and familiar scales, such as buying a house, or vast international rankings, such as investing and trading on the stock exchange.
- *Banking*: AI is widely used for customer services, considerably reducing costs. Moreover, AI predictions can determine the profitability of a loan or an investment.

- *Healthcare*: here, the aim of AI is twofold. The first is to reduce costs and improve logistics and management tasks. The second is to support doctors and patients by improving diagnosis quality and saving time. In addition, AI tools help analyse, manage, and facilitate decision-making in critical situations such as pandemics, as in the case of COVID-19.
- *Law*: the digitalization of legal documents is an ideal terrain for the analytical capacity of AI, which can significantly reduce timeframes and improve the research quality, allowing professionals to concentrate on other tasks.
- *Manufacturing*: the introduction of robots and intelligent systems, which can analyse a situation and take a decision autonomously, has improved the speed and flexibility of the production chain. Machines can now carry out several tasks simultaneously (e.g., assembly and quality control) and choose the right action according to needs.
- *Design and Engineering*: AI software can actively assist designers and engineers in developing specific components to improve performance, reduce the amount of material required, predict and fix errors, etc.
- *Security*: the field of digital security is getting more and more critical, with every company and institution holding confidential information digitally. Thanks to its ability to identify recurring patterns, AI is an ideal system to recognize and prevent cyber-attacks.
- *Transportation*: AI manages marine, air, and land traffic. In particular, it is noted for its ability to efficiently scan traffic lights and optimize route selection for the latter. Moreover, autonomous vehicle driving has become a reality in recent years and is under constant development thanks to AI.

3. A Role for Artificial Intelligence in the Design Process

1. Collaborative Intelligence

The radical socio-technical changes we have witnessed since the second half of the 20th century are mainly due to personal computers' advent in people's lives. Like a prosthesis of the mind, the new tools made available by computers have enabled human beings to break down their limits and expand their vision of the future, achieving incredible results until recently. This concept remains valid also for AI, which is simply the next step in the fruitful collaboration where technology is more and more part of a person's mental apparatus and less a mere tool (Stoimenova & Price, 2020). Thus, although AI is often perceived as a replacement for human work, it maintains the relationship of complementarity where humans and machines cooperate to make up for each other's deficiencies and improve the final quality of the output. After analysing 1500 companies, Wilson & Daugherty (2018) stated that:

> firms achieve the most significant performance improvements when humans and machines work together [...]. Through such collaborative intelligence, humans and AI actively enhance each other's complementary strengths: the leadership, teamwork, creativity, and social skills of the former, and the speed, scalability, and quantitative capabilities of the latter (Wilson & Daugherty, 2018, p. 5)

So, including AI in the creative process in design aims to overcome humans' limitations and improve their capabilities, optimizing the allocation of resources and enhancing creativity.

2. AI as a Creativity Enhancement

Embracing the conceptual line of collaborative intelligence, it is essential to frame our discourse around the specific professional figure of our interest: the designer.

Since we aim to investigate changes in the design process, we must consider creativity. Indeed, its role is crucial in the designer's work to find original solutions to wicked problems. Therefore, understanding if and how AI, through collaborative intelligence, can influence and impact the designer's creativity, and consequently, each phase of his work, is a core topic of our research.

AI, even though revolutionary, is still at its base a computational technology used by designers like other project support systems. As such, it «can contribute to both divergent and convergent processes, which underlie creativity» (Bonnardel & Zenasni, 2010, p. 189).

When speaking of technology applied to creativity, we must consider that there are different kinds of creative processes, which underline many different types of invention, and each of these would require a specific study. Lubart (2005) investigated this issue by trying to identify the prominent roles that technology can play in enhancing human creativity, concluding that computers:

> may facilitate (a) the management of creative work, (b) communication between individuals collaborating on creative projects, (c) the use of creativity enhancement techniques, (d) the creative act through integrated human–computer cooperation during idea production (Lubart, 2005, p. 365).

A step forward has been achieved in human-machine collaboration with AI systems: technology now becomes a partner almost equal to humans. Therefore, in this new relationship, we do not have any more an instrument (the computational tool) that acts as a facilitator of the intentions of the instrumentalist (the human being). Instead, we have two teammates establishing a continuous and productive exchange between them. Indeed, both the designer and the machine can receive input and send output to the counterpart, generating a *cycle* of back-and-forth that ends only when one of the two parties is satisfied with the result achieved (Lubart, 2005) (fig. 1).

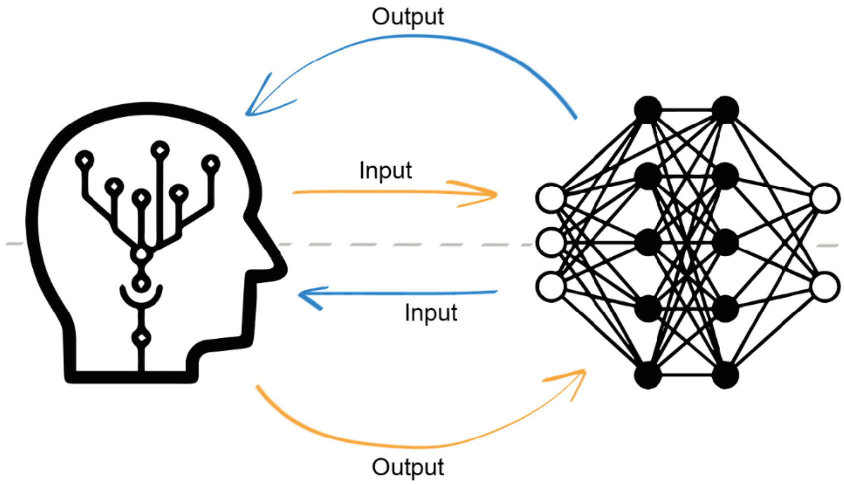

Fig. 1 - The back-and-forth cycle established in a human-AI collaboration.

This substantial change in the creative dynamics within the design group is a turning point for the design discipline: the human user is no longer the only one capable of reasoning out how to solve a particular problem. The consequence is that consolidated disciplinary aspects, even fundamental ones such as the designer's expertise and the tasks to be accomplished during the design process, can now be called into question.

Yannakakis et al. (2014) refer to this new collaboration as *mixed-initiative co-creativity* (MI-CC), defining it as:

> the task of creating artifacts via the interaction of a human initiative and a computational initiative. […] MI-CC paradigm is more than an enabler for human creativity, a mere computer-assisted design tool or a facilitator of human co-creativity such as any CAD tool or an implicit co-creation enabler such as social media. Instead, through the mixed-initiative perspective we assume an autonomous computational system that explores the possibility space in its own ways as guided by human lateral decisions during the creative process, realizing and fostering human-machine co-creativity (Yannakakis et al., 2014, pp. 1, 8).

So, a non-human agent (in this case, AI) assumes inductive and deductive behaviour towards problem-solving, capable of inspiring, triggering, suggesting, and even evaluating choices and actions.

A scenario in which a human agent and a non-human agent proactively contribute to solving a problem is now possible. Thereby, a solution reached through MI-CC can no longer be ascribed exclusively to either the human or the machine but to both (Liapis et al., 2016).

Mixed-initiative co-creativity can incorporate many levels and types of human-machine collaboration, stimulating and influencing creativity in various ways. However, one of the most significant relevance for design is the so-called *random stimulus principle of lateral thinking* (Beaney, 2005). This principle outlines the value of including foreign conceptual elements during the creative processes, which can break the designer's prejudices and patterns of reasoning. While developing an innovative solution, there is a possibility that the designer fossilizes on a particular paradigm or idea, making her more likely to stagnate on a limited solution that is not the result of an open creative process employing lateral thinking. Against this danger, introducing an external stimulus, even a random and sudden one, can be helpful as it potentially reshuffles the values at stake and allows the designer to reframe the problem and find new ways forward.

The work of Liapsis et al. (2016) shows that AI, through proactive actions, has a remarkable ability in providing to the human agents precisely these random stimuli, able to trigger lateral thinking. In particular, how human users interact with four different software that implement AI functionalities with other purposes and timings was analysed (Sentient Sketchbook, Sentient World, Iconoscope, 4Scribe) (fig. 2). This permitted us to verify that, even when AI suggestions are not explicitly followed, significant changes in the final output still occur. Furthermore, recalling the concept of MI-CC, as AI affects the designer's creativity, the designer strongly affects the output of AI, achieving a collaborative exchange.

This exchange becomes clear when we consider a practical example such as sketch-rnn (Ha & Eck, 2018), a recurrent neural network (RNN) capable of conducting stroke-based drawings of everyday objects. The neural network can identify several solutions to an incomplete illustration and complete it (fig. 3). This result is possible thanks to the dataset used for AI training: *QuickDraw*, composed of the innumerable vector drawings from *Quick, Draw!*, an online game in which a human user is asked to draw a predefined object in twenty seconds.

Fig. 2 - The user interfaces of Sentient Sketchbook. On the right, we can see the AI suggestions to modify the map on the left (Liapis et al., 2016).

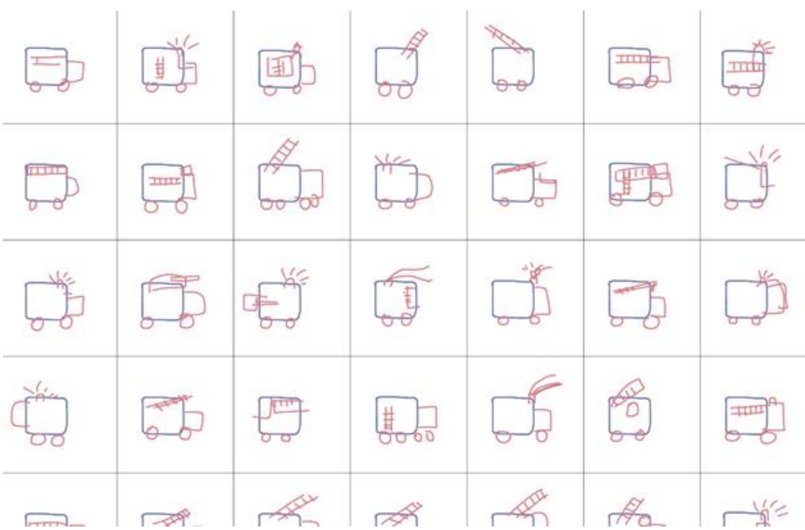

Fig. 3 - Firetruck drawings suggestions by sketch-rnn starting from a user-drawn square (Ha et al., 2017).

In this example, the human-machine collaboration takes place on several levels: the first one is the choice of the thing to draw; at this moment, the user is communicating to the machine her intention and limiting the possible outcomes. Then the user starts drawing the chosen object, again sharing her idea with the device; after analysing the user's strokes, the machine proposes possible conclusions to the drawing. The user receives these proposals, evaluates them, and chooses whether to follow the machine's suggestion and modify her initial idea or continue without variations; at this point, the first collaborative cycle is concluded, and the second one, made up of the same steps, starts. The achievement of an outcome coincides with the interruption of the collaborative cycles, which occurs when one or both parties are satisfied with the results.

Even in a simple example like this, it is possible to highlight the fundamental steps of MI-CC, such as the random stimuli offered by the AI to the user and the close human-machine cooperation in which both parties have a proactive attitude towards solving the problem.

Finally, in the specific case of sketch-rnn, this collaboration reaches a more profound level thanks to the *QuickDraw* dataset provided by human users who have voluntarily drawn countless sketches over time. The human helps the machine improve, so the device can subsequently improve the quality of its contribution to the human.

3. AI in the Idea Development Phases

On a theoretical level, AI could potentially impact the idea development stage of a project, where the most critical choices of the whole design process occur. On a practical level, however, there is an «observed comparative lack of discourse across the design discipline regarding this topic» (Stoimenova & Price, 2020, p. 45).

In particular, the number and impact of possible applications of AI in design thinking practices are still unknown (Cautela et al., 2019). Hence, we are interested in shifting the focus from the purely theoretical and potential dimension to a more practical one.

Cautela et al. (2019) analysed twenty start-ups, investigating in which phases of the project and how often AI was implemented in the design process. The results show the predominance of AI applications in the research, team building, and task management steps. Predictably, AI is predisposed to manage and analyse information effectively, handling large amounts of data and quickly finding meaningful patterns. However, what draws attention is that, through data, AI can also detect qualitative information, such as users' emotional states, prejudices, and attitudes. Therefore, the qualitative knowledge that the designer could obtain in the old days by filtering data and information with her empathy and sensitivity can now be acquired by AI's capacity for analysis. For instance, CRIS (Conversational Research Insight System) is an ML-driven chatbot capable of conducting one-to-one chat-based interviews collecting qualitative and quantitative data on a secure web-based messaging platform.

At the same time, Cautela et al. (2019) noted that AI is barely implemented during the creative stages of the design process, such as the concept phase, highlighting the need to investigate this aspect in further depth.

The question naturally arises: if the role of AI in research is easy to understand, what can be its role in the remaining steps of the idea development? An excellent answer can be found in the work of Liao et al. (2020). Their study elaborated a framework for new design tools incorporating AI, outlining three potential roles in developing a design idea.

1. AI as *representation creation*.
2. AI as an *empathy trigger*.
3. AI as *engagement*.

Concerning the first role, Liao et al. discuss how AI systems can act «to provide inspiration, widen design scope or trigger design actions by suggesting texts or images» (Liao et al., 2020, p. 27). In this way, AI-generated visual data can act like external stimuli to a designer's creativity on various levels, even as a random trigger (Beaney, 2005), while significantly reducing the costs and timescales usually required by traditional design methods.

Moving on to the second role, AI as an *empathy trigger*, AI could support the designer's descriptive thinking, often applied for building scenarios and valuable to widen the scope of possible design ideas. In this specific case - although this is valid for most human-AI collaborations, AI applications are not meant to replace the designer's sensitivity, especially concerning the empathic and emotional aspects of the project. However, AI can provide the designer with new and unexpected information that inspires her.

Lastly, in the third role, AI as *engagement,* AI can help the designer avoid fossilization, incentivizing her to perform typical design actions, such as reframing the problem, considering different knowledge fields, applying lateral thinking, etc.

In conclusion, according to the *knowledge-driven principle*, we can agree with Liao et al. that «the outcomes generated by AI could be a new form of design knowledge» (Liao et al., 2020, p. 23). The designer can exploit such knowledge in new and original ways to enhance her creativity.

4. Artificial Intelligence in the Research Phase

1. New Research Methods

The research phase is usually the first step in the design process: whether a freelance designer or a multinational corporation, it is crucial that choices about the product to be developed are made in this stage. During the research phase, several tasks are performed by the designer/ the design team:

1. Opportunity identification. The study of competitor products available on the market and of present and future trends. The purpose is to identify market opportunities or, ideally, new business segments.
2. Identifying customer needs. The study of people's desires, needs, behaviours, and habits aims to understand their demands. The aim is to design a product they will be happy to use (Ulrich & Eppinger, 2016).
3. Technical analysis. The study of technologies and materials already in use or likely to be used in the near future. The purpose is to assess the feasibility of the project and the possible ways of optimising its production.

The research results are usually condensed into a *design brief*, a written and visual output that describes the main features of the product to be designed. The brief defines the limits and critical points within which the designer can operate confidently without going off-topic during the design process.

The importance of the research in the project and the amount of information needed, which can be both quantitative and qualitative, implies that a large number of resources, mainly personnel and time, should be dedicated to this phase. In this respect, AI, thanks to its calculation and analysis capabilities, can play an increasingly important role in cutting down the resources required and improving the final output of the overall research.

Through the digital world we all interact with daily, such as social networks, blogs, digital newspapers, IoT, and many more, society generates more than 2.5 quintillions (10^{18}) bytes of data each day (Wu et al., 2014).

In this regard, Poetz & Schreirer (2012) compared the quality of design ideas generated by professionals using traditional methods with those generated by ordinary users through crowdsourcing systems, revealing that the latter are often better and more original. This happens because the idea is drawn from a wider pool, and one of the primary limits of today's design process is to overcome the user's direct involvement. Indeed, despite studies showing how involving users during the design process actively leads to better outcomes, with traditional research methods, users must be physically present with the design team, significantly limiting:

> the size, heterogeneity, and quality of customers (Editor's Note: Users) that can evaluate the potential success of a design artifact. As a result, a substantial number of products that are purchased by customers each year are returned, resulting in wasted design efforts, wasted natural resources, and a decrease in long term customer satisfaction (Tuarob & Tucker, 2015b).

In conclusion, the tangible improvements resulting from the implementation of AI in design research relate to more complete and deeper analysis of data, a much larger user pool to draw from, and an overall reduction in costs and resources employed.

2. Data Mining Applications

Before focusing on AI systems applied to the research phase, we must first discuss data mining applications. This field, included in data science, is closely related to AI, with which it shares several points of contact, to the extent that it is possible to confuse them. Data mining consists of processing an enormous amount of data to identify recurrent patterns, from which it is possible to extract useful information and knowledge on what is or was. In contrast, AI also tries to understand what will be.

In design and non-design research, data mining is already a central tool that has forever revolutionized the field. The main difference with traditional research methods, such as interviews, focus groups, customer surveys, and design reviews, is the incomparable amount of data processed, which permits the extraction of hidden information that is difficult to obtain in any other way.

Among the most straightforward data mining applications, we can mention the capacity to identify the most-cited keywords concerning a certain product, reports of positive-negative reviews, and explicit costumers' needs. Beyond that, data mining models can be applied to identify, from a pool of social network users, the so-called *lead user* (Tuarob & Tucker, 2015a), i.e., a customer who has expressed a particularly innovative idea and who is potentially ahead of market trends and solutions. Therefore, this automated model allows the researcher to detect lead users and their expressed opinions and needs, thus generating potentially helpful information for developing new design concepts.

Another possible application of data mining is the development of a methodology that can help the design of product families.

> In the first step of this methodology, data mining algorithms were used for customer segmentation. Once a set of customers was selected, an analysis of the requirements for the product design was performed and association rules extracted. The second step created a functional structure that identified the source of the requirements' variability. Options and variants are designed to satisfy the diversified requirements based on a common platform. The last step elaborated on a product structure and distinguished modules to support the product variability (Agard & Kusiak, 2004, p. 2967).

To conclude, data mining is a field of research in continuous development, where new applications and functionalities that can be combined with AI are launched every year. In general, data mining is able to process and analyse a large amount of data and information, enabling the generation of new knowledge otherwise impossible to obtain.

3. AI Applications

As already mentioned, AI is more focused on predicting possible future scenarios compared to data mining (fig. 1). This feature is undoubtedly considering the widespread uncertainty of today's society: now more than ever, it is necessary for creative people to try to decipher and comprehend what is to come (Cooper, 2019).

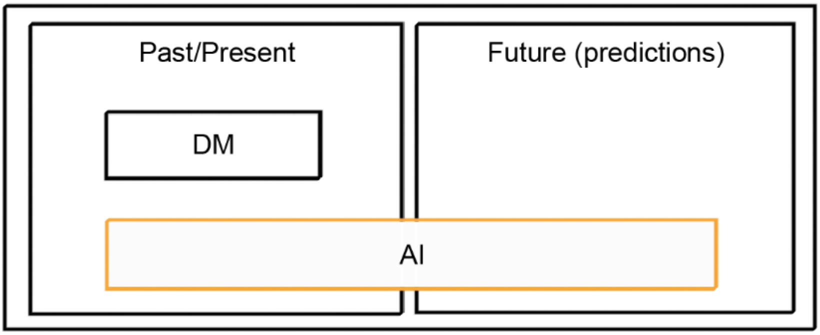

Fig. 1 - Data mining vs Artificial intelligence.

The critical feature brought into play by AI is the ability to recognise and predict people's emotions and behaviours through the analysis of data (Kern et al., 2016). This AI capability becomes even more significant considering the fast spread of IoTs, which become more powerful day after day and can detect spatial, temporal, multisensory, and behavioural data from the experience of a large number of people with greater frequency and accuracy (Xue & Desmet, 2019). Therefore, AI systems will have increasingly detailed and efficient data at their disposal in the future.

Better quality data constitute richer datasets available to AI systems, which can then formulate predictive hypotheses and suggestions with higher precision. For instance, Tucker & Kim (2011) developed a machine learning model that captures emerging user preference trends within the market space. This is possible thanks to the introduction of a subcategory of data change mining called *preference trend mining* (PTM), capable of classifying product's attributes relevance over time, thus guiding the development of the new product's architecture by indicating when certain features should be included or excluded in the next product's generations (fig. 2).

Via its proactive and predictive intervention, AI directly influences the renewal and innovation of the products, highlighting future trends and guidelines that should be followed to satisfy the users' needs better. From the research phase, companies obtain a high level of knowledge on their products, enabling them to effectively allocate the available resources. Stakeholders can concentrate these resources on the relevant features and cut them from obsolete or not in line with the user's wishes.

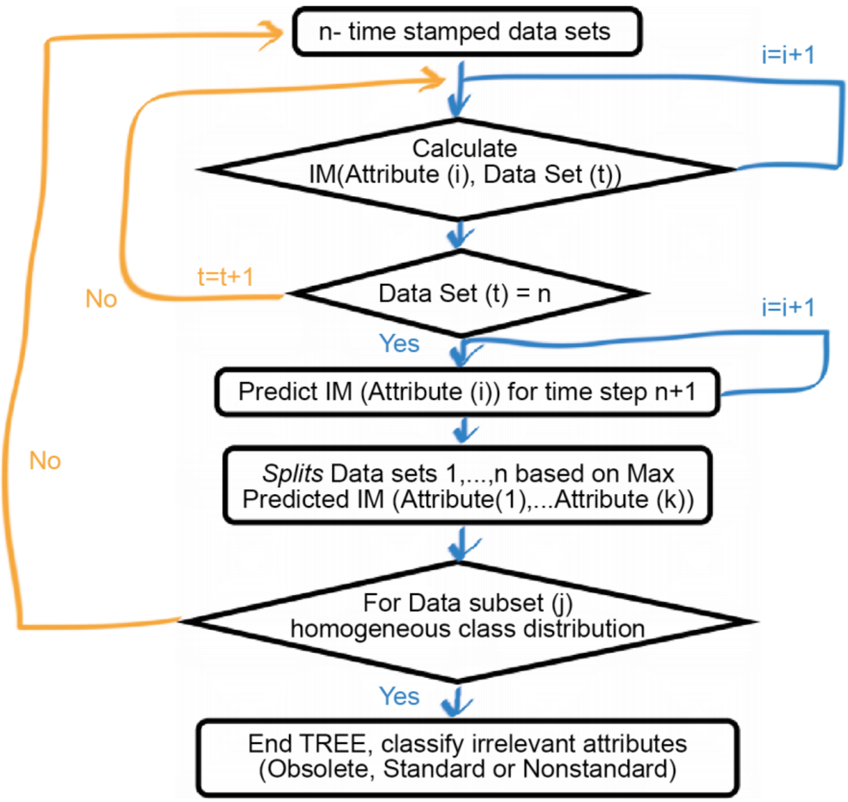

Fig. 2 - Overall flow of preference trend mining (PTM) methodology (Tucker & Kim, 2011).

AI models such as the one developed by Tucker & Kim are an excellent example of how AI can impact design research, outperforming traditional design methods in terms of time, human resources, and amount of data processed. However, traditional methods remain fundamental to the project, as they represent the part of knowledge filtered by the designer's sensitivity. Consequently, a correct and effective research phase should include traditional and new AI research methods at the current state of the art. One type of knowledge does not exclude the other, but instead, they can be considered complementary.

In recent years, researchers and companies have been working on new AI models with targeted research applications capable of producing knowledge at an even higher level of depth. For example, thanks to the potential offered by neural networks, AI capabilities and applications in research are growing significantly, to the point that the term *deep design* has been coined to define this new field of study. In this respect, Pan et al. (2017) proposed a deep learning model capable of predicting and interpreting customer perceptions of design attributes and aesthetics for heterogeneous markets. Understanding why a product is perceived as aesthetically appealing to a specific category of customers and unappealing to others, therefore segmenting the market, is one of the most recurrent challenges designers face during the design process.

This is particularly pronounced, for example, when considering distinct geographical areas, where different cultural backgrounds can significantly alter individuals' aesthetic tastes. As a possible solution to this design uncertainty, the proposed approach takes as input 2D design images and associated labels, customer data corresponding to heterogeneous market segments, and the perceptions of these customers across aesthetic design attributes to visually identify the *salient design regions* on a product (fig. 3). In this manner, it is possible to highlight the link between a feature's aesthetics and a market segment, which is «an incredibly important information to designers as they relate physical design details to psychological customer reactions» (Pan et al., 2017, p. 1968). Despite needing further development to overcome certain limitations, this approach predicted the design attributes *sporty*, *appealing*, *innovative*, and *luxurious* with an accuracy of 75,07%, 67,29%, 75,44%, and 75,09% raising hopes for future progress.

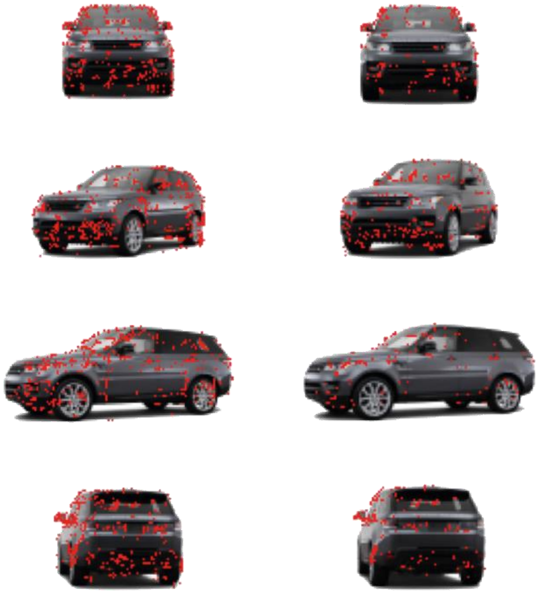

Fig. 3 - Visualization of salient design regions for the 2014 Range Rover Sport. The first column shows salient regions for «Suburban – Women», while the second column shows salient regions for «Rich – Men - Over 40» (Pan et al., 2017).

These AI applications in design research provide, and will provide even more in the future, new knowledge and data to enhance the designer's awareness and comprehension of the project while also reducing the time and costs of traditional research design practices.

4. Google AI

A brief mention of Google AI is in order regarding the research phase. Even if it might seem odd, given the popularity and familiarity of this search engine, Google is one of the leading companies in the field of AI research and application. It means that any search made through Google's search engine is, for a few years now, an AI-driven operation in which the system analyses the search query and tries to predict what information the user expects to find, accordingly proposing possible results. This applies to any output provided by Google, such as websites, social network pages, videos, and photos. Google's AI features are already influencing our research actions, including, of course, those related to the design process. Whether it is a quick or an in-depth search, Google is undoubtedly among the most immediate and exhaustive tools available.

For this reason, opening Google's home page is one of the first and everyday actions that a researcher, or designer, performs when approaching the research phase. Taking as an example the task of selecting a photograph for a design mood board, the designer will probably scroll through the pages of Google Images, which again, through AI, tries to predict the very best results from the many millions of images collected in the database. Similarly, other companies are also implementing similar AI functionalities, such as Adobe Spark, which supports the user in choosing images and constructing a mood board through Adobe Sensei AI.

It would be interesting to learn to what extent Google AI is already influencing design projects nowadays without designers being aware of it: the answer might be surprising.

5. Artificial Intelligence in the Concept Phase

1. The Concept Phase

Once the research phase is completed, the designer understands the given design challenge and can start looking for creative solutions. This phase, which includes several steps, is known as the concept phase. Its initial input is the brief resulting from the research phase. The final output is one or more concepts, i.e., design ideas, aesthetic choices, main functions, user interaction modalities, and technical solutions are all defined. In other words, by the end of the concept phase, the designer has established the design direction and has a reasonable degree of awareness regarding the feasibility of the product. Usually, the outputs of this phase are very visual, so tools such as mood boards, inspiration boards, material boards, usage storyboards, colours palettes, sketches, 2D and 3D renders are widely adopted.

The concept phase is the heart of the design process, and it usually demands many resources taking care of many activities. Moreover, according to their educational background, experience, and sensitivity, designers develops their modus operandi, which can be incredibly personal and unique. AI, in this respect, should not be understood as a tool that standardises and flattens individualities but instead as an impressively versatile instrument capable of preserving and enhancing them, enabling each designer to act in the way she prefers.

A series of AI applications relevant to the concept phase is described hereafter. They could significantly impact the idea development in the design process, either now or in the near future.

The selected applications were grouped into five categories, distinguished by the tasks they perform: *image generator*, *sketching assistant*, *model generator and modifier*, *facilitator* and *concept evaluator*.

2. Image Generator

When the product takes its first tangible form during the concept phase, the designer's primary skills, such as creativity and lateral thinking, are tested. As previously seen, AI can act as a powerful medium for enhancing human creativity, especially if it plays the role of visual stimulus, either intended or random.

To date, collecting visual information to stimulate the designer's creativity can be challenging; this is particularly true for design topics that are still largely unexplored, thus undermining the reliability of traditional methods mainly based on already-existing data.

AI systems can overcome this obstacle with excellent results, generating visual inputs that are entirely new and targeted to the specific design topic. For this kind of application, the mainly employed AI models are based on the so-called *generative adversarial networks* (GANs), which have undergone a significant boom in recent years and can generate high-quality images with high accuracy from the provided input data.

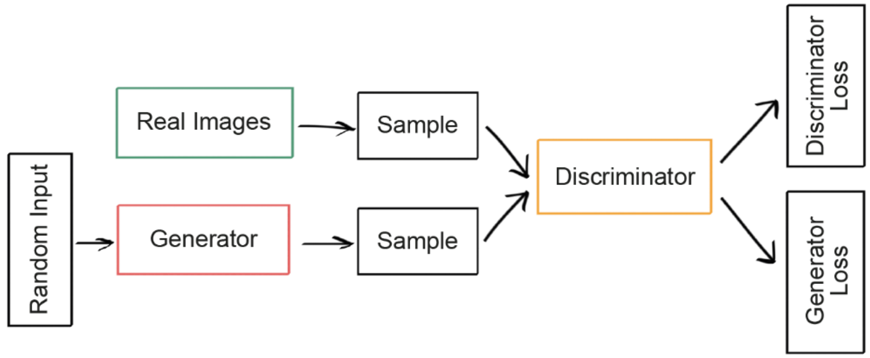

Fig. 1 - Overview of a basic Generative Adversarial Network (GAN) structure.

Speaking of GANs, it is here enough to know that they are a machine learning framework of generative modelling through deep learning methods, thus capable of generating new data similar to the training data. For example, through GANs, it is possible to create the image of a high quality and realistic, but non-existent, person's face from a dataset composed of images of existing people. This is done by coupling a generator, which generates new data, to a discriminator, which distinguishes the generated data into true and false: if the data produced by the generator is considered true by the discriminator, then the result obtained is maintained or it is discarded (fig. 1). Building from this basic model, researchers and professionals have already found further developments to improve and specialise the performance of GANs.

Incredibly compelling and therefore very popular, the generation of novel images through the GANs model's application can inspire the designer's work. In this case, the model, trained with an appropriate dataset, can provide the designer with new visual material explicitly generated for a design project.

In this context, the best-known example is the Chair Project (Four classics) (Schmitt & Weiß, 2018), where Schmitt & Weiß successfully trained a DCGAN with 600 images of iconic chairs from the 20th century to generate pictures of new chairs. Given the relatively small dataset employed, the resulting AI-generated images (fig. 2) are pretty interesting since, excluding those that are unrecognizable, they combine the identity elements of the chair archetype with a certain level of non-definition, resulting in a set of «engaging, semi-abstract visual prompts» (Schmitt & Weiß, 2018, p. 1) that can inspire designers.

Fig. 2 - AI-Generated designs (Schmitt, n.d.).

In the case of the Chair Project, Schmitt transformed a selection of four images into physical prototypes (fig. 3), resulting in an art exhibition (fig. 4) which demonstrates the practical impact of AI systems on human creativity and product development.

Fig. 3 - The process from image to physical prototype (Schmitt, n.d.).

Fig. 4 - The final four chairs (Schmitt, n.d.).

Francesco Isgrò (2020), inspired by the Chair Project, defined a new design tool for his master's thesis at Politecnico di Milano: the *Augmented Moodboard*, i.e., a mood board consisting of a selection of images generated through AI. He proposed a mood board of AI-generated images of lamps (fig. 5) to three designers asking them to sketch lamp ideas. The designers responded with highly positive feedback, certifying the tool as a powerful stimulant for human creativity in the idea development phase of the design process.

Fig. 5 - The Augmented Moodboard (Isgrò, 2020).

Further exploring the possible applications of GANs, Dosovitskiy et al. (2017) showed that a generative adversarial network, while generating data that resembles the source data, can also be trained to:

learn a generic implicit representation, which allows it to smoothly morph between different object views or object instances with all intermediate images being meaningful (Dosovitskiy et al., 2017, p. 703).

Thus, having defined two distinct images as reference, for instance, a chair and an armchair, the model can generate various interpolation steps, each with its own and specific representation (fig. 6). Compared to the previous application, it is possible to considerably reduce the number of parameters involved, which are now mainly dictated by the two reference images, thereby obtaining much more specific and targeted results if needed.

Fig. 6 - Example of morphing different chairs (Dosovitskiy et al., 2017).

An approach that lies halfway between the twos mentioned above is proposed by Chen et al. (2019), who used a GANs model to generate images that synthesize the archetypes of *spoon* and *leaf* to create a set of novel images (fig. 7):

able to produce semantic and visual stimuli for ideation, and improve the quantity, variety, and novelty of ideas generated (Chen et al., 2019, p. 20).

Vizcom, a company that specialised in the development of AI design tools, has released *Generator*, a tool that, interpolating a small number of selected images provided by the user, can synthesise a new image, which the designer can use as a starting point for their work (fig. 8).

Fig. 7 - Randomly AI-synthesized images from training dataset of spoons and leaves (Chen et al., 2019).

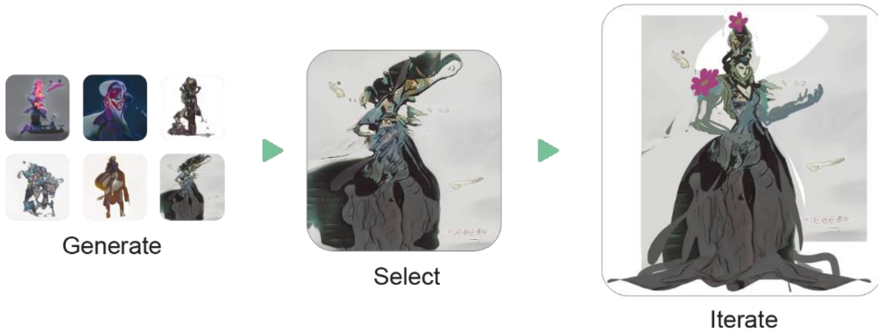

Fig. 8 - Vizcom Generator (https://www.vizcom.co).

Moving to more specific functionalities of AI applications, with the *neural style transfer* method it is possible to generate a new image through interpolating the style of one image, the *style image*, with the content of another, the *content image*. Gatys et al. (2016) developed one of the first successful applications of image style transfer using convolutional neural networks. The system generates new images by manipulating the content and style images. The result is that random photos (content image) are given the appearance of famous works of art (style image) (fig. 9).

Fig. 9 - Neural style transfer (Gatys et al., 2016).

This AI capability acquires new relevance if applied to the concept phase of product design, as demonstrated in the model proposed by Quan et al. (2018), where Kansei Engineering and a neural style transfer system cooperate to achieve a ready-made product autonomously. Here the first system identifies the users' preferences, and based on these, the second one generates the final image (fig. 10).

Fig. 10 - Examples of Style transfer applied to products (Quan et al., 2018).

The presented GANS applications and similar (Chai et al., 2018) can generate a detailed product idea without human intervention, providing the designer with a new type of visual material that is quick to develop and consumes far fewer resources than traditional design methods. Furthermore, GANs and style transfer models have only been studied for a few years now. Soon, they will be able to generate more realistic and detailed images consistently (Karras et al., 2018, 2019).

All the mentioned AI applications require similar inputs, i.e., supplying the generative adversarial networks with at least two existing images.

On the other hand, they present variable outputs:

- The generation of an unedited image.
- The visualization of the interpolation steps between two images.
- The transfer of the style of an image in the content of another one.

The applications of GANs we are about to describe reverse this pattern. While keeping constant the output (i.e., the generation of a realistic but non-existing image), they ask for different inputs from the user. Accordingly, the machine interprets and translates the various inputs provided into new visual material.

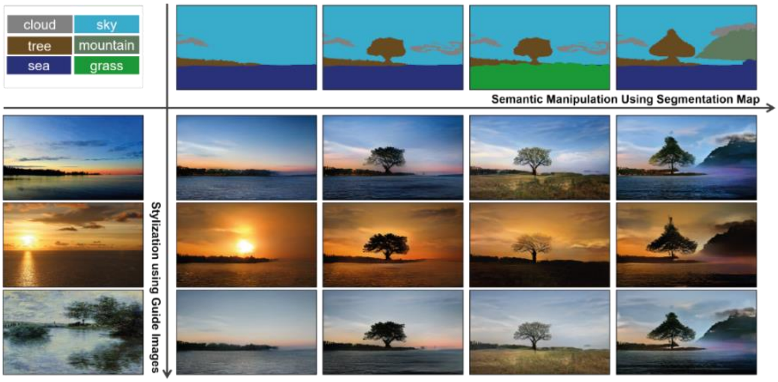

Fig. 11 - The model allows user's control over semantic and style (Park et al., 2019)

For example, Park et al. (2019) developed a layer for synthesizing photorealistic images given a user-provided semantic input layout. As seen in figure 11, the user builds a layout composed of different colours, that are associated to different semantic segments (e.g., cloud/grey, sea/blue, grass/green). The machine then reads the input layout and associates each colour with the corresponding realistic visual details. The result is an autonomously generated image from the layout provided with a reduction in time and compensation for any artistic and technical shortcomings of the user, who may not complete the same work manually with equally good outputs.

In the method Zhang et al. (2018) proposed, we can find another AI application that incorporates a different input type: it generates photographic images from the textual input of semantic image descriptions. The model analyses the text provided by the user recognises the semantic elements that should be present in the final scene, and synthesises a new image accordingly (fig. 12).

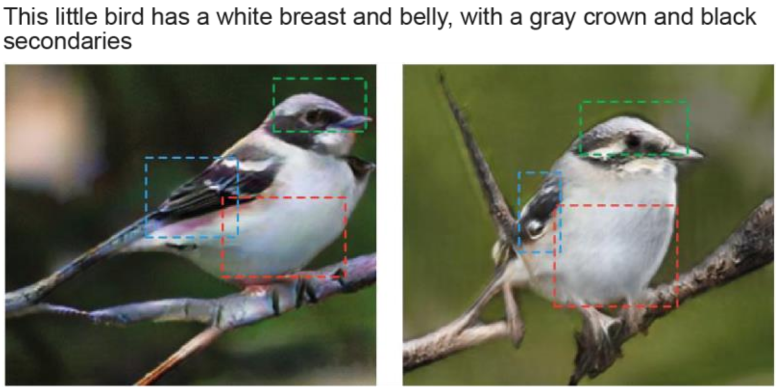

Fig. 12 - AI-generated images based on the textual input «This little bird has a white breast and belly, with a grey crown and black secondaries» (Z. Zhang et al., 2018).

The AI program Dall-e, although developed by OpenAI (https://openai.com) recently, has already demonstrated incredible potential, generating images of non-existing things by combining very distant concepts, contents, and styles, such as the *Avocado armchair* (fig. 13).

Such tools can provide the designer with specific material to be employed in several ways throughout the concept phase, such as inspirational material, sketches, aesthetic and chromatic tests, and scene building. These cases are particularly significant because the designer is no longer expected to translate their ideas through purely visual schemes, such as drawing, but can also use textual schemes, thanks to the collaboration and task sharing with AI.

Lastly, Reed et al. (2016) proposed a new model, the *Generative Adversarial What-Where Network* (GAWWN), which combines the text-based input of the image's semantic description with a topological input, associating what should be displayed with the location in which it should be displayed (fig. 14). In this way, the user is given greater control and consequently a more comprehensive range of possible uses over the output generated.

Fig. 13 - AI-generated images based on the textual input «An avocado-shaped chair» (Ramesh et al., 2021).

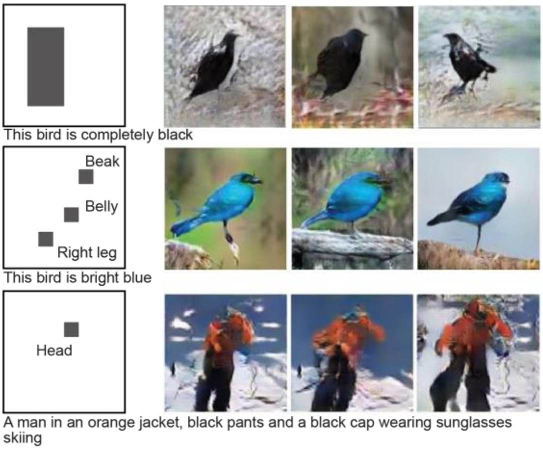

Fig. 14 - GAWWN Text-to-Image examples (Reed et al., 2016).

3. Sketching Assistant

Sketching is an activity present throughout the entire design process, but it becomes essential during the concept development. When drawing, the designer gets the chance to experiment and provoke; to obtain instant feedback helpful in assessing the value of the idea and its degree of feasibility; to trace strokes that are the result of a stream of consciousness, similar to a brainstorming session, or of a targeted choice, to define a particular detail. In short, drawing is the designer's tool by definition. As well as being a visualizing and communicating medium, it is also a reasoning tool in which creativity and reflection are stimulated.

AI systems can enter precisely into this creative action, as a trigger, and as a cognitive enhancement, in a way comparable to how a teammate brings her vision to the project. AI's role, here too, is to act as a creative stimulus, leading the designer to reframe the situation, reshuffle the values at stake, re-evaluate her assumptions and avoid fossilising on a specific idea. For this reason, although AI applications for sketching are still few and limited, they are among those of the most significant impacts for the design process in the near future.

Sketch-rnn (Ha & Eck, 2018), already presented when we discussed the effect of AI on human creativity, is one of the most established sketching tools. It allows the user to draw specific objects in strict collaboration with *recurrent neural networks* (RNN) system, which tries to predict the conclusions of the sketch.

Using sketch-rnn as a reference model, Fan et al. (2019) developed *Collabraw*: a web-based environment for the collaborative sketching of simple visual concepts. Humans and AI draw a line alternately until the drawing is complete.

The case study shows that collaboratively completed drawings maintain the recognisability of the drawn object thanks to the maintenance of its semantic properties, which are attributable neither exclusively to humans nor machines, but to the effort of both, establishing AI as a thinking companion in the creative process (fig. 15).

In another collaborative sketching tool, proposed by Davis et al. (2016) and called *Drawing Apprentice*, AI can recognise the semantic information contained in the input drawing provided by the user and, based on that, draw from scratch either identical or complementary objects (fig. 16). For example, when the user draws an aircraft, in the first case, the AI responds by drawing another plane, while in the second case, the AI responds by drawing clouds.

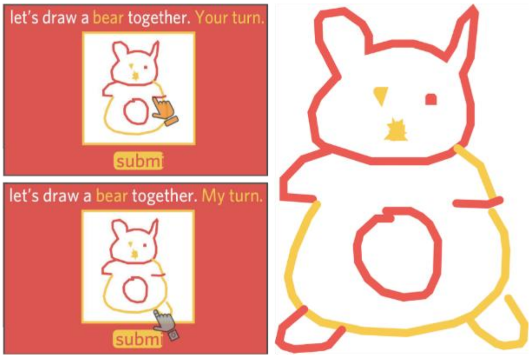

Fig. 15 - Collabdraw (Fan et al., 2019).

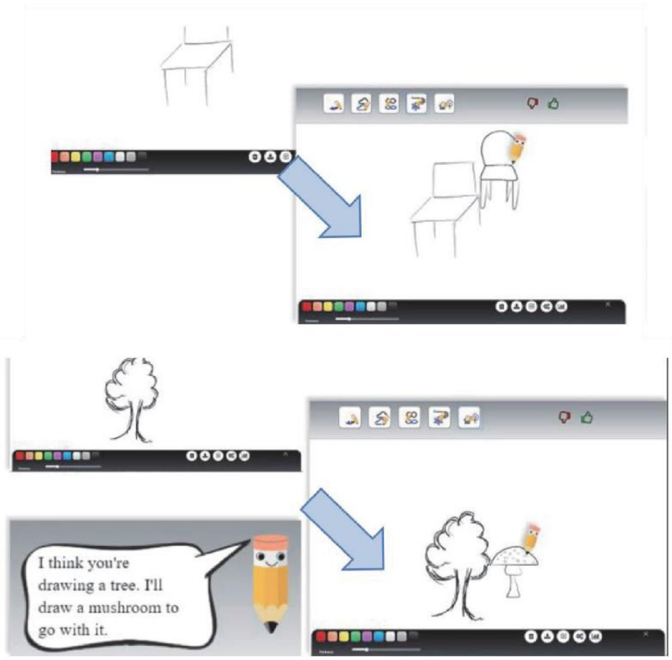

Fig. 16 - Drawing modes using sketch recognition to draw similar (top) and complimentary (bottom) objects next to the user's most recently drawn object. The agent explicitly expresses what it recognizes and plans to draw (Davis et al., 2016).

The model received positive feedback from the designers who tested it, specifying the ability to assist the designer during the idea development. Indeed, through the action of pair brainstorming:

> two individuals engage in a collaborative design session where they each come up with different versions of a target design. This type of brainstorming helps designers fully explore the design space and help understand the design problems. They noted that the Drawing Apprentice could perform the role of their partner so they may engage in this productive form of collaborative brainstorming more often without a human partner. In particular, these designers liked how the system would mimic their designs with slight alterations in unexpected ways, or drew different versions of the same object (Davis et al., 2016, p. 14).

In brief, the sketching phase is essential for developing the idea and achieving a valid concept. In this phase, AI can be an crucial ally both as a facilitator, reducing timeframes and making up for eventual shortcomings in the designer's manual sketching, and, as a teammate, by generating an honest pair dialogue consisting of a continuous exchange of information from one side to the other.

4. Model Generator and Modifier

The construction of a 3D model is a common practice in the later stages of a project, in which an already well-defined concept must become accurate, feasible, and ready for production.

In these advanced stages, AI is widely used with many applications and functionalities, such as speeding up the production chain and improving quality control actions. However, these AI tools will not be considered here, as they are external to our focus. For the concept phase, nonetheless, the 3D model loses its executive role of detail definition and becomes an additional tool at the designer's disposal when developing an idea, as it provides unique final outputs, and therefore unique information, different from those obtainable with sketching. The construction of a 3D model in the early design process allows collecting visual and structural feedback otherwise tricky to obtain. For this reason, also helped by smarter and faster modelling software, more and more designers resort to these tools even in the initial stages of their project. From this perspective, design is witnessing a trend of *fluidification* of the design tools, driven primarily by AI systems. A given tool, which now becomes intelligent and capable of generating an exchange with the designer, is no longer necessarily exclusive to a particular project phase but is versatile thanks to its ability to adapt its output according to the designer's intentions. Consequently, the design discipline might implement new applications and tools, such as AI tools, and review and reinterpret the traditional ones. Hypothetically speaking, as 3D modelling is gaining relevance in the early stages of the design process, in the future other creative tools, such as sketching, adequately supported by AI systems, might also gain relevance in the engineering phases. So future generations designers will have to deal with a reshuffling of the forces at play and incorporate these various levels of change into their practices.

Returning to AI applications for 3D modelling deemed helpful in the concept phase, the best-known example is *Project Dreamcatcher* (Autodesk), a software capable of generating thousands of different 3D models starting from the input provided by the human user. Through AI, Dreamcatcher receives the criteria established by the designer on the desired product, such as the type of object, dimensions, weight limits, stress, materials, cost, and reference models, and synthesises them into coherent proposals. In this way, within a short time, the designer has at her disposal a large number of ready-made models, which are formally correct and with unique solutions, to choose from (fig. 17).

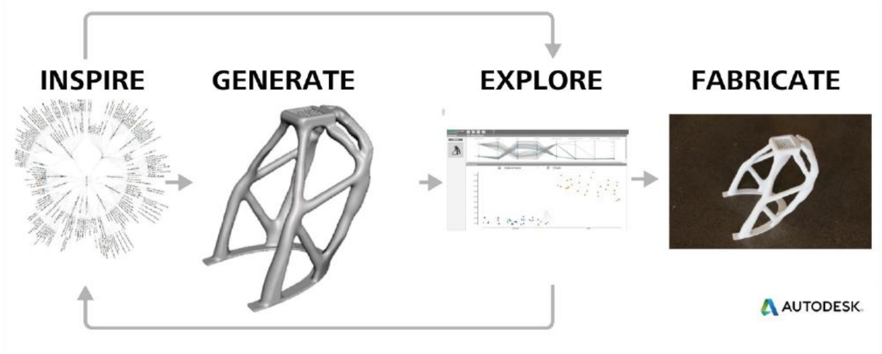

Fig. 17 - Autodesk Dreamcatcher (Williamson, 2017).

> Throughout the iterative process, Dreamcatcher performs the myriad calculations needed to ensure that each proposed design meets the specified criteria. This frees the designer to concentrate on deploying uniquely human strengths: professional judgment and aesthetic sensibilities (Wilson & Daugherty, 2018, p. 6).

Another framework conceptually similar to Dreamcatcher, which considers both engineering performance and aesthetics simultaneously, has been proposed by Oh et al. (2019). From a simple input provided by the user, the model can autonomously generate several topologically optimised solutions of varying complexity (fig. 18).

The next step in the technology will be to recognise the engineering and aesthetic properties mentioned above and the semantic properties. In this way, the designer will provide AI with both quantitative inputs, such as numerical limits and reference models, and qualitative and perceptual ones, such as *dynamic, light, open, elegant, calm,* and *different* (Zwierzycki et al., 2020).

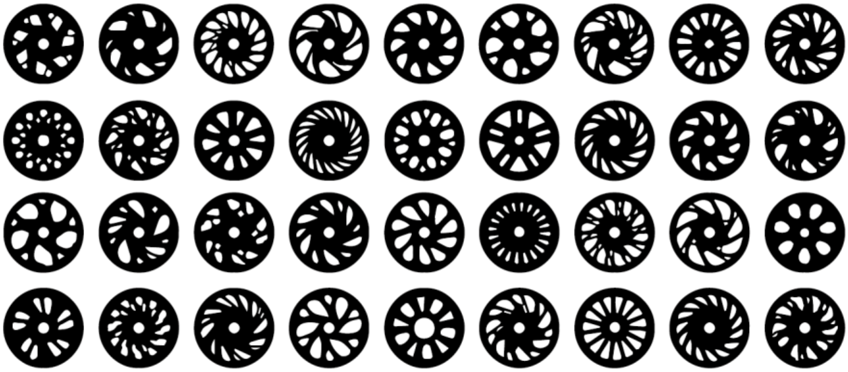

Fig. 18 - Generated design options (Oh et al., 2019).

5. Facilitator

Knowing that AI applications generally act as facilitators by their nature, reducing costs and time required for a given action, this section will only analyse those exclusively so applications. In other words, the next AI systems are meant to streamline and simplify the number of actions to be performed by the user. These applications are primarily used in the multimedia field, such as communication design, photography, graphics, and video editing. Still, they are also often used in industrial product development, given the broad spectrum of activities included in the design process.

Among the most popular systems is Adobe *Sensei*. Adobe embedded artificial intelligence in its software, predicting the user's intentions and related input commands to speed up specific actions, such as selecting a tool (fig. 19), segmenting an image, auto-adjusting parameters, and searching for ideas for mood boards.

Fig. 19 - Adobe Sensei subject select tool (Crewe, 2020).

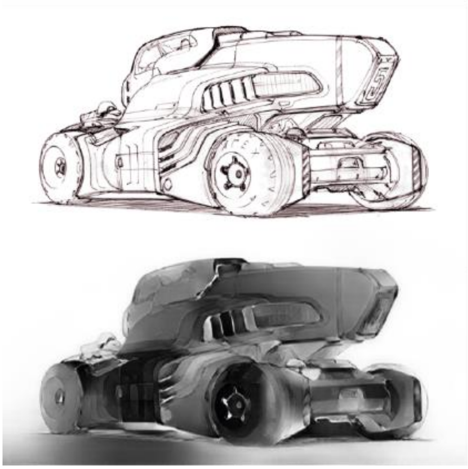

Fig. 20 - Sketch2Render (https://www.vizcom.co)

Further on, a particularly significant type of application for the concept phase concerns AI models capable of generating colour palettes in line with user input, such as *Coolors.co*, *Colourlab AI* and *Khroma*.

Sketch2Render (S2R), a software developed by Vizcom, detects the sketch provided by the user and generates an output that simulates the rendering of a 3D model (fig. 20).

For this type of AI application, we are not talking about fundamental changes in the design process, but rather speeding up everyday and iterative actions, which in the long run considerably reduce the human resources employed, or instead, optimise their allocation.

6. Concept Evaluator

Camburn et al. (2020) presented a method of automatic evaluation of design concepts through ML-based creativity metrics from a large set of crowdsourced design ideas using a machine learning-based approach. The system is a concept benchmarking tool, capable of analysing many design proposals, evaluating them according to the parameters of *Novelty* and *Level of Detail*, and ranking them from best to worst (fig. 21).

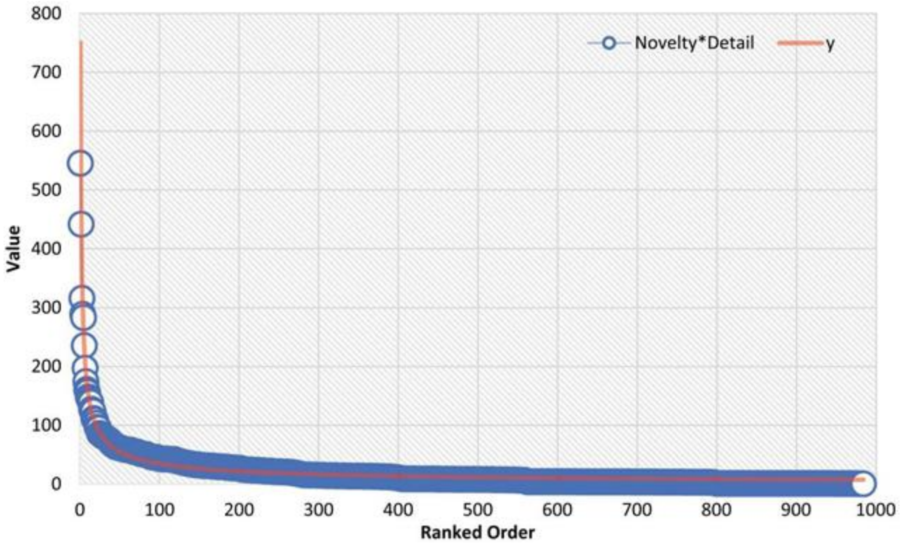

Fig. 21 - AI-Ranked distribution (Camburn et al., 2020).

Similar tools would allow designers to generate, evaluate, and select a more significant number of design ideas, thus expanding the pool from which drawing for their concept, improving the overall design quality. Until now, designers, due to time constraints, lack of resources, and human limitations, could only manage a restricted number of design ideas to turn into valid concepts, considerably reducing the available solutions and affecting the final product outcome.

Again, the introduction of automatic operations, performed by intelligent systems, in the initial stages of design does not aim to «replace the human designer but to empower them to gain deeper insights from existing data» (Camburn et al., 2020, p. 10), optimising the allocation of human resources and increasing the level of awareness of the product to be designed.

The concept benchmarking tool is a clear example of how AI can in the future take on new roles and perform new tasks, even unthinkable today, with a significant impact on the design process and the designer's profession.

6. The Collaboration between Humans and Artificial Intelligence

1. New Team Dynamics

Up to this point, we focused on providing a comprehensive overview of AI in the design process, analysing its different roles, the impact on the designer's creativity, and the possible applications in the idea development stages. As mentioned in the first chapter, a crucial assumption of our research is to consider AI a collaborator of the designer rather than a tool she uses.

Indeed, unlike most other tools implemented in the design process, AI can autonomously perform cognitive tasks and communicate with humans through an exchange of inputs and outputs. Such capabilities suggest that AI collaborative technologies are shifting from performance-enhancing tools towards becoming teammates (Seeber et al., 2020). Therefore, designers and AI can establish a human-machine relationship strikingly similar to the human-human relationship (Krämer et al., 2012). This leads to a transition from groups of humans to groups consisting of both humans and machines, resulting in still largely unknown teamwork dynamics. Given how critical is the social and emotional functioning of groups and teams for the success of a project (Barsade & Gibson, 2007), a study on the impact of AI in the design process would be incomplete without considering the implications on design teams of human-AI collaboration. This need is even more relevant considering that the growth in the frequency with which humans and AI are expected to collaborate is not reflected by equally dynamic academic research (Jung et al., 2017), resulting in a varying level of knowledge surrounding the topic (Alhaji et al., 2020).

In particular, while there is a lively debate on how machines should facilitate collaboration with humans, the same cannot be said for the situations in which humans are requested to integrate the device into their work. Similarly to the way AI systems advance in their capabilities, humans also need to learn to relate to the machine and progressively optimize teamwork. Neglecting to do so would inevitably lead to poor team performances, possibly leading to partial technology exploitation and, in the worst case, becoming counterproductive for the whole project in the end.

2. The Impact on Design Teams

According to Salas et al. (1992), a group is:

> a distinguishable set of two or more people who interact dynamically, interdependently and adaptively towards a common and valued goal/objective/ mission, who have each been assigned specific roles or functions to perform, and who have a limited life span of membership (Salas et al., 1992, p. 4).

While for Bratman (1992), the key factors that define a group are:

- the commitment to mutual support and the overall activity;
- the responsiveness of the members to each other's needs;
- the meshing of the team members' individual plans into a joint program.

Reading both definitions, it might be argued that the definition of a group is strictly related with the description of the interrelation between its members. Therefore, in our view, the nature of the intelligence of the group members might be different (i.e., human or artificial), as their identification as a group is more related to how they are involved and how they mutually relate with each other. For this reason, these two definitions might still be valid if the group includes non-human agents as well (i.e., AI systems). It follows that to achieve the status of *group*, both parties must fulfil their duties as teammates, and in particular:

> not only does the machine have to relate to and accommodate human wants and needs, but also, to some extent, the human is called to reciprocate (Degani et al., 2017, p. 1).

To do this, however, a human must acquire a greater awareness of the subject through a deeper understanding of machines' limits and capabilities. Pandya et al. (2019) and Zhang et al. (2021) demonstrated that, so far, human-machine collaboration can achieve better outcomes when the paired machine performs (slightly) better than the human. On the contrary, it is likely to achieve poorer results if the machine performs the same or worse than the human. In other words, when the human-AI collaboration is implemented to execute a certain task, the AI should provide outputs that consistently increase the team's performance. For example, Zhang et al. (2021) tested the impact of AI on human design teams through a human subject study, which consisted in designing a bridge in accordance with specific criteria. The results showed that «AI boosts the initial performance of low-performing teams only but always hurts the performance of high-performing teams» (G. Zhang et al., 2021, p. 21). We defined this principle as the *AI>human* rule which means that, in order to achieve optimal results for a specific task, AI agents should be more performing than human agents. The *AI>human* principle determines a series of relevant consequences that can provide a better understanding of how to employ AI more effectively in a given specific activity (fig. 1).

The first consequence is the acknowledgment of the *AI's predisposition in performing simple and repetitive tasks*, which do not require complex cognitive skills of problem-solving. In such tasks, AI is usually more efficient than humans, especially for the speed of execution and management of big data. In addition, a redistribution of activities within the design process that streamlines the number of alienating and repetitive tasks allows humans to concentrate on activities that are more suited to their capacities, enhancing them (Rajpurohit et al., 2020).

This leads to the second consequence, namely the *importance of complementarity* in collaboration with the machine. Indeed, although humans and AI can establish a collaborative relationship, they have (still) distinct capabilities and characteristics, meaning that the correct allocation of tasks and competencies is crucial for the work's success. As stated earlier, improper use of AI in a field of action where it does not reach the same level of human performance would lower the quality of the whole phase, thus being counterproductive.

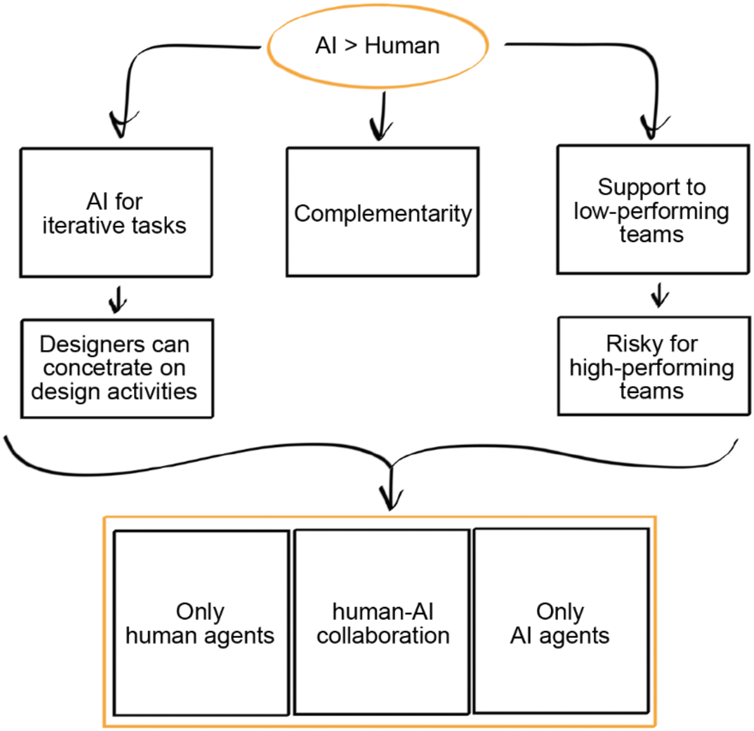

Fig. 1 - The main consequences of the rule AI>Human.

Finally, the last consequence concerns the tendency of AI to *improve the quality of work of low-performing teams* (Pandya et al., 2019; G. Zhang et al., 2021). Low-performing human teams expand the possibilities of using the machine, which can eventually compensate for the team's shortcomings. Although this may seem of little interest, AI could guarantee a minimum level of performance for a team, stabilising the quality of output and avoiding or limiting design failures.

On the other hand, in the context of a high-performing team and at the current state of the technology, AI should be employed carefully, within fewer fields of action such as iterative or AI-exclusive activities, since the possibility of worsening the overall performance of the team becomes higher. Understanding the human and machine's limits is crucial for proper human-AI collaboration. It makes it possible to define the forces in play according to the *AI>Human* rule, allowing a conscious redistribution of the team's resources to ensure improved performance. Based on this, it is recommended to carefully plan who will carry out a given activity*: only the AI system* if the human agents could hinder it; *only the human agents* if the AI system could slow them; or *both* if combining efforts would lead to greater efficiency and better results.

It is essential to clarify that these assumptions apply as long as the design process is linear. Group dynamics may be altered when unforeseen or unexpected events occur, such as the redefinition of the problem addressed in the project. The study by Demir et al. (2019) indeed shows that groups formed by both human and non-human agents referred to as *synthetic groups* exhibit a high level of stability, which also leads to a high level of rigidity. Therefore, a synthetic group presents a double face: on the one hand the group is highly efficient when operating in a stable environment; on the other hand, due to the low adaptability caused by rigidity, the group's efficiency may vary and be impaired when operating in a highly dynamic environment.

However, the work of McNeese et al. (2021), which builds upon the research of Demir et al. mentioned above, also reveals that in contrast to groups composed entirely of human agents, synthetic groups can significantly improve their efficiency – described as *coordinated awareness of the situation by teams* (CAST), over time. The potential conflicts caused by a contingency in the design process may result from the human agents' inexperience to work alongside non-human agents under certain circumstances. This implies that conflicts may possibly be lessened due to the human-machine dynamic and that:

> developing coordination and team situation awareness (TSA) in human-machine teams is feasible depending on the context in which the teamwork is taking place" (McNeese et al., 2021, p. 11).

In conclusion, the integration of AI within project teams may present some challenges and require a certain degree of awareness to be positively employed. It will be far more intuitive and safer in the future, thanks to the constant development of technology paired with the continuous learning of human agents in interacting with it.

3. The Need for Proper Training

The educational issue gains a renewed relevance since designers can learn and improve over time to collaborate with AI agents. Proper training on the implementation and usage of AI systems would expand the knowledge of designers, encouraging them to introduce and optimise the use of these technologies, which would bring competitive advantages on team effectiveness (Rajpurohit et al., 2020).

On the contrary, an educational program that does not acknowledge the importance of disruptive technologies, especially AI, will form uncertain professionals (Mortati & Bertola, 2021) catapulted into a world they do not fully comprehend. Therefore, training and higher education programs must prepare students for the inevitable digital transformation by equipping them with the right tools and supporting their competences development to properly approach these new technologies with a proactive and welcoming attitude (Torre et al., 2021) while being aware of the limits and risks associated. Precisely because of this, without a planned training and period of familiarisation, these new systems: «may constitute more of a concurrent task than an effective support for users» (Bonnardel & Zenasni, 2010, p. 189) in the future.

4. Critical Issues in Human-AI Collaboration

Until now, scholars have analysed human-AI collaboration according to the impact and consequences generated by introducing non-human agents into a design team of human agents, investigating potential risks, and proposing guidelines on which to build a conscious and successful collaboration. We will refer to these issues, related to the competencies of both AI and humans and to their management, as *technical criticalities*.

However, when considering collaboration of any kind, these technical criticalities are not enough to describe the whole dynamic. It is widely acknowledged that any relationship is shaped mainly by the participants involved, with their own experiences, sensibilities, and inclinations. In addition to the technical criticalities, we must also consider what we call *sensitive criticalities*, which are subjective and nuanced, hard to be framed using objectives rules and, therefore, to manage. Among the sensitive criticalities, we will focus our attention on the following:

- *predisposition criticalities;*
- *perception criticalities;*
- *communication criticalities*.

Regardless of the design issue at stake, a designer may not establish a healthy human-AI collaboration especially if they have not received any training to familiarise with it. The result is likely to be an altered and non-functional relationship, where the human agents grant an inappropriate or insufficient level of trust towards the non-human agent, eventually leading to costly consequences in the design process.

We can define *trust* as:

> the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party (Mayer et al., 1995, p. 712).

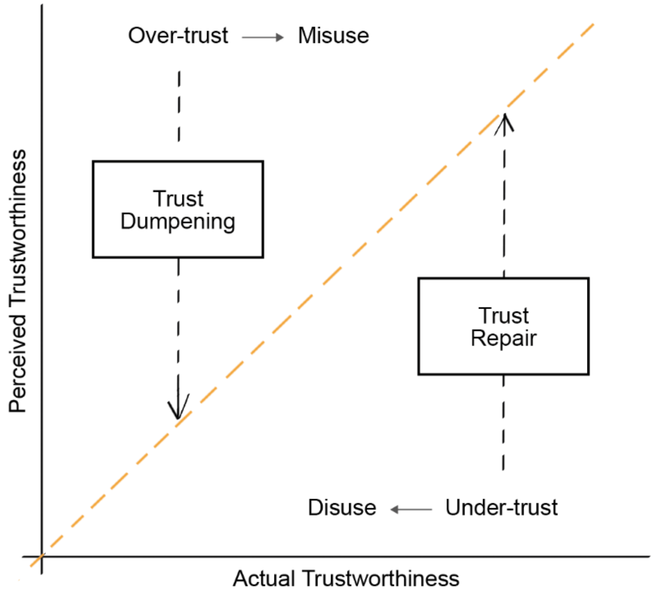

Fig. 2 - Over-trust, under-trust, and calibrated trust as a function of perceived trustworthiness versus actual trustworthiness. Adapted from de Visser et al. (2020).

Trust is a crucial element within any team, particularly in groups involving non-human agents that are less familiar and more difficult to assess for humans, increasing the risk of trusting non-humans too much or too little. *Over-trust* can condition human agents into complacent states and misuse, leading to costly mistakes. *Under-trust*, on the other hand, «can cause inefficient monitoring and unbalanced workload, leading to disuse of a machine or the avoidance of a person» (de Visser et al., 2020, p. 460) (fig. 2).

4.1. Predisposition Criticalities

This type of criticality derives from the person's predispositions, which manifest mainly as biases, intended as preconceived opinions based on personal convictions and general assumptions that can strongly condition one's vision, attitude and evaluation, thus possibly leading to errors.

The above-described condition is typical of highly debated socio-technical issues, including AI. Here, many theses clash with anti-theses, and people often lack the necessary in-depth knowledge to have balanced opinion.

Lopez et al. (2019), after finding that gender, education level, experience and age can influence the designer's decision-making when interacting with generative design tools, investigated the designer's possible biases towards computer-generated sketches. They found that, on average, AI-generated drawings were perceived as equally functional to those generated by human users when anonymous and less valuable when presented with a label. This demonstrates that the perceived functionality of drawings may be subject to bias during the evaluation process.

Bias, mainly caused by inexperience, can lead to *over-trust* or *under-trust* towards AI systems, in both cases hindering the designer's decision-making process. A period of usage combined with a more profound knowledge of AI technology is the easiest way to break down the designer's preconceptions and increase the chances of establishing an efficient and satisfactory collaboration with the machine.

4.2. Perception Criticalities

The distribution of tasks and responsibilities between human and non-human agents within the design process can be highly beneficial, but also possibly dangerous for the perception of the work done. In fact, due to the reduction of actions carried out by the human agents, their overall knowledge of the project decreases, creating the risk that their ability to evaluate it is also altered once the work is completed.

This situation is well illustrated by the study of Zhang et al. (2021), in which it was assessed the impact of AI on distributed human design teams through a human subject study that includes an abrupt problem change.

> In the post-experiment questionnaire, participants in the high-performing hybrid teams believe they accomplish the design task more successfully compared to participants in the high-performing human-only teams, but in fact their performance is worse. Participants in the high-performing hybrid teams also perceive less mental demand compared to participants in the high-performing human-only teams (G. Zhang et al., 2021, p. 12).

Thus, it might be assumed that an altered perception does not allow the designer to analyse their project in-depth, to find possible mistakes, to fix them,and look for possible improvements. Indeed, designers:

> may be less motivated to create better designs in the study, which may lead to the less human effort in solving the design problem and result in the reduced performance of their teams (G. Zhang et al., 2021, p. 20).

So, designers who show signs of *over-trust* towards AI systems can display an unconscious attitude of laziness in their work. Once again, extended use of the AI system would allow the designer to familiarise with it and refine their evaluation methods by reducing the conditioning of their perception.

4.3. Communication Criticalities

One of the most debated and recurrent issues concerns the communicative aspect when considering AI systems. This is because these systems work as a *black box*, in which the human agent only knows the inputs and the outputs, not the reasoning process in between. Consequently, although the designer is well-aware of the output generated by the machine, there is no insight as to why or how that specific output was achieved in the first place, which may lead the designer to contest these results and be reluctant in accepting them in critical applications (Luhmann, 2018).

The inability of the machine to be completely transparent is undoubtedly one of the most deep-rooted and complex criticalities in human-AI collaboration, as it enhances the attitudes and inclinations of human agents that cause an imbalance in the trust relationship. Since the human agent cannot see the process behind the output, it is likely to blindly rely on the machine if it is predisposed to *over-trust* or ignore it if it is predisposed to *under-trust*.

In recent years, there have been considerable efforts to solve this problem by implementing forms of communication capable of displaying the hidden process in AI systems, thus improving the human agents' expertise to calibrate trust in the relationship. The idea is to make AI systems more and more similar to human agents, thanks to the establishment of a communicative exchange that is not exclusively based on inputs and outputs, but also on the development of:

> methods for explainable AI (XAI) for adequate human understanding and appreciation (including trust) of symbolic and sub-symbolic agent performance (Neerincx et al., 2018, p. 205).

It is not enough for AI systems to communicate for human agents to establish a proper trust relationship: how and when they speak is equally important. As evidence of this, Bansal et al. (2021) showed in their research that:

> the accuracy of a human-AI team can be improved when the AI explains its suggestions, but these results are only obtained in situations where the AI, operating independently, is better than either the human or the best human-AI team (Bansal et al., 2021, p. 14).

Consequently, the improvement in collaboration is not mainly determined by the communicability of the machine but rather by its performance. AI Explanations positively impacted team performance when the machine was correct but also negatively impacted when it was not. For example, if performed in the wrong way and at the wrong time, the communication action can cause an unwarranted increase in trust that leads the human agent to blindly follow the AI instead of leading to a balanced level of reliance. In this respect, one precaution is the development of machine communication models aimed at informing rather than convincing.

The AI transformation process from *black box* to transparent agent still has to overcome several obstacles before it is completed. Therefore, the need for the human agent to properly interface with AI systems remains one of the key drivers for proper human-AI collaboration.

In conclusion, the human agents, as long as AI systems do not communicate properly, should focus on the analysis of the outputs provided by the machine, which is the most consistent way to obtain a lucid and unbiased evaluation of the work.

5. An Updated Role for Designers

With the integration of AI systems in the design process, a non-human agent is added next to the designer in the role of an artificial intelligent group member capable of reasoning and carrying out proactive actions to solve the given design problem. Consequently, even if the design phases remain the same as before, their execution potentially changes, for example, by redistributing the activities to be performed. These modifications also affect the designer, who must reassess her contribution to the project in relation to the machine, adopting a new role, with new priorities, tasks, and skills.

This readjustment of the designer figure due to the integration of AI systems is a significant step in the discipline and an explicit necessity: it is not reasonable to establish effective collaboration between humans and AI if the former do not adapt. But, the extent and how the designer must adapt is still undefined.

The attribution of responsibility in a team composed of both human and non-human agents might help clarify the issue. The research by Lei & Rau (2021) studied the attribution of credit for success and of blame for failure in a human-machine team in three different situations, obtaining the following results:

> first, people attributed more credit and less blame to the robot member than to themselves. Second, people attributed similar levels of credit and less blame to the human member than to themselves. Third, the robot member was more blamed than the human member, whereas they received similar levels of credit (Lei & Rau, 2021, p. 374).

In summary, the results do not reveal any consistent pattern. Depending on factors such as context, success, or failure of the outcome and group members, a human agent may feel more or less free to credit or blame the non-human agent.

In this situation of uncertainty, it is essential to establish to which extent AI shares responsibility. Given the current state of technology, our answer is that the designer is totally responsible for the design process and the outcome. This is because AI systems and human-AI collaboration are not infallible. Consequently, it is up to the designer to evaluate the machine's work and choose whether to consider its output or discard it if it does not meet expectations. The new role of the designer, when AI will be assigned more and more operational problem-solving tasks, is primarily that of an *arbiter*.

Design arbiter is our way to define a figure who combines the skills and sensitivity typical of the designer with excellent critical analysis expertise, helpful in evaluating the outputs provided by AI systems and appropriately implementing them in the design process. This is because the *designer arbiter*, relieved of the operational responsibility taken on by AI and less involved in individual manual activities, assumes a privileged position within the design process more focused on management and supervision tasks, in line with the distinctive qualities of the profession.

The *designer arbiter* more intensively applies her expertise at a higher level, such as the project's general direction, the understanding and framing of the problem, and her sensitivity, intuition, and know-how into the design process. Among the key competencies of the *designer arbiter* is the ability to manage collaboration with AI systems, or better, the ability to design for AI (Verganti et al., 2020). In other words, the designer should perform the set of decisions and actions necessary to enable the AI to work effectively on the project and coherently with the team, which include:

> to understand which innovation problems are meaningful, framing the innovation effort, and set up the software, data infrastructure, and problem-solving loops that will solve them (Verganti et al., 2020, p. 225).

In conclusion, the *designer arbiter* is a figure with solid evaluation and management skills, capable of understanding the project and the AI systems at a deeper level and maximizing the human-AI collaboration to significantly expand the design process's potential and final output.

7. Testing Artificial Intelligence in the Design Process Early Stages

1. Three Questions to Ask

From the literature review on the impact of AI introduction in the early and most creative phases of the design process, three main research questions emerged:

- Are *technical* (AI>Human) and *sensitive* criticalities (predisposition, perception, communication) and their implications in Human-AI collaboration verified?
- Is the *random stimulus of the lateral thinking* concept in AI applications dependent on Human-AI collaboration criticalities?
- Considering a design process where designers and AI agents alternate moments of collaboration and moments of autonomous work, how does the alternation affect the Human-AI collaborative?

A workshop was structured to test the main dynamics of a Human-AI collaboration, focusing on changes in creativity and in the trust relationship. Furthermore, *continuous* and *discontinuous* Human-AI collaboration were compared to verify divergences, unique repercussions on the creative process, and participants' perception of the different working conditions.

2. The Design Workshop

The workshop was structured to simulate, in a simplified manner, a design process up to the definition of one or more concepts through three typical creative phases: the research, the sketching, and the colour selection phase.

A specific AI system was provided for each step to support the participants during their design activity:

- The search engine Google for research;
- The sketching assistant Sketch-rnn for sketching;
- The colour palette builder Coolors.co for colour selection.

The sixteen participants[1] worked in pairs, forming eight groups, split into two distinct types, *simultaneous* and *delayed*. Simultaneous groups worked throughout the whole duration of the workshop alongside the AI systems. Instead, delayed groups alternated between an initial period, per phase, without the help of an AI system, followed by a subsequent period with it. For instance, *simultaneous* groups had twenty minutes to develop their research phase using Google search, while *delayed* groups started their research without it and were asked to use the search engine only in the last ten minutes.

The groups were asked to design in an hour a *frog-sofa* that, being uncommon and deliberately vague, was chosen as an element of surprise, encouraging participants to generate their interpretation while working and explore unique and personal solutions.

The total duration of the workshop was one hour, subdivided into three phases and with slight variations between simultaneous and delayed groups.

Participants were given two forms to fill in during the workshop. Form *A* was given before the design activity and intended to verify possible pre-existing biases of the participants. Form *B* was given after the conclusion of the design activity to verify potential biases' changes and investigate the workshop experience.

At the end of the design activity, a forty-minute focus group was conducted to generate a discussion driven by the following two open questions:

- «To what extent and in which way do you feel AI has influenced your creativity? »,
- «In terms of trust, how do you feel about the AI suggestions during the workshop? ».

[1] Alejandro Alcaraz, Walter Brattelli, Elia Gambelli, Moritz Hedrich, Ahmed Hegazy, John Helou, Francesco Lamperti, Célian Le Bolloch, Mika Lessmann, Michela Moretti, Francesca Piazzo, Nicolle Ruiz, Fulvio Seva, Alessia Stifano, Riccardo Tonin, Julian-Malte Wenning.

3. The Selected AI Tools

The AI systems Google, Sketch-rnn and Coolors.co (fig. 1) were selected according to three criteria.

- *Ease of use*. given the short timeframe of the workshop, participants needed to interface with the machine immediately and intuitively. The aim was to ensure that the development of the human-AI relationship, which was the proper focus of the investigation, was not hindered by critical issues associated with using the AI systems. Moreover, the selection of familiar tools allowed participants to see how AI is already present and often hidden in everyday digital systems.

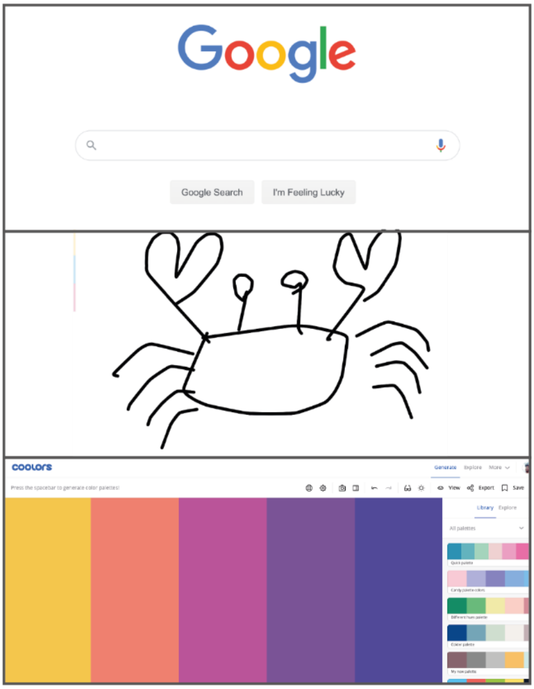

Fig. 1 - In order: Google, Sketch-rnn and Coloors.co.

- *Affinity with the design phase*. the selected AI systems needed to fit coherently into the three design phases of research, sketching, and colour selection, and to assist the participants in generating the final outputs.

- *Different human-AI relationships*. different AI systems were chosen in terms of familiarity, efficiency, and purpose, to investigate the collaborative relationships established. Google, familiar and efficient, was selected to play the role of *professor* within the groups, i.e., an extremely competent figure who is easily trusted and hardly questioned. Sketch-rnn, engaging but still limited, plays the role of a *non-expert teammate* in sketching. Coloors.co, specialised in colour palettes, is much closer to the figure of an *expert teammate* in the knowledge of chromatic matching.

4. The Results of the Workshop

The results of the workshop were collected with a qualitative approach by analysing (fig. 2):

- the participants' responses to the form A and B;
- the workshop outcomes provided by the design activity;
- the results of the focus group run by two facilitators at the end of the design activity.

Hereafter, all the results are described according to the specific phase of the design activity.

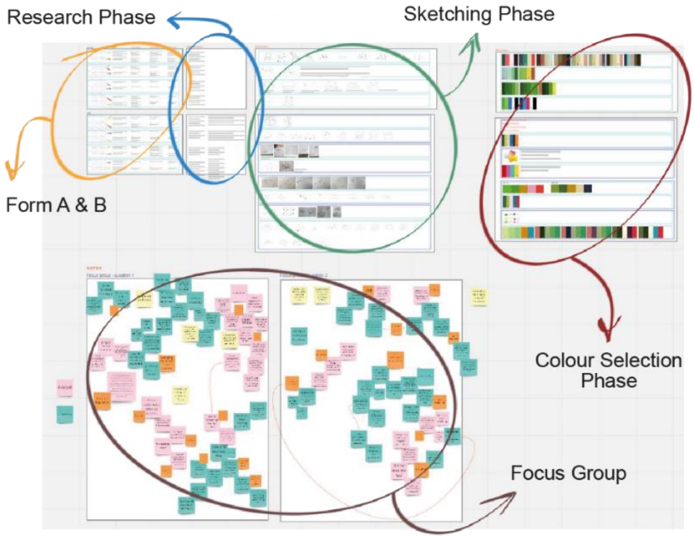

Fig. 2 - Data collected from the workshop.

4.1. Participants’ Attitude Towards AI

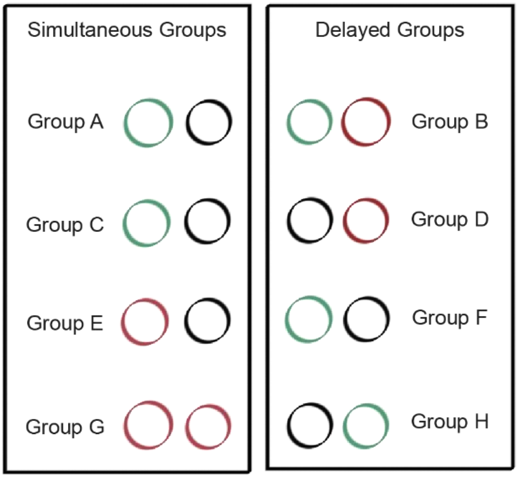

Fig. 3 - In red: participants who have worsened their view; in green: participants who have improved their view.

The participants’ responses to form A show their neutral position towards introducing AI systems and demonstrate an overall welcoming attitude towards the treated issue. After the design activity, these results were compared with the participants’ answers to form B. Ten out of sixteen participants substantially changed their opinions. Of these ten, five took a more favourable position and five a more contrarian one, including slight and drastic shifts.

The type and extent of the shifts are not explicitly related to being the respondent in a simultaneous or delayed group, as shown in fig. 3.

4.2. Research Phase

The participants’ answers to the form B show that Google had significantly influenced their research. On a scale of 1 to 10, they had followed Google’s advice with an average of 6.625. However, if we consider the subdivision of the groups into simultaneous and delayed, the average fluctuates considerably, resulting in 7.875 and 5.375, respectively.

We can observe that participants who were always supported by the AI tool perceived the influence of the technology on their research with greater intensity. In contrast, participants, who had the opportunity to conduct an autonomous brainstorming session before using Google, perceived that they followed its outputs less and that the overall contribution to the project was more attributable to themselves. This difference in perception can be explained by simultaneous groups basing all their searches on Google's outputs until they achieve the final list of keywords. Delayed groups, instead, built their research without AI, favouring its subsequent use as a tool for expanding, deepening, and detailing their initial set of keywords.

In practice, Google played the role of an *intrusive teammate* for simultaneous groups. In contrast, for delayed groups, it played the role of an external figure, the *expert* capable of generating new insights starting from the work of the two human agents.

This distinction is also visible in the participants' final outputs of the research phase (tab. 1). The keywords of the simultaneous groups, although exhaustive in quantity and diversification, targeting both the general and the detailed, present a particular pattern and common elements, such as the features of the frog (*green, eyes, roundness, mouth, fingers, biomimetics, paws, agility, pattern*), the emphasis on the playful and childlike aspect (*cartoon, bouncy, funky, playful, informal, memes, kids, funny*) and the features of the sofa (*softness, comfy, soft, adjustable, cosy*). Thus, despite excellent cognitive support, there is a risk of being excessively conveyed by Google, generating a standardisation of the obtained results. On the other hand, the keywords provided by the delayed groups indicate that without Google, the team's probability of facing a blockage in the design process increases. However, there is a more remarkable uniqueness of the keywords, including totally unexpected ones, absent in the lists provided by the simultaneous groups.

Despite the chance to use Google after the first brainstorming session, delayed groups often limited its usage to what they had already done without expanding their research in new areas of knowledge. This behaviour demonstrates that they remained excessively attached to their initial idea and resulted in a narrow view of the design challenge, which could lead to ignoring any external inputs and hindering the creative process.

Tab. 1 - Research phase output: keywords from all the groups.

Group	*Without AI*	*With AI*
A	Eyes; Green; Mouth; Pattern; Seated Shape; Bumpy; Fingers; Bouncy; Cartoon.	
B	For Frog and Frog owner; what makes a frog comfortable?; Frog size?; Human and frog at eye level; Can frogs climb?; Who is the typical frog owner - is there frog owner association?; Human and frog snack dispenser.	Frog owners love merch with frogs on it → frog sofa should look like a frog too; Frogs can eat worms not just flies; Frog size ca 9 cm; Frogs can climb!; Frogs live in swamps: high humidity low airflow; Tadpole-tank for hatching and making the adult frog feel more at home; Typical frog tanks have both land and water, lots of plants.
C	Green; Biomimicry; Comfy; Bouncy; Softness; Elastic; Roundness; Agility.	
D	Inflatable; Frog form; Jumping; Spring.	Frog form; Inflatable; Jumping balloon; Frog face; Transparent cheeks.
E	Playful; Funky; Soft; Informal; Free Form; Fluid; Daniel Landini; Memes.	
F	Sympathetic; Energetic; Relaxed; Soft.	Group chilling; waterlily sitting; Very social.
G	Green, Rounded; Big eyes; Adjustable; Kids; Funny; Paws;Cosy.	
H	Frog; Eyes; Smile; Comfortable; Soft; Sponge; Playful; Nature; Animal Friendly.	Creative; Children; Green; Adventure; Explorer; Play; Jump; Jungle; Water lily; Tiny; Comfortable; Soft; For 1 or 2 people at maximum

In conclusion, both proposals have positive and negative aspects, with more individual and personal results for the delayed groups and more complete results for the simultaneous groups in terms of quantity and variety of content. The work of simultaneous groups was also characterised by a closer human-AI collaboration, as if constantly working with technology can foster human and non-human agents' alignment, decreasing the possibility of generating misunderstandings and conflicts inside the team. However, if not aware of the possible influence of Google in orienting the research, simultaneous groups may run the risk of being overly conveyed by the AI system during the research phase, hindering an efficient creative process.

4.3. Sketching Phase

The sketching phase was undoubtedly the most challenging for the participants, who, as the forms prove, rarely followed the advice provided by Sketch-rnn.

For both simultaneous and delayed groups, the limitations of a system that is still largely under development and not specifically designed for product design purposes became a significant obstacle in the creative development of the sketch. From this point of view, however, it is interesting to note how the various groups reacted to the technical limitations of the AI system and pursued new solutions through distinct approaches and methods of work, resulting in unique final outputs.

The main difference between the work of the two types of groups, similarly to the research phase, is the continuity of the collaboration between human agents and Sketch-rnn, with the simultaneous groups characterised by a strong continuity and the delayed groups by a strong discontinuity. In the first case, the participants, who constantly worked within the boundaries established by Sketch-rnn, learned its working mode and limits in a short time, progressively adapting their working methods to the AI system to reach one or more outcomes. Therefore, we can affirm that simultaneous groups operated within a well-defined working space, where humans and AI share common working practices, intentions, and goals, generating an efficient environment. However, the same environment risks being limited and favouring a convergent rather than a divergent thinking. This is because the established collaboration between humans and AI, although allowing group members to be aligned, is the result of an intrusive and unidirectional action of the AI towards the human agents, forced to comply with the needs of the machine without any possibility of negotiation (fig. 4).

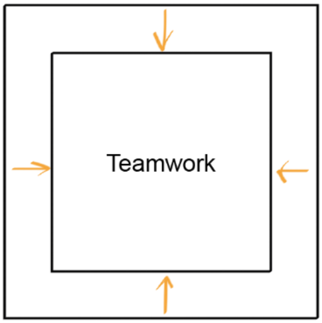

Fig. 4 - AI forces its constrictions to the simultaneous team.

In the case of delayed groups, instead, the participants' development of the project idea without AI significantly increases the risk of generating a contrast when AI is introduced into the creative process. This happens because the initial concept, born from the work of the two human agents, must be submitted to Sketch-rnn, implying a realignment (fig. 5) with its limits and functionalities.

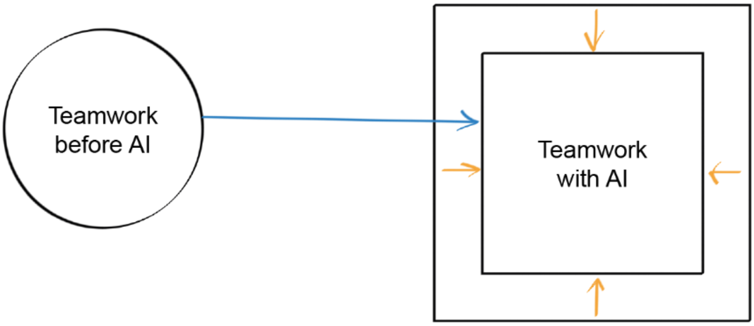

Fig. 5 - Process of realignment.

The realignment is simple if the initial idea matches the AI needs by coincidence or planning. It is complex if the initial idea requires adjustments to be suitable for AI. It is impossible if readaptation is not feasible in any way.

If the realignment is complex, the group is in a condition of discontinuity that causes an impoverishment in the quality of work and an increase in costs and timescales.

If the realignment is impossible, the group experience a fracture, where the designers and the AI system work on two distinct and incompatible levels, with different intents, different methods, or different objectives, impeding the project's continuation unless critical changes are made.

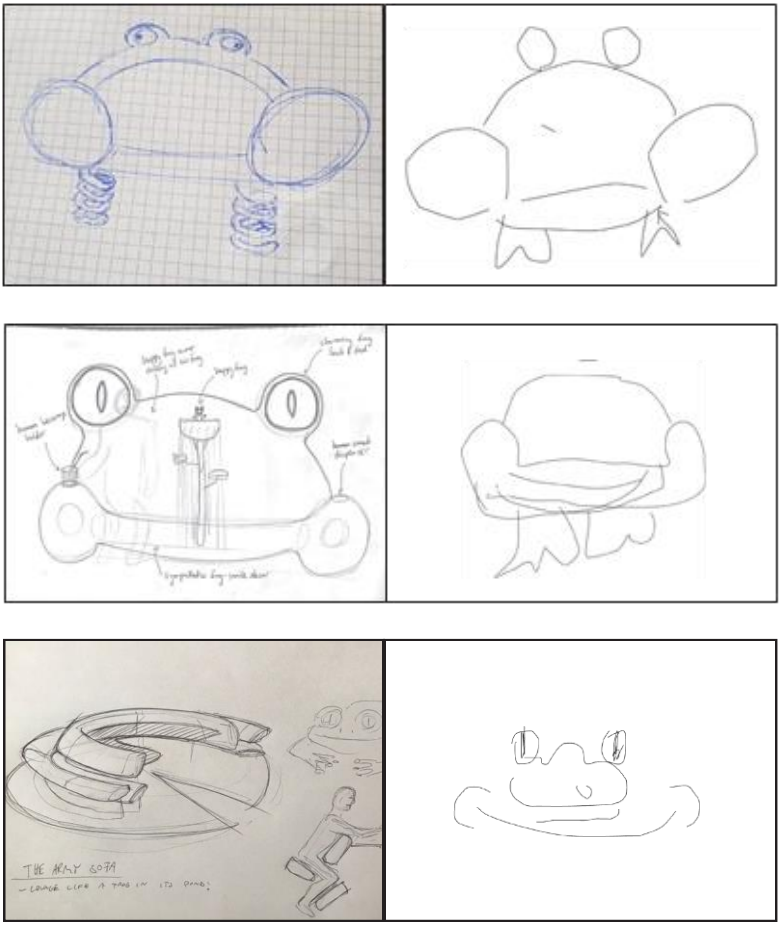

Fig. 6 – Three types of realignment were observed in delayed groups between initial human sketches (left side) and Human-Sketch-rnn sketches (right side). (1) Simple realignment – The human sketch is already aligned with AI rules. (2) Complex realignment – The human sketch is too detailed and needs simplification to realign with AI rules. (3) Impossible realignment – the human sketch is a «sofa that makes you sit like a frog» in contrast to the AI's interception of «a sofa that looks like a frog».

This scenario can be observed in the output of group F, which did not interpret the frog-sofa in a purely formal dimension like AI is meant to do (i.e., *a sofa that reminds a frog*). Instead, they based their design idea on the way of seating (i.e., *a sofa that makes you sit like a frog*), generating a fracture between human and non-human agent objectives. Said fracture compromised any collaboration attempt in the team (fig. 6).

We can also observe that the participants in delayed groups, since they did not have to come to terms with the AI systems at the beginning of the sketching phase, had greater freedom of thought, resulting in sketches that were often more complex, detailed, and original than those obtained from the simultaneous groups. However, this higher level of sketches' quality often compromised the subsequent collaboration with Sketch-rnn. In most cases, the human agents valued their idea far superior to the suggestions provided by the AI system and, therefore, hardly accepted any change emerged in collaboration with Sketch-rnn. This attitude, which can be traced back to the phenomenon of fossilisation in the design process, is visible in the outcomes of the delayed groups: the sketches performed with Sketch-rnn are often only attempts to reproduce their previous sketches, demonstrating that the collaborative relationship between the human agent and the AI has never taken place.

In conclusion, if the outputs are excessively ascribable to AI for the simultaneous groups, they are overly due to the human agent for the delayed groups. This leads to two polarizing instances, both presenting positive and negative aspects and neither reaching an optimal performance level. The solution, therefore, may lie in a middle zone between these two extremes, where designers are called upon to continuously evaluate between two options: *to follow or not to follow the machine*.

Thanks to the use of the AI system, the participants of the simultaneous group can learn *not to follow* the machine if it only gives predictable pieces of advice. In contrast, the participants of the delayed group can learn to remain open to the machine's bits of advice, even if predictable, to help them re-evaluate their preconceived ideas, avoid fossilisation, and improve or consolidate specific details already present in the design.

4.4. Colour Selection Phase

During the colour selection phase, the participants generally followed and incorporated the pieces of advice given by the AI system into their works. As in the previous steps, the human-AI collaboration struggles to find a balance for both simultaneous and delayed groups, showing excessive intrusiveness of the AI in the first case and the human in the second.

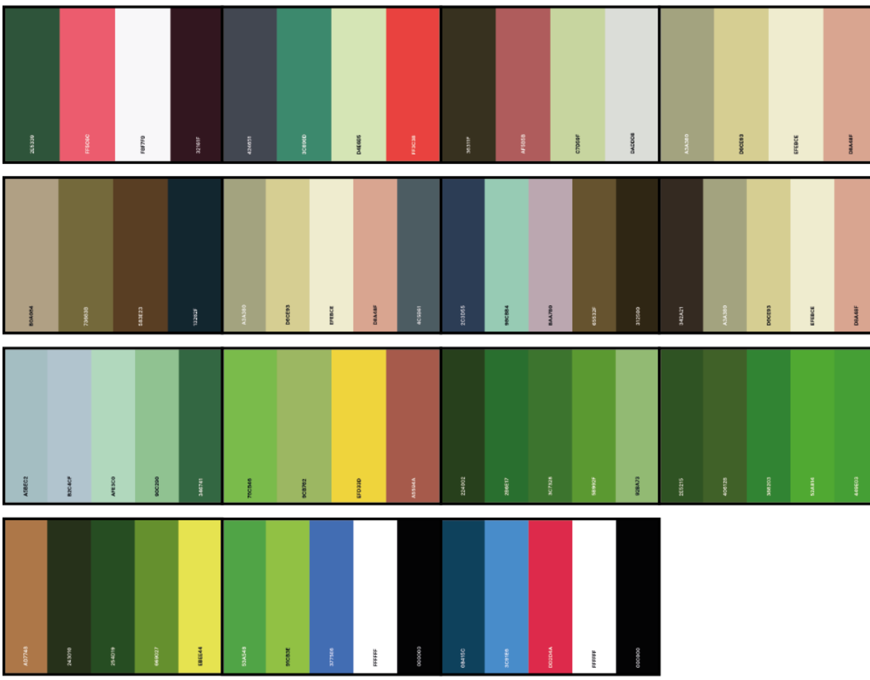

Fig. 7 - Colour palettes from simultaneous groups.

Participants from the simultaneous groups built colour palettes that were very similar to each other and, to some extent, almost monochromatic (fig. 7). On the contrary, after defining their colour palette autonomously, the human agents of the delayed groups hardly made any change following the suggestions of the AI system, often limiting its usage to obtaining a copy-paste result of the initial palette. This indicates a creative process heavily cantered on the human agent, where human-machine collaboration never occurs.

These two different employments of AI are consequences of the imposition of the machine's intentions upon the participants. In the specific case of coolors.co, this imposition concerns considering the chromatic dimension as the only criterion for colour selection: simultaneous groups, immediately having come into contact with the AI, were induced unconsciously to adopt this criterion without putting it into question (fig. 8).

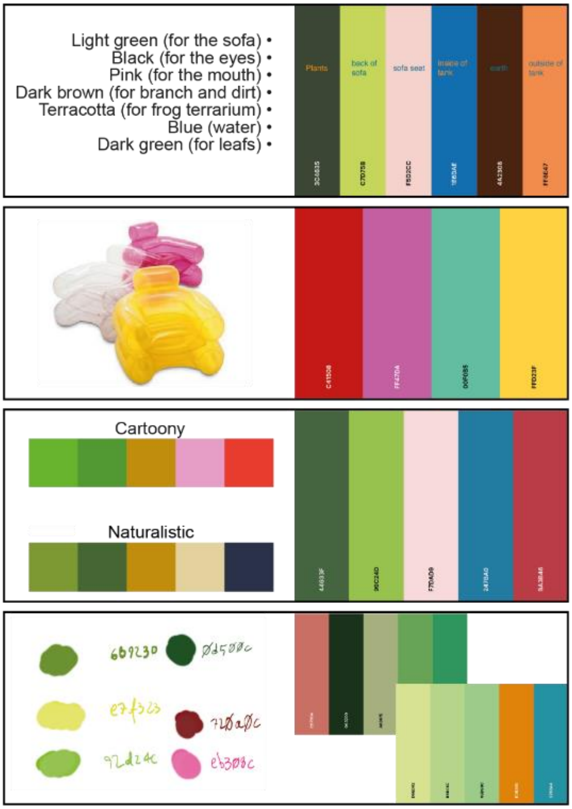

Fig. 8 - Colour palettes from delayed groups. Outputs without AI on the left and outputs with AI on the right.

On the other hand, the delayed groups, having some time to work before introducing AI, were free to consider different dimensions related to colour, such as the semantic value, material, or context. The AI system does not recognize all these aspects and thus generates a moment of discontinuity, or even fracture, in the intentions' realignment between human and non-human agents.

Here again, for simultaneous groups, AI played the internal role of an intrusive companion capable of providing a significant amount of valuable knowledge in a short time. On the other side, human agents did not demonstrate enough capacity to re-elaborate the AI-generated knowledge when necessary.

For delayed groups, AI took the external role of an expert, capable of extending the creativity space by generating specific information and variables but often not listened to because too extraneous to the design process.

8. The Effects of Artificial Intelligence on Creativity and Teams' Dynamics

1. An Uncertain Relationship

The workshop experience significantly impacted how participants perceived the introduction of AI systems in the design process.

None of the participants showed deep-rooted prejudices about the issue. Still, being enrolled in a Master's Degree Course, they are in a delicate phase of evolving thinking and experimentation that will eventually establish their position towards AI in design. Consequently, their first experience of collaboration with AI systems may shape their future human-AI relationships, including the generation of biases that may lead them to over-trust or under-trust the machine.

To avoid misuse and disuse, we want to stress the importance of providing a proper and gradual introduction to disruptive technologies, including AI, to design students, allowing them to gradually understand the technology in a safe environment and through a period of familiarisation.

2. AI as Supporting System

The outcomes of the three design phases confirmed the AI capability of supporting the designer's work by providing a significant volume of information in a short period and facilitating numerous design process tasks. When employed, Google, sketch-rnn and Coolors co speeded up the design phases, allowing the groups to generate new information and variance quickly. At the same time, they decreased the risk of blockage and fossilisation, as demonstrated by the number of outputs obtained using AI exceeding those obtained without AI.

3. Human-AI collaboration in Simultaneous Groups

Simultaneous groups performed the workshop always alongside the AI systems, sharing intentions, limitations, and working formats from the outset. This generated a collaborative environment marked by continuity: participants did their research within Google workspace, sketches within Sketch-rnn, and color selection within Coolors.co.

Even if the shared rules allowed continuity in work, they resulted solely from the participants' adaptation to the AI interfaces. In other words, participants could not evade or operate differently. This limited the creative process that was excessively conveyed and one-dimensional, addressing the design challenge exclusively from the point of view of the AI system.

Indeed, the final outputs of the simultaneous groups often resemble each other and are somewhat deficient in human creativity, leading to foreseeable design solutions.

In this scenario, Google, Sketch-rnn, and Coolors.co could be seen as intrusive group members, coercing human agents to adapt to their rules. In such circumstances, human agents are required to display a high level of awareness, enabling them to assess accurately when it is necessary to adapt to the machine and when it is necessary to ignore it. This iterative evaluative effort can be simplified and summarised as *following or not following the AI output*.

4. Human-AI Collaboration in Delayed Groups

Delayed groups worked alternating phases without and with an AI system, generating a highly discontinuous working environment. Such discontinuity required a realignment process between the work carried out outside the rules of the machine and the machine itself.

We can divide the critical moments of realignment observed in delayed groups into three recurrent types.

- *Simple realignment* occurred when the human agents conducted, by planning or by coincidence, their autonomous tasks (i.e., research, sketching, colour selection) in conformity with the machine rules.

- *Complex realignment* occurred when the task performed autonomously by human agents did not conform to the machine rules, needing modifications to integrate the AI system in the collaboration on the job. This led to delays, which might, in professional contexts, determine additional costs.
- *Impossible realignment* occurred when the task performed autonomously by human agents was in no way re-adaptable to the machine rules, generating a fracture. A scenario leading to a fracture happens when the human agents operate on dimensions unknown to AI. An example from our workshop is humans focusing on how the object is used, while AI concentrated on its shape. Another example is humans considering the semantic value of a colour, while AI focused on matching colour combinations.

The result is a human-AI collaboration unbalanced in favour of human agents. In the most extreme case of a delayed group, the human-AI collaboration did not happen since the human agents remained attached to their idea, entirely rejecting any AI suggestion. In other words, the risk of human fossilisation was more marked and evident in delayed groups.

In conclusion, the designer must preserve her work, which can be far superior in terms of innovation and uniqueness and keep an open mind towards AI stimuli and suggestions, which could be helpful both to improve the initial idea and generate variance from it.

5. Three Guidelines on the AI Role

During the workshop, it was possible to test and analyse the human-AI collaboration between the participants and three AI systems: Google, Sketch-rnn and Coolors.co. The AI>human rule is respected in the case of Google and Coolors.co and not respected in the case of Sketch-rnn. Google and Coolors.co proved to be efficient partners, capable of improving the design process both as teammates and stimuli for the human agents. On the other hand, although Sketch-rnn is a cutting-edge system, it can only generate suggestions following its paradigms. Thus, it is still limited in supporting a designer in sketching ideas. Consequently, the human-AI collaboration presents a high risk of slowing and worsening the group's performance. Nevertheless, the

AI capacity of providing random stimuli remains valid regardless of the AI>Human rule. Indeed, Sketch-rnn remained valuable to participants as an item of comparison, revaluation, and reflection, capable of counteracting biases, fossilisation, and blockage.

In conclusion, three guidelines emerged.

1. When the *AI>Human rule* is respected, AI can assume the role of a teammate.
2. When the rule is not respected, the *designer arbiter* needs to adjust the machine's scope of intervention in accordance with its contribution to the team, up to the total exclusion if necessary.
3. AI as an *external stimulus* to designers, proper to inspire and generate variance while also preventing fossilisation, remains valid whether the rule is respected. Therefore, in the current state of technology, the role of external stimulus is the most constant and safe assumed by AI in the idea development stages of the design process. However, the inspiration offered by AI is still subjected to the evaluation process of the designers, highly influenced by the designer's trust in the human-AI relationship.

6. A Corollary: Trust in Human-AI Collaboration

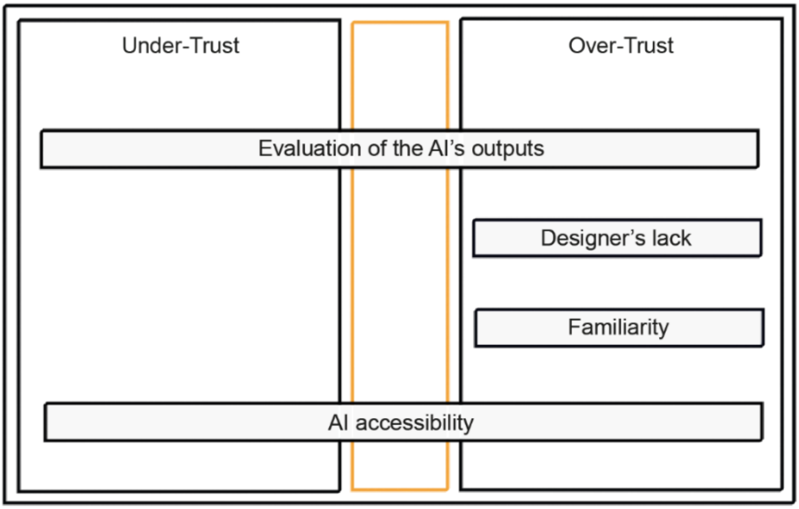

Fig. 9 - Discriminating factors that can affect the balance of trust in a Human-AI collaboration related to Under-trust and Over-trust attitudes.

The human-AI relationship must consider the balance of trust between the parts involved. During the workshop, participants followed Google and Coolors. co's suggestions more frequently than Sketch-rnn ones, showing how groups adopted a more or less open stance towards the three AI systems used.

The main factors that can significantly affect the balance of trust in a collaborative Human-AI relationship are (fig. 9):

1. *Evaluation of the machine's outputs*. The human agent receives, analyses, and evaluates the AI system's work repeatedly and gradually increases her understanding of the machine. This process establishes the designer's judgment on the level of AI competence and the consequent trust she is comfortable granting. This can lead to over-trust when AI provides numerous useful outputs and under-trust when not. An example of this last phenomenon is the participants' progressive rejection of Sketch-rnn's suggestions.
2. *Designer lack of knowledge and expertise*. The human agent, not having a deep understanding of the addressed issue, is more likely to rely on the outputs provided by the machine. This precludes humans from adequately evaluating the machine's results, forcing them to make an approximate decision on following it or not. An example of this phenomenon is the participants' confidence in Coloors.co due to their lack of knowledge in colour theory.
3. *Familiarity*. When the human agent is familiar with the AI system due to frequent interaction, she develops consolidated trust patterns. In this scenario, specific collaboration dynamics to verify the machine's competencies, such as the designer's evaluation of the machine's output, are possibly unconsciously repressed or avoided. An example of this phenomenon is the low level of critical assessment by the workshop participants of the results displayed by Google search.
4. *AI accessibility*. The human agent is inclined to follow with greater acceptance the machine's output if she can view and intervene on its outputs through editable parameters. AI systems, as already seen, generally operate as black boxes, where it is possible to know only the result and not the intermediate process, thus providing incomplete information to human agents. This can lead the designer to under-trust if the machine offers poor communication, as in Sketch-rnn. On the contrary, when a higher level of

communication is reached through parameters control, as in the case of Google and Coolors.co, the result could be over-trust, reinforced by the AI systems attitude to convince the human agents rather than just explain (Bansal et al., 2021). In conclusion, designers should consider exclusively the quality and usefulness of the output provided by the AI system, regardless of the communicative elements.

7. The Answers to Our Questions

Following our extensive literature review, we asked ourselves three questions concerning different aspects of the human-AI collaboration in the early stages of the design process (see paragraph 7.1). To respond to these questions, we organized a design workshop. Hereafter, we give our answers to the posed questions.

Technical (AI>Human) and sensitive criticalities (predisposition, perception, communication) and their implications in Human-AI collaboration are verified?

The rule *AI>Human* is verified. Google and Coolors.co complied with the rule and allowed a functional and positive Human-AI collaboration. Sketch-rnn, instead, did not respect the rule and showed a high risk of hindering the creative process of the groups.

Sensitive issues are also verified. Specifically, participants showed both under-trust and over-trust attitudes, mainly caused by the AI system's level of competence, familiarity, and accessibility. Moreover, we observed that most participants showed judgemental shifts, demonstrating uncertainty regarding the AI tools.

Is the random stimulus of the lateral thinking concept in AI applications dependent on Human-AI collaboration criticalities?

Here again, the distinction between technical and sensitive criticalities is useful. Let's consider the first category. The answer to the question is no, meaning that, regardless of the skills brought into play by the machine and the designer, the ability of AI to offer external stimuli remains valid and valuable to the design process. However, if we consider sensitive criticalities, the inspiration provided by AI is subject to the perception and evaluation process of the designer, influenced by their trust in the human-AI relationship. Therefore, even if the random stimulus of the lateral thinking concept remains valid, designers may perceive it in a subjective and possibly misleading way.

Considering a design process where designers and AI agents alternate moments of collaboration and moments of autonomous work, how does the alternation affect the Human-AI collaborative?

The results show that in the simultaneous groups, characterised by continuous human-AI collaboration, the AI assumed the internal role of an intrusive groupmate, leading to an AI-driven creative process. On the other hand, in the delayed groups, AI took the outer part of an expert capable of generating variance, leading to a human-driven creative process. Furthermore, even if both cases highlighted issues, the ones displayed in delayed groups were far more complex to solve because they required a realignment every time a new AI system was introduced in the creative process. So, in this second scenario, which may frequently occur, a detailed work-planning must be considered to make the human-AI collaboration more stable.

8. The Limits of Our Experiment

Although an attempt was made to compose heterogeneous working groups, diversifying them in gender, culture, and education, the sixteen participants were all students at the Politecnico di Milano in the Design & Engineering Master of Science. This considerably influenced the homogeneity of the profiles participating in the workshop.

A second limitation concerns the AI systems used during the workshop (i.e., Google, Sketch-rnn and Coolors.co), as they were suitable for the purpose but very general. Indeed, each AI system fostered different human-AI relationship dynamics and allowed us to observe them throughout the workshop. However, the three chosen AI systems did not generate particularly complex or singular scenarios. Therefore, we are aware that not all the possible aspects of a human-AI collaboration within the design process have been covered exhaustively.

9. Final Remarks

We proposed an analysis of the implementation of AI systems into the early and creative stages of the design process. In our intention, this analysis can help designers deal with the increasing complexity surrounding their projects. AI is a powerful means to enhance the designers' creativity, primarily through random stimuli that can trigger designers' lateral thinking by providing new data, variance, and inspiration while reducing the risk of blockage and fossilisation.

In our view, this process is an example of emerging collaborative design activity, where the human-AI relationship appears very similar to the human-human one. For this reason, AI could significantly impact the creative phases of the design process, mainly if applied considering our human-AI collaboration guidelines, based on technical and sensitive criticalities (see paragraph 8.2).

We introduced the figure of the designer arbiter to describe the new role designers should play. The designer arbiter operates at a higher level of management and supervision and optimizes the human-AI collaboration through a deep knowledge of the design process and excellent evaluative skills.

The main aspects covered by the study were tested in a workshop in which sixteen participants, divided into simultaneous and delayed groups, had to collaborate throughout the three creative stages of research, sketching and colour selection, using three different AI systems. The results show that in the simultaneous groups, characterised by continuous human-AI collaboration, the AI assumed the internal role of an intrusive groupmate within the team, leading to an AI-driven creative process. In contrast, in the delayed groups, characterised by discontinuous human-AI collaboration, AI assumed the external role of an expert capable of generating variance outside the team, leading to a human-driven creative process.

Implementing AI systems into the design process is a critical issue, still largely unexplored. Aspects that could hinder the efficiency of the Human-AI collaboration, such as teamwork dynamics, AI applicability, applications, and ethics, should be investigated further. This research represents a first attempt to study human-AI interactions within collaborative design tasks qualitatively and provides insights into how humans' trust dynamics affect the inclusion of AI systems as team members. In general terms, we aim to contribute to the debate around using AI systems in design and pave the way for possible future developments. Future studies might provide frameworks to understand human-AI design collaborations and investigate further the design arbiter role to prepare the next generations of professionals to deal with AI technologies. Indeed, we consider it key to fostering proper and safe relationships in human-AI collaborations by guaranteeing efficiency for the design process and well-being for the designers.

References

Agard, B., & Kusiak, A. (2004). Data-mining-based methodology for the design of product families. *International Journal of Production Research, 42*(15), 2955–2969. https://doi.org/10.1080/00207540410001691929

Alhaji, B., Beecken, J., Ehlers, R., Gertheiss, J., Merz, F., Müller, J. P., Prilla, M., Rausch, A., Reinhardt, A., Reinhardt, D., Rembe, C., Rohweder, N., Schwindt, C., Westphal, S., & Zimmermann, J. (2020). Engineering Human – Machine Teams for Trusted Collaboration. *Big Data and Cognitive Computing*, *4*(35). https://doi.org/10.3390/bdcc4040035

Bansal, G., Zhou, J., Fok, R., Ribeiro, M. T., & Weld, D. S. (2021). Does the Whole Exceed its Parts? The Effect of AI Explanations on Complementary Team Performance. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (p. 16). Association for Computing Machinery. https://dl.acm.org/doi/10.1145/3411764.3445717

Barsade, S. G., & Gibson, D. E. (2007). Why does affect matter in organizations? *Academy of Management Perspectives*, *21*(1), 36–59. https://doi.org/10.5465/AMP.2007.24286163

Beaney, M. (2005). *Imagination and Creativity*. Open University Worldwide.

Bonnardel, N., & Zenasni, F. (2010). The Impact of Technology on Creativity in Design: An Enhancement? *Creativity and Innovation Management*, *19*(2), 180–191. https://doi.org/10.1111/j.1467-8691.2010.00560.x

Brand, R., & Rocchi, S. (2011). Rethinking value in a changing landscape and business transformation. In *Philips Design*.

Bratman, M. E. (1992). Shared Cooperative Activity. *The Philosophical Review*, *101*(2), 327–341. https://www.jstor.org/stable/2185537

Brown, T. (2009). *Change by design: How design thinking transforms organizations and inspires innovation*. HarperBusiness.

Bürdek, B. E. (2015). *Design: History, Theory and Practice of Product Design* (2nd ed.). Birkhäuser Verlag GmbH.

Camburn, B., He, Y., Raviselvam, S., Luo, J., & Wood, K. (2020). Machine learning-based design concept evaluation. *Journal of Mechanical Design, Transactions of the ASME*, *142*(3), 1–15. https://doi.org/10.1115/1.4045126

Cautela, C., Mortati, M., Dell'Era, C., & Gastaldi, L. (2019). The impact of artificial intelligence on design thinking practice: Insights from the ecosystem of startups. *Strategic Design Research Journal*, *12*(1), 114–134. https://doi.org/10.4013/sdrj.2019.121.08

Chai, C., Liao, J., Zou, N., & Sun, L. (2018). A one-to-many conditional generative adversarial network framework for multiple image-to-image translations. *Multimedia Tools and Applications*, *77*(17), 22339–22366. https://doi.org/10.1007/s11042-018-5968-7

Chen, L., Wang, P., Dong, H., Shi, F., Han, J., Guo, Y., Childs, P. R. N., Xiao, J., & Wu, C. (2019). An artificial intelligence based data-driven approach for design. *Journal of Visual Communication and Image Representation*, *61*(1047–3203), 10–22. https://doi.org/10.1016/j.jvcir.2019.02.009

Churchman, C. W. (1967). Guest Editorial: Wicked Problems. *Management Science*, *14*(4), B141–B142. //www.jstor.org/stable/2628678

Cooper, R. (2019). Design research - Its 50-year transformation. *Design Studies*, *65*, 6–17. https://doi.org/10.1016/j.destud.2019.10.002

Crewe, D. J. (2020). *First Update to Photoshop for iPad Released – Includes Adobe Sensei AI Powered Subject Select Tool*. https://www.slrlounge.com/first-update-to-photoshop-for-ipad-released-includes-adobe-sensei-ai-powered-subject-select-tool/

Davis, N., Hsiao, C.-P., Singh, K. Y., & Magerko, B. (2016). Co-Creative Drawing Agent with Object Recognition. *The Twelfth AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE-16)*, *October*, 9–15. www.aaai.org

De Bono, E. (1967). *The use of lateral thinking.*

de Visser, E. J., Pak, R., Shaw, T. H., Peeters, M. M. M., Neerincx, M. A., Jung, M. F., & Kohn, S. (2020). Towards a Theory of Longitudinal Trust Calibration in Human – Robot Teams. *International Journal of Social Robotics*, *12*(2), 459–478. https://doi.org/10.1007/s12369-019-00596-x

Degani, A., Goldman, C. V., Deutsch, O., & Tsimhoni, O. (2017). On human–machine relations. *Cognition, Technology and Work*, *19*(2–3), 211–231. https://doi.org/10.1007/s10111-017-0417-3

Demir, M., Likens, A. D., Cooke, N. J., Amazeen, P. G., & McNeese, N. J. (2019). Team coordination and effectiveness in human-autonomy teaming. *IEEE Transactions on Human-Machine Systems*, *49*(2), 150–159. https://doi.org/10.1109/THMS.2018.2877482

Djajadiningrat, T., Wensveen, S., Frens, J., & Overbeeke, K. (2004). Tangible products: Redressing the balance between appearance and action. *Personal and Ubiquitous Computing*, *8*(5), 294–309. https://doi.org/10.1007/s00779-004-0293-8

Dosovitskiy, A., Springenberg, J. T., Tatarchenko, M., & Brox, T. (2017). Learning to Generate Chairs , Tables and Cars with Convolutional Networks.

IEEE Transactions on Pattern Analysis and Machine Intelligence, *39*(4), 692–705.
Fan, J. E., Dinculescu, M., & Ha, D. (2019). collabdraw : An Environment for Collaborative Sketching with an Artificial Agent. *Proceedings of the 2019 on Creativity and Cognition*, 556–561. https://doi.org/10.1145/3325480.3326578
Findeli, A. (2001). Rethinking Design Education for the 21st Century: Theoretical, Methodological, and Ethical Discussion. *Design Issues*, *17*(1), 5–17. https://doi.org/10.1162/07479360152103796
Gatys, L. A., Ecker, A. S., & Bethge, M. (2016). Image Style Transfer Using Convolutional Neural Networks. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2099–2104. https://doi.org/10.1109/ICRIEECE44171.2018.9008937
Ha, D., & Eck, D. (2018). A neural representation of sketch drawings. *6th International Conference on Learning Representations, ICLR 2018 - Conference Track Proceedings*.
Ha, D., Jongejan, J., & Johnson, I. (2017). *Draw Together with a Neural Network*. https://magenta.tensorflow.org/sketch-rnn-demo
Heskett, J. (1980). *Industrial Design*. Thames and Hudson.
Isgrò, F. (2020). *Artificial Intelligence in Design* [Politecnico di Milano]. https://www.politesi.polimi.it/handle/10589/165335
Johansson-Sköldberg, U., Woodilla, J., & Çetinkaya, M. (2013). Design thinking: Past, present and possible futures. *Creativity and Innovation Management*. https://doi.org/10.1111/caim.12023
Jung, M. F., Šabanović, S., Eyssel, F., & Fraune, M. (2017). Robots in groups and teams. In *CSCW 2017 - Companion of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing* (pp. 401–407). Association for Computing Machinery. https://doi.org/10.1145/3022198.3022659
Karras, T., Aila, T., Laine, S., & Lehtinen, J. (2018). *Progressive growing of GANs for improved quality, stability, and variation*. 1–26.
Karras, T., Laine, S., & Aila, T. (2019). A style-based generator architecture for generative adversarial networks. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, *2019-June*, 4396–4405. https://doi.org/10.1109/CVPR.2019.00453
Kern, M. L., Park, G., Eichstaedt, J. C., Schwartz, H. A., Sap, M., Smith, L. K., & Ungar, L. H. (2016). Gaining insights from social media language: Methodologies and challenges. *Psychological Methods*, *21*(4), 507–525.
Krämer, N. C., Pütten, A. M. Von Der, & Eimler, C. (2012). *Human-Computer Interaction: The Agency Perspective*. *396*(January), 263–285. https://doi.org/10.1007/978-3-642-25691-2
Krippendorff, K. (2006). *The semantic turn: A new foundation for design*. CRC/Taylor & Francis.

Lei, X., & Rau, P. P. (2021). Should I Blame the Human or the Robot? Attribution Within a Human – Robot Group. *International Journal of Social Robotics*, *13*(2), 363–377. https://doi.org/10.1007/s12369-020-00645-w

Liao, J., Hansen, P., & Chai, C. (2020). A framework of artificial intelligence augmented design support. *Human-Computer Interaction*, *35*(5–6), 511–544. https://doi.org/10.1080/07370024.2020.1733576

Liapis, A., Yannakakis, G. N., Alexopoulos, C., & Lopes, P. (2016). Can computers foster human users' creativity? Theory and praxis of mixed-initiative co-creativity. *Digital Culture & Education*, *8*(2). https://www.um.edu.mt/library/oar/bitstream/123456789/29476/1/Can_computers_foster_human_users_creativity_theory_and_praxis_of_2016.pdf

Lopez, C. E., Miller, S. R., & Tucker, C. S. (2019). Exploring Biases Between Human and Machine Generated Designs. *Journal of Mechanical Design, Transactions of the ASME*, *141*(2). https://doi.org/10.1115/1.4041857

Lubart, T. (2005). How can computers be partners in the creative process : Classification and commentary on the Special Issue. *International Journal of Human Computer Studies*, *63*(4-5 SPEC. ISS.), 365–369. https://doi.org/10.1016/j.ijhcs.2005.04.002

Luhmann, N. (2018). *Trust and Power*. John Wiley and Sons.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model of Organizational Trust. *The Academy of Management Review*, *20*(3), 709–734.

McNeese, N. J., Demir, M., Cooke, N. J., & She, M. (2021). Team Situation Awareness and Conflict: A Study of Human–Machine Teaming. *Journal of Cognitive Engineering and Decision Making*. https://doi.org/10.1177/15553434211017354

Mortati, M., & Bertola, P. (2021). Saperi indisciplinati nell'era digitale. In *Diid disegno industriale. Vol. 70-71-72: Design 2030: saperi Formazione pratiche* (pp. 135–141).

Neerincx, M. A., Waa, J. Van Der, & Kaptein, F. (2018). Using Perceptual and Cognitive Explanations for Enhanced Human-Agent Team Performance. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 1, pp. 204–214). Springer International Publishing. https://doi.org/10.1007/978-3-319-91122-9

Oh, S., Jung, Y., Kim, S., Lee, I., & Kang, N. (2019). Deep Generative Design: Integration of Topology Optimization and Generative Models. *Journal of Mechanical Design*, *141*(11). https://asmedigitalcollection.asme.org/mechanicaldesign/article/141/11/111405/955342/Deep-Generative-Design-Integration-of-Topology

Óhéigeartaigh, S. S., & Liu, Z. (2020). Overcoming Barriers to Cross-cultural Cooperation in AI Ethics and Governance. *Philosophy and Technology*, *33*(4), 571–593.

Oxman, R. (2006). Theory and design in the first digital age. *Design Studies*, *27*(3), 229–265. https://doi.org/10.1016/j.destud.2005.11.002

Pan, Y., Burnap, A., Hartley, J., Gonzalez, R., & Papalambros, P. Y. (2017). Deep design: Product aesthetics for heterogeneous markets. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, *Part F1296*(1), 1961–1970. https://doi.org/10.1145/3097983.3098176

Pandya, R., Huang, S. H., Hadfield-menell, D., & Dragan, A. D. (2019). Human-AI Learning Performance in Multi-Armed Bandits. *AAAI/ACM Conference on AI, Ethics, and Society (AIES '19)*, 369–375.

Park, T., Liu, M. Y., Wang, T. C., & Zhu, J. Y. (2019). Semantic image synthesis with spatially-adaptive normalization. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, *2019-June*, 2332–2341. https://doi.org/10.1109/CVPR.2019.00244

Plattner, H., Christoph Meinel, & Larry Leifer. (2011). *Design Thinking Understand – Improve – Apply*. Springer. https://doi.org/10.1007/978-3-642-13757-0

Poetz, M. K., & Schreier, M. (2012). *The Value of Crowdsourcing : Can Users Really Compete with Professionals in Generating New Product Ideas?*. *29*(2), 245–256. https://doi.org/10.1111/j.1540-5885.2011.00893.x

Quan, H., Li, S., & Hu, J. (2018). Product Innovation Design Based on Deep Learning and Kansei Engineering. *Applied Sciences*, *8*(2397). https://doi.org/10.3390/app8122397

Rajpurohit, N., Saxena, M., Yadav, R., & Chande, P. K. (2020). Investigating Impact of Artificial Intelligence in Deployment of Effective Project Teams. *International Journal of Advanced Science and Technology*, *29*(8), 382–391. http://sersc.org/journals/index.php/IJAST/article/view/10518

Ramesh, A., Pavlov, M., Goh, G., & Gray, S. (2021). *DALL·E: Creating Images from Text*. https://openai.com/blog/dall-e/

Rampino, L. (2018). *Evolving Perspectives in Product Design: From Mass Production to Social Awareness*. FrancoAngeli.

Redström, J. (2006). Towards user design? on the shift from object to user as the subject of design. *Design Studies*, *27*(2), 123–139. https://doi.org/10.1016/j.destud.2005.06.001

Reed, S., Akata, Z., Mohan, S., Tenka, S., Schiele, B., & Lee, H. (2016). Learning what and where to draw. *Advances in Neural Information Processing Systems*, *Nips*, 217–225.

Salas, E., Dickinson, T. L., Sharolyn A. Converse, & Tannenbaum, S. I. (1992). *Toward an understanding of team performance and training.*

Schmitt, P. (n.d.). *The Chair Project (Four Classics)*. Retrieved February 9, 2022, from https://philippschmitt.com/work/chair

Schmitt, P., & Weiß, S. (2018). The Chair Project : A Case-Study for using Generative Machine Learning as Automatism. *32nd Conference on Neural Information Processing Systems (NIPS 2018)*, 1–3.

Schön, D. A. (1983). *The Reflective Practitioner*. Basic Books, Inc. https://doi.org/10.4324/9780203963371

Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G. J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G., & Söllner, M. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Information and Management*, *57*(2), 103174. https://doi.org/10.1016/j.im.2019.103174

Simon, H. A. (2019). *The sciences of the artificial*. MIT press.

Stoimenova, N., & Price, R. (2020). Exploring the Nuances of Designing (with / for) Artificial Intelligence. *DesignIssues*, *36*(4), 45–55.

Tessier, V. (2021). *Étude exploratoire sur le travail en équipe d'étudiants dans l'atelier de design : vers un modèle d'évaluation*. Université de Montréal.

Theobald, O. (2017). *Machine Learning For Absolute Beginners*.

Torre, D. La, Colapinto, C., Durosini, I., & Triberti, S. (2021). Team Formation for Human-Artificial Intelligence Collaboration in the Workplace: A Goal Programming Model to Foster Organizational Change. *IEEE Transactions on Engineering Management*, 1–11. https://doi.org/10.1109/TEM.2021.3077195

Tromp, N., Hekkert, P., & Verbeek, P. P. (2011). Design for socially responsible behavior: A classification of influence based on intended user experience. *Design Issues*, *27*(3), 3–19. https://doi.org/10.1162/DESI_a_00087

Tuarob, S., & Tucker, C. S. (2015a). *Automated Discovery of Lead Users and Latent Product Features by Mining Large Scale Social Media Networks*. *137*(July), 1–11. https://doi.org/10.1115/1.4030049

Tuarob, S., & Tucker, C. S. (2015b). Quantifying product favorability and extracting notable product features using large scale social media data. *Journal of Computing and Information Science in Engineering*, *15*(3), 1–12. https://doi.org/10.1115/1.4029562

Tucker, C. S., & Kim, H. M. (2011). Trend Mining for Predictive Product Design. *Journal of Mechanical Design, Transactions of the ASME*, *133*(November), 1–11. https://doi.org/10.1115/1.4004987

Verganti, R., Vendraminelli, L., & Iansiti, M. (2020). Innovation and Design in the Age of Artificial Intelligence. *Journal of Product Innovation Management*, *37*(3), 212–227. https://doi.org/10.1111/jpim.12523

Wang, L., Shen, W., Xie, H., Neelamkavil, J., & Pardasani, A. (2002). Collaborative conceptual design - State of the art and future trends. *CAD Computer Aided Design*, *34*(13), 981–996. https://doi.org/10.1016/S0010-4485(01)00157-9

Williamson, J. (2017). *How does generative design unlock engineering innovation?* https://www.themanufacturer.com/articles/how-does-generative-design-unlock-engineering-innovation/

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative Intelligence : Humans and AI Are Joining Forces. *Harvard Business Review*.

Wu, X., Zhu, X., Wu, G.-Q., & Ding, W. (2014). Data mining with big data. *IEEE Transactions on knowledge and data engineering*, *26*(1), 97–107.

Xue, H., & Desmet, P. M. A. (2019). Researcher introspection for experience-driven design research. *Design Studies*, *63*, 37–64. https://doi.org/10.1016/j.destud.2019.03.001

Yannakakis, G. N., Liapis, A., & Alexopoulos, C. (2014). Mixed-Initiative Co-Creativity. *Proceedings of the International Conference on the Foundations of Digital Games*. https://www.um.edu.mt/library/oar//handle/123456789/29459

Zhang, G., Raina, A., Cagan, J., & McComb, C. (2021). A cautionary tale about the impact of AI on human design teams. *Design Studies*, *72*, 23. https://doi.org/10.1016/j.destud.2021.100990

Zhang, Z., Xie, Y., & Yang, L. (2018). Photographic Text-to-Image Synthesis with a Hierarchically-Nested Adversarial Network. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 6199–6208. https://doi.org/10.1109/CVPR.2018.00649

Zwierzycki, M., Garivani, S., Masini, L., Droogmans, C., Jaramazovic, E., & Buerba, L. J. (2020). *Ai Generated Furniture*. http://www.iaacblog.com/programs/ai-generated-furniture/