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Abstract

Artificial Intelligence (AI) is affecting the scenario in which innovation takes place. What are the implications for our understanding of design? Is AI just another digital technology that, akin to many others, will not significantly question what we know about design? Or will it create transformations in design that our current frameworks cannot capture?

To address these questions, we have investigated two pioneering cases at the frontier of AI, Netflix and AirBnB (complemented with analyses in Microsoft and Tesla), which offer a privileged window on the future evolution of design.

We found that AI does not undermine the basic *principles* of Design Thinking (people-centered, abductive and iterative). Rather, it enables to overcome past limitations (in scale, scope and learning) of human-intensive design processes. In the context of AI factories solutions may even be more user-centered (to an extreme level of granularity, i.e. being designed for every single person), more creative, and continuously updated through learning iterations that span the entire life cycle of a product. Yet, we found that AI profoundly changes the *practice* of design. Problem solving tasks, traditionally carried on by designers, are now automated into learning loops that operate without limitations of volume and speed. These loops think in a radically different way than a designer: they address complex problems through very simple tasks, iterated exponentially. The article therefore proposes a new framework for understanding design practice in the age of AI. We also discuss the implications for design and innovation theory. Specifically, we observe that, as creative problem solving is significantly conducted by algorithms, human design increasingly becomes an activity of *sense making*, i.e. to understand which problems make sense to be addressed. This shift in focus calls for new theories and brings design closer to leadership, which is, inherently, an activity of sense making.

1. Introduction

The adoption of artificial intelligence (AI) has received enormous attention and emphasis across virtually every industrial setting, from healthcare delivery to automobile manufacturing. In combination with the ubiquity of digital sensors, networks and software-based automation, AI is transforming our economy and defining a new industrialization age. From Alibaba to Airbnb, this new “Age of AI” is defined by the emergence of a new kind of firm, based on a “digital” operating model, creating unprecedented opportunities and challenges (Iansiti and Lakhani, 2020).

As firms evolve to embrace an increasingly AI-centric operating model, they are digitizing an increased number of important business processes, removing human labor and management from the critical path in the execution of many critical operating activities. Unlike processes in traditional firms, no worker sets the price on an Amazon product or qualifies a business for a loan on Ant Financial’s bank. While humans developed the algorithms and wrote the software code, the actual real-time creation of the solution is automated and enabled entirely by digital technology.

As the economy continues to transform, the process of design is also changing rapidly, making use of sensors, digital networks and algorithms. Whether our product is embodied entirely in software, as with an iPhone app, or whether it is a more traditional hardware centric artifact, as in a Tesla automobile, modern products are increasingly connected to the organization that designed them, providing a continuous flow of data that details many aspects of the use experience. In addition, the software embedded in the products themselves enables information coming the other way, from the designer to the user, to create a specific solution for a specific user, and constantly improve the experience in real time. These instant, two-way, feedback loops nowadays characterize an increasing range of products and services, from Netflix video streaming to a Tesla Model 3. Effectively, these products designs evolve in real time as the user experiences them.

AI may therefore profoundly transform the context where design takes place. What are the implications for design practice and our understanding of design-driven innovation? This article investigates the

changes that AI is bringing to design, by exploring the strategies of pioneering organizations at the intersections between AI and design thinking, such as Netflix and AirBnB.

Our analysis addresses three questions:

- AI and the *practice* of design: to which extent AI is likely to change the way design is practiced? Is the transformation of the context induced by AI changing the design *process* and the *objects* of the design actions?
- AI and the *principles* of design: if so (i.e. if AI induces significant changes in the design practice), are these changes so deep to question the fundamentals of design, such as, for example, user centeredness? Is design practice, in the age of AI, informed by significantly different principles?
- the *theory* of design: what are the implications for the theoretical frameworks that we use to interpret design? Does the age of AI call for new research questions and for a new understanding of how design drives innovation in organizations?

The article is structured as follows. We start by introducing the practice and principles of design, which will enable us to address the first two questions above. The principles are rooted in the existing theory of design thinking. The practice is broached on the basis of a framework that compares the nature of human-intensive design and of design in the age of AI. The framework is then instantiated through the illustration of two cases of Netflix and Airbnb. Next, we discuss the cases (with support of additional information from the experiences in Tesla and Microsoft) to analyze the extent to which the design principles and practice are affected by AI. We then conclude with an analysis of implications for design theories and the new role of designers in AI-driven companies.

2. Design and its Operating Context

To investigate whether and to which extent AI transforms our understanding of design, we frame our discussion according to two levels of analysis (Orlikowski, 2010): practice and principles. The design practice refers to the phenomenology of design in a specific context: its process (the “how of design”, such as its phases, methods, tools, or collaborative practice) and the object of design (the kind of solutions it creates). The design principles refer to the perspective and philosophy that inform the act of designing, and that constitute an ontology of what design is. The distinction between these two levels of analysis enables to better discern the nature of the impacts of AI on design. Is AI changing the way we design, or is even acting at a deeper level, by reframing the basic principles that inspire the act of designing? To answer this question, let’s start by introducing the principles of design, as they emerge from the current discussion on design theory; then we illustrate how these principles have been instantiated into design practice before the advent of AI, and finally, we introduce a framework to analyze how these principles are enacted in the new context of AI Factories.

2.1 *The principles of design.*

Ultimately, to design is to “devise courses of action aimed at changing existing situations into preferred ones” (Simon, 1982). In moving towards preferred situations, to design implies to create solutions that are more meaningful to people (Krippendorf, 1989 and 2006, Verganti 2008 and 2009). What are the principles that inform this practice of designing? The scientific debate on the ontology of design is significantly developed in the realm of design theories, with an enormous richness of contributions (see for example Margolin 1989, Margolin and Buchanan 1996, Love 2000, Galle 2002). Given our focus on design practices in organizational contexts, we tap here into the most recent developments of a specific stream of studies: design thinking. Although the term is affected by ambiguities (hence our use, in this article, of the word “design”, which enables connection with a broader and more consolidated scholarly

tradition), the efforts of management scholars to distill the principles of design when applied into organizational context, converge towards three essential principles (see Seidel and Fixson 2013, Micheli et al 2019, and especially Liedtka 2015 for a re-composition of the principles of design thinking with the principles of design theories):

- *People-centered*: innovation, when driven by design, is inspired by empathy with users. Rather than being driven by the advancements of technology and by what is possible, design-driven innovation stems from understanding a problem from the user perspective, and from making predictions about what could be meaningful to her. For example, we can recognize this principle in the practice of ethnographic research.
- *Abductive*: design has a generative approach to create solutions. Rather than leveraging solely on deductive reasoning (how things are) and inductive reasoning (how things likely are), design creates through abductive reasoning, i.e. by making hypotheses about how things might be. Abductions often lead to reframing the problem and the question that informs the design. For example, we can recognize this principle in the practice of brainstorming.
- *Iterative*: abductions are continuously adapted and improved through fast testing cycles. Prototypes act as “playground” for conversation and learning. They engage the team and the users, enable to communicate ideas, fail, learn, and drive progress until a satisfying solution is achieved. For example, we can recognize this principle in the practice of building rudimental mockups early in the design process.

2.2 *Design in the context of traditional operating models*

The way these design principles are enacted into practice depends of course on the operating context in which design takes place. The context in which most of the design practices we know today have been conceived rely on labor and management. The design of a new product entailed the creation of complex process architectures that could effectively deliver the product at scale. For the presence of this bulky

organization, traditional firms released new products in series, and with consequential cycles of design (the generation of a meaningful solution), make (the production and marketing of that solution at scale), and its use by customers (see Figure 1). As it was not practically possible nor economically convenient to design a different solution for each individual user, products and services were designed for “segments” of users, including then possibilities for customization during production.

After a product was released, the context evolved. For example, the market changed, or new technological opportunities emerged. In addition, designers could learn new insights from how customers actually used the existing product. Yet, as the operating model entailed significant effort and investment to redesign a product, innovation was postponed until the marginal value of a new product would oversize the cost of its design. At this point, a new design cycle started.



Figure 1 – Design practice in the context of traditional human-intensive operating models

A structure of this kind therefore implied a significant separation in time between two consequent design initiatives. During this period, learning cycles were frozen and, consequently, solutions became rapidly “old”. New learnings and ideas could only be incorporated in future solutions that were released in lumps, episodically and for customer segments.

2.3 *Design in the context of AI Factories*

Traditionally, design activities are heavily human intensive, but AI enables to revolutionize this scenario. First, in the context of AI Factories, the process of design can be fueled with real-time data coming from customer interactions or from the ecosystem in which the firm lies. In addition, and even more

interestingly, these data can inform AI engines. And these engines have problem solving capabilities: if properly conceived, they can generate specific solutions for an individual user autonomously, with no human effort involved (Iansiti & Lakhani, 2020). We will discuss how this new scenario works in the next section, thanks to cases from organizations that are pioneering the use of AI in design, namely Netflix and AirBnB. Before digging into the illustration of the cases, we introduce here a framework that allows to better capture the innovations that those organizations have introduced in their design practice (see Figure 2).

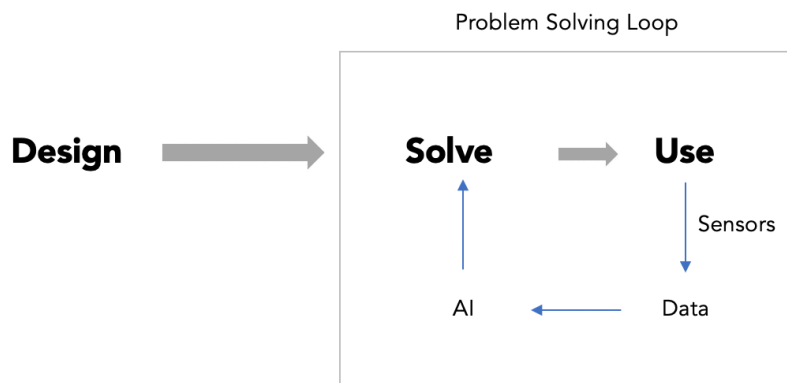


Figure 2 – Design practice in the context of AI Factories

To design implies to take a number of decisions. A few of them are highly sophisticated and require high levels of imagination and creativity. But most decisions, especially during development, ask less for imagination and more for specific problem-solving skills. Examples of these detailed decisions are the choice of the functional shape of an object, the design of the product interface for a user, or which information to display on a screen. There are plenty of detailed problems to be addressed during design. AI offers the intelligence to solve them.

In the context of AI factories, designers have the opportunity to release themselves from the burden of detailed development. A specific solution, i.e. what an individual user actually interacts with, is designed by an AI engine, in what we call “problem solving loops”. These loops collect data (insights) on one user,

combine them with other data, and funnel them into an algorithm that develops the best solution for that precise user; the solution is designed right in the moment in which the user needs it. Even more, as new data are continuously collected, and the AI engines embed learning capabilities, the problem-solving loops improve their predictions about the user needs and behaviors and therefore design better solutions. In other words, solutions are continuously improved and innovated.

In the age of AI, the work of designers is not to ideate products to be commercialized at scale, but to conceive a new offering and then design the problem solving loops that will develop and deliver the specific solutions for specific users. The problem-solving loops consist of two main capabilities. First, the capability to gather, clean, and normalize data, through sensors, and integrate them into an enterprise data lake. Second, the capability to solve a customer's challenge: in this article we refer specifically to AI engines, that are the set of rules, theories, programs and algorithms that perform intelligent tasks (from recognizing objects to processing natural language, from making predictions to drawing conclusions), and that incorporate learning capabilities (i.e. machine learning), that enable them to provide improved solutions over time.

Problem-solving loops are hence autonomous and human-capital-free design systems that replace people with computing power when it comes to the development of a specific solution: they are resilient to variations in volumes without the need to redesign or upgrade their operating model, and can provide an ample variety of solutions without huge efforts in R&D.

3. AI-Empowered Design in Practice

To see how the framework of Figure 2 works in practice, we examined the cases of Netflix and AirBnB. We selected these two cases, as, being at the frontier of AI applications, they offer a glimpse into the future of design in the context of AI Factories.

3.1 *Netflix and the data-driven, design thinking machine*

Netflix has completely transformed the media landscape by harnessing the power of big data and AI. The core of Netflix is its data and AI centric operating model. It is powered by software infrastructure that gathers data and trains and executes algorithms that drive virtually every aspect of the business, from personalizing the user experience to picking winning movie concepts to produce. In this section, we detail the Netflix approach to design, by digging into some of the machine learning techniques that Netflix has deployed into its problem solving loops.

Netflix started to leverage AI at least as early as 2010, to fuel its recommendation engine. In 2014, Netflix expanded the factory to understand user behavior and develop a specific streaming experience for each user. The application screens that a user today sees are “designed in the moment” by a machine. Many boundaries and parameters are specified by human designers at the outset of the process. But the decisions about which movies to show, how to display them, which pictures to represent them with and many other design decisions are done by algorithms embedded in the AI problem solving loops. Let’s dig into these algorithms, which effectively resemble different aspects of a process of design.

The basic problems most AI systems try to solve to shape a design experience relate to predicting an outcome. The tool for making that prediction is an algorithm—the set of rules a machine follows to solve a particular problem. AI can incorporate many types of algorithms (Domingos, 2012) used for a broad variety of applications. Some of the most interesting algorithms have a built-in process for updating and improving, most often based on “Markov Decision Processes”, which seek to model a sequence of actions, each shaped by a policy, and followed by a reward. One example is the Netflix algorithms that dynamically update its user interface, based on the actual behavior of the user, as indicated by her clicks (while the policy decides what is displayed, the click is the “reward”).

While applications have exploded over the last decade, the foundations of algorithm design have been around for a while. The conceptual and mathematical development of classical statistical models like linear regression, clustering, or Markov chains dates back more than a hundred years. Today's neural networks were initially developed in the 1960s and are only now being put to use at a scale with production ready outputs. The vast majority of production-ready and operational AI systems at Netflix use one of three general approaches to developing accurate predictions using statistical models, also known as machine learning. These are supervised learning, unsupervised learning, and reinforcement learning.

Supervised Learning. The basic goal of supervised machine-learning algorithms is to come as close as possible to an expert (or an accepted source of truth) in predicting an outcome. The classic case is analyzing a picture and predicting whether the subject is a cat or a dog. In this case, the expert would be any human being with good eyesight who could label photos as cat or dog. The first step in supervised learning is to create (or acquire) a labeled data set. The data are then split between training and validation. As we compare the algorithmic model's prediction of the outcome to the validated labeled outcomes, we can determine if we are satisfied with the error between prediction and expert. If we are not satisfied, we can go back and choose a different statistical approach, get more data, or work on identifying other features that may be helpful in making a more accurate prediction. Netflix uses supervised learning in a variety of scenarios. For recommendations, Netflix has used labeled data sets made up of actions and results (e.g. movies chosen and liked) by people who are deemed by the algorithm to be similar to a given user. A large data set of user choices calibrated by characteristics of the user and of the decision context can lead to effective recommendations.

Note that supervised learning resembles elements of human design, as instantiated earlier in the first principle of design (people centered). Just as human designers immerse themselves in the context of use and observe all possible aspects of the user experience, the algorithms are trained by a relevant stream of *user data*, with significant information on the *context of use* (e.g. the type of device, time and place of action,

and so on). The more the observation and the richer the process, the more the problem solving loops are effective.

Unsupervised Learning. Unlike supervised learning models, which train a system to recognize known outcomes, the primary application of unsupervised learning algorithms is to discover insights in data with few preconceptions or assumptions. Whereas in supervised learning the data inputs are labeled with a given outcome, in unsupervised learning algorithms aim to find “natural” groupings in the data, without labels, and uncover structure that may not be obvious to the observer. In our example of photos of cats and dogs, an unsupervised learning algorithm might find several types of groupings. Depending on how the clusters are structured, these could end up separating cats and dogs, or indoor and outdoor photographs, or pictures taken during day or night, or virtually anything else. In these cases, one does not know exactly what to look for, but is searching for related groups, or events that fit or don't fit established patterns. Netflix uses unsupervised learning to discover related groups of customers in analyzed viewing data, to create customer segments for marketing campaigns, or to create different versions of the user interface that match different usage patterns. Even more advanced, Netflix uses data and AI algorithms to predict which content to create in the first place. The first application of predictive analytics was back in 2013, to evaluate the potential of House of Cards, in collaboration with Media Rights Capital. The new series was a hit and Netflix continued to develop content in response to detailed predictive analytics on market and user behavior. Cindy Holland, vice president of original content, noted in an interview: “We have projection models that help us understand, for a given idea or area, how large an audience size might be, given certain attributes about it. We have a construct for genres that basically gives us areas where we have a bunch of programs and others that are areas of opportunity.” (Spangler, 2018)

Note that unsupervised learning is an unstructured design process, where the patterns that emerge at the end do so based strictly on the observations (the data) and are not set up at the outset of the process. Although at its core, the algorithm simulates induction, when perpetuated on an extremely large quantity

of data, unsupervised learning provides insights and hypotheses that mirror the abductions of humans, or the dynamics of ideation and brainstorming. Hence, unsupervised learning also embeds the basic perspectives of design thinking into the problem solving loops of the AI factory.

Reinforcement Learning. Reinforcement learning makes up the third machine learning paradigm, and is the closest in structure to a traditional design process. The applications of reinforcement learning may be even more impactful than those of supervised and unsupervised learning. Rather than starting with data on an expert's view of the outcome, as in supervised learning, or with a pattern and anomaly recognition system, as in unsupervised learning, reinforcement learning just requires a starting point and a performance function. The system starts somewhere, and probes the space around, using as a guide whether it has improved or worsened a performance. The key tradeoff is whether to spend more time exploring the complex world around or exploiting the model built so far to drive decisions and actions. Let's say we take a cable car up a tall mountain and we want to walk our way down. It's a really foggy day and the mountain does not have any clearly marked paths. Since we can't just see the best way down, we have to walk around and explore different options. There is a natural tradeoff between the time we spend walking around and getting a feel for the mountain, and the time we spend actually walking down once we believe we have found the best path. This is the tradeoff between exploration and exploitation. The more time we spend exploring, the more we will be convinced we have the best way down, but if we spend too long exploring, we will have less time to exploit the information and actually walk down. This is pretty close to the way the Netflix algorithm actually personalizes movie recommendations and the visuals they are associated with. Through the analysis of user data, Netflix recognized that viewers have enormous diversity in taste and preferences. So, it decided that each user should be shown a cover artwork specifically designed for her, drawn from the frames of a movie. The artwork would highlight the aspects of the title that are specifically relevant to that specific user (Chandrashekar et al. 2017). The problem was complicated, as the Netflix team needed to figure out which movie selection to present, and then which artwork to combine with that movie to maximize the match between user and

recommendation. A single season of an average TV show (about 10 episodes) contains nearly 9 millions total frames. Asking creative editors to efficiently sift through that many frames of videos to design an artwork that would capture the audience's attention would be tedious and ineffective. Designing an artwork for each specific user according to its preferences would simply be impossible. But AI Factories, and in particular reinforcement learning loops, can address this design problem effectively. In a way similar to our previous example (finding our way down the mountain), Netflix uses reinforcement learning (and in particular multi-arm bandit algorithms) to spend some time exploring options, and some time exploiting the solution offered by its models. To explore visual options and refine the prediction model, Netflix systematically randomizes the visuals shown to a user. Netflix then exploits the improved model to show a specific user a slew of recommendations with improved visuals. The Netflix service continues to improve dynamically, by automatically cycling between periods of exploration and exploitation, designed to learn the most about the preferences of a complex human being, and maximize the engagement of this specific user over the long haul.

Note that with its emphasis on balancing exploitation and exploration, reinforcement learning resembles the process of human design in many facets, and in particular the principle of iterations enunciated earlier. Just as we see with traditional design approaches, opening the funnel with broad exploration can lead to more interesting and innovative decisions, but must be balanced with the increased challenges in making sure the exploitation phase converges on a usable solution.

In its earliest days two decades ago, Netflix operating model consisted of shipping DVDs. With this mail delivery service, Netflix could only track which titles users viewed, how long they kept a DVD, and how they rated each title, but they could not monitor actual viewing behavior. Although Netflix already recognized the importance of using data to improve customer experience, the heaviness of its assets and operations gave limitations to its capability to design. But when in 2007 Netflix launched its streaming service, the company seized the opportunity to transform its operating model into an AI factory. With streaming, Netflix could track the full user experience—when viewers pause, rewind, or skip during a

show, for example, or what device they watch it on. This enabled to design several problem solving loops that bring design principles to its extreme level: a user centered design for every single user. And, even more, to constantly innovate the solution for that specific user. So that she experiences, in a given moment in time, the more meaningful state of the art solution for her. Thanks to its problem solving loops, every user experience, at Netflix, is therefore individually designed in the moment. As Joris Evers, Netflix's then-chief of communications, says "*there are 33 million different versions of Netflix.*" (Carr, 2013)

3.2 *How AirBnB reframed the design practice in the hospitality industry*

The case of Netflix offered a unique opportunity to understand the design practices of an organization, as it transitions from a traditional operating model to an AI factory. In particular, it illustrated how problem solving loops work, which different configurations they can take, and how they enable to create people-centered solutions. How this new form of design compares to other practices? To this purpose, the hospitality industry offers interesting insights, as its competitive arena contrasts players with traditional and AI-enabled operating models.

Achieving people centricity in hospitality businesses is extremely complex by nature, because their ecosystems are characterized by diversities in cultures, ages, backgrounds, and travel purposes. As an indication of cultural complexity, consider that the chatbot of Booking.com translates in 43 different languages. In face of this complexity, the traditional operating model of the industry was based on heavy investments in real estate (hotels and their spaces and rooms) and labor-intense processes, with people that need to be hired, educated, and coordinated. Rooms of asset-heavy companies therefore need to be designed in a more or less standardized fashion, and they remain static for a significant span of time. Similarly, the user experience, and the related back-end of the service, is designed and formalized, so that it can later be delivered to users with good standards of quality. This operational model creates significant challenges to deliver experiences that can fit individual users. To address this challenges, the industry has

witnessed in the last decades some of the most frequent and popularized initiatives of consolidated design thinking practices. Examples of design thinking initiatives in the industry included projects conducted by IDEO for Intercontinental Hotels Group. One project, for example, targeted short-stay travelers and aimed to create a convenient experience that could be delivered with confidence and consistency. Another project targeted business travelers and resulted in the design of proper spaces for meeting and working. Another one focused on revamping the Holiday Inn Express brand by redesigning everything from how you check in to the look and feel of the room itself (Wilson, 2015). All these projects were framed according to a linear design practice, typical of traditional operating models: running ethnography to understand stakeholders' needs, ideating to formulate effective experiences for the target segment, and waging on rough prototyping for the identified solutions. To this purpose the innovation trend within the sector has been to create innovation labs, that are spacious places where design teams can prototype rooms on a 1:1 scale, and visualize new ideas before implementing them on a wider scale. Sometimes innovation in room design was taken to the extreme, and it was conducted directly on site: Marriott and Hilton selected real hotels to run β -tests, where customers could directly get in touch with new ideas, providing a more judicious assessment of the proposed innovation. The projects were then frozen into a design (of rooms, of processes, of IT applications) that the asset-heavy operating machine could deliver in a proper consistent way at scale.

In the last part of the 2000s, a significant transformation of the hospitality sector began. New companies with a lighter operating model entered the industry, colliding with traditional asset heavy business models. Airbnb offered the same service as Marriot: providing space to guests who need it. Consigning the onus of managing the operations to hosts themselves, Airbnb was able to get over traditional operating architectures' growth-bottlenecks, as the necessity to build rooms to scale. The capability of AirBnB to offer a state-of-the-art solution fully focused on the needs of the individual user, and all of this at full scale, depends on two factors. First, the creativity of design options. For example, in 2017, Airbnb (which was founded in 2007), spread over more than 190 countries and 80,000 cities, and counted more than 3

million hosts: three times Marriott International's rooms, although it was founded in 1927. And, even more, these 3 million rooms were all different from each other. Three million of designs. A similar richness of options and creativity in physical design would have been impossible to achieve by design practices in the traditional asset-intensive business. Second, this enormous creativity had to be connected to the needs of each individual user. And here is where AI Factories come into place. AirBnB collects an enormous amount of data from the interaction with its user. In 2016, the data science team has designed an extensive logging within the booking flow that allows AirBnB to collect insights on what guests see, how they react to different types of interfaces, how much time they spend on a listing page, how long they take to make a booking request, or the exact time in which they decide to go back to search (Dai, 2017). When a customer interacts with Airbnb's search engine, a new event log (i.e. a list of user activity event data) is sent to a central repository. These logs pile up and detail the customer profile, shaping the sense of her preferences and behavior (Mayfield et al. 2016). Every time a customer reconnects to the service, in search for a new traveling experience, Airbnb replies by instantaneously closing his problem-solving loop: data is extracted from the repository and processed by an AI-engine to create a new solution, personalized not only for the customer herself, but for the specific interaction. The system works in a similar way then what we discussed in the case of Netflix. Even more interesting, AirBnB is "two-sided market", i.e. it interacts in real time with two categories of users (guests on one side, and hosts on the other). Its AI factory has therefore different problem solving loops that work in parallel for each specific user type. An example of problem solving loop that provides the most effective solution on the side of the host is the how AirBnB designs the price of each individual list in an instantaneous and dynamic way: by ticking a box, a host accepts Airbnb's AI-engine to leverage data streams to automatically refine the price of their accommodation, within a price range. The AI-engine processes a vast number of different information collected from the ecosystem (Chang, 2017), such as the check-in lead time variation as the check-in date approaches, the listing popularity (i.e. how many people search around the host's area and how many of them click into the host's page), and the booking history, to understand how customers are

reacting to price variations. The outcome is that the price is designed in the moment every time a guest asks for that specific property (Srinivasan, 2018).

Thanks to this capability of being user centered on both sides of the platform, through independent problem solving loops that leverage on the same data lake, AirBnB provides user-centered experiences suffer less from the limitations that traditional operational model have in balancing the needs of different stakeholders. This design strategy enabled AirBnB to quickly become a central node of its network. Scale created a ripple effect therefore, allowing Airbnb to improve its credibility, enriching the user base because of the host volume, and gaining new hosts for the opposite reason. This is ultimate people centeredness: focused on each individual person, belonging to different user categories, in a dynamic way that improved iteratively the solutions over time. It would have been impossible to achieve it with traditional design practices.

4. Discussion

As AI is diffusing in our society, design scholars and practitioners wonder how this will impact our understanding of design. Will it affect the way we practice design? And, if so, will it even question its basic principles? Let's start by addressing the first question.

4.1 *Artificial Intelligence and Design Practice*

Up until today digital technologies have mainly spread into the operations of organizations, reducing the costs and time of manufacturing and delivering products and services. But the design of those products and services was essentially a human intensive process. Referring back to Figure 1, even if the “making” was fast and cheap, the “designing” was heavy in time and resources. It necessarily was an intermittent activity, conducted occasionally and for a segment of users, through projects.

Artificial intelligence dramatically changes this scenario, in a way that is central for innovation scholars: it moves digital automation upstream, into the space of design. On a simpler level, these automation capabilities can be used to enable designers do what they did before, but faster. For example, AirBnB is developing an AI system that supports the automation of a typical design task: the translation of mock-ups drawn by designers directly into component specifications for software engineers. The system is based on standardizations and classifications of all design components. AI can recognize Airbnb's design components that may have been hand-drawn on a drawing board and automatically render them into the actual specification and source code for prototypes (Saarinen, 2017; Schleifer, 2017).

If the use of AI would be limited to automation of existing design tasks, as in the example above, the essence of design practice would remain untouched. However, the cases of Netflix and AirBnB discussed in the previous session, show that the impact of AI on design goes well beyond automation of existing design practice; it profoundly transforms it. In other words, AI is the marker for an epiphany in the way we look at design (Verganti 2009, 2011a and 2011b).

What lays the foundation for reframing design practice are the problem solving capabilities incorporated in AI. Through machine learning, they enable to delegate to algorithms the definition of detailed design choices typically made by designers: which interface to show to a user, which content to create, how to position a product compared to competitors. This has profound implications both in terms of the object and of the process of design.

The first dramatic change is in the object of design practice (the "what" of design). Traditionally, designers created solutions (products, services, experiences) to be delivered at scale. What a customer experienced was previously conceived and developed by designers; down to the level of details: e.g. an image to be displayed on a screen. Conversely, with AI, the specific solution experienced by an individual user (i.e. what she sees on the screen of her mobile phone), is not only delivered but also *designed* "in the moment" by a problem solving loop powered by AI. In other words, in the context of AI, designers do not design solutions (these are generated by the AI engine); they design the problem solving loops.

This change of object has disruptive implications. Especially because most AI algorithms do not reason as a designer, i.e. they just not automate the thinking of a designer; they work in a different way. Whereas we tend to assume that AI simulates human behavior and reasoning (what is usually referred to as “strong AI”), most of the applications we discussed in the cases of Netflix and AirBnB are instances of “weak” AI: they are based on extremely simple tasks (such as recognizing a shape in an image or if two images have different shapes). To put it simply, weak AI is inherently “dumb”. Yet, by replicating these tasks millions of times (and by nurturing them with masses of data), weak AI can provide complex predictions, which even surpasses human capabilities. At least in terms of cost and speed of problem solving.

The consequences for scholars and educators of design are impressive. How do you design problem solving loops? How do you conceive design rules that are based on extremely simple tasks, but that once replicated times and times again, can autonomously provide extremely complex solutions to users? Designers are not educated this way. Their mental frames are trained to systemically embrace complex tasks. To leverage the power of AI, they need an unprecedented capability: to imagine what a dumb system can do when operating at scale.

As the object of design changes (from designing solutions to designing problem solving loops) also the process of design (the “how” of design) changes as well. This is evident if we compare Figure 1 with Figure 2 previously illustrated: in the context of AI Factories, the design process is split into two chunks. First, a human-intense design phase where the solution space is conceived and the problem solving loops are designed; and then an AI-powered phase, where the specific solution is developed for a specific user by the algorithm. As this second chunk of the process requires virtually zero cost and time, the development of the solution can be activated for each individual user, in the precise moment in which she asks for it. Which in turn enables to leverage the latest available data and learning, and therefore to create, every time, a better novel solution. There is no more product or service blueprint that act as a buffer between design and use. Design, delivery, and use, they all happen, in part, simultaneously.

Although this new practice is clearly visible in the realm of digital experiences based on software (such as Netflix and AirBnB), it is gaining traction also in industries based on physical products. Take for example the case of Tesla. Its operating model reflects Netflix or Airbnb's, as it gathers a massive amount of data from internal and external car sensors to design individualized user experiences. However, to enable problem-solving loops Tesla is confronting with a tangible hindrance: the car. Hardware cannot be (yet) designed in real-time, remotely and automatically. To unleash the power of AI, Tesla had therefore to reimagine the design of the car, acting in two diverse directions. First, it got rid of all the physical interacting elements (e.g. buttons) to embed most of the controls into digital user interfaces, e.g. into the large central touchscreen (Lambert, 2018). Second, it overloaded cars with sensors to collect data. Data are sourced from external sources (typically ultrasound equipment, GPS input, cameras, radar transmitters, and LIDAR) as well as from internal sensors. As cars go, sensors are collecting data with a high frequency to reinforce Tesla's datasets and training its learning algorithms. Interestingly enough, some of these sensors are "silent", meaning they are not already used to provide direct value to customers, but placed "in perspective". They are activated remotely after product release to enable new loops and provide new services to customers. Model 3, for example, is armed since 2017 with a cabin-facing camera placed in the rearview mirror. This camera was initially dormant (Lambert, 2017). Only in June 2019 the camera was used, thanks to new software updates, to recognize occupants and adapt the adjustable components, such as the seats, vehicle mirrors, music or driving mode preferences, in accordance with the user profile (Lambert, 2019).

4.2 *Artificial Intelligence and Design Principles*

Our cases show that in the context of AI Factories, design practice changes dramatically both in terms of the object of designing and the process of designing. Does AI also undermine the core principles that underpin design? In other words, is this new design practice still people centered, abductive, and iterative? Or is it rooted in different principles?

Our observations suggest that AI does not question the fundamental principles of design thinking. Rather, it further reinforces them.

To support this statement, we consider how AI removes limitations in traditional human-intensive design. More specifically, we start from the finding of an extensive study of AI-powered strategies conducted by one of us (Iansiti and Lakhani, 2020). The study shows that AI affects the operating model of an organization by eliminating three limitations: scale, scope, and learning. Let's see how, by removing these limitations, AI empowers design's capability to be people-centered, to create abductions, and to innovate through iterations.

Scale and people centeredness. Traditional design practices had significant scale limitations. Being one of the most intense human-based activities, it required the investment of significant resources and time, especially during development where several detailed decisions were taken. This made it unreasonable to design a solution every time a user needed it. With the exception of large engineer-to-order systems - whose price fully repaid the cost of design, solutions were designed in the form of products and services, that targeted several users, or segments of customers. Although some form of customization was possible during production and delivery, the design phase was conducted in occasional projects, where users were addressed in terms of average archetypes (hence the use of "personas" in classic design thinking processes). This scale limitations therefore posed significant constraints to people centeredness.

AI enables to remove significant scale limitations in design, as the development of specific solutions is performed by machines. First, these machines embed design rules that are inherently user centered. As seen in the case of Netflix, supervised learning leverages a rich stream of data on *each individual user*. Second, this focus on individuals can be scaled with no limitations on the number of users and the complexity of data. The detailed solution that a specific user experiences (e.g. what a user sees in the screen of the Netflix application) has been developed just for her, *on the basis of her own data*. Interestingly,

the relationship between scale and people-centeredness is now inverted. In human-intensive design, the larger the number of users and the complexity of insights, the more difficult was to focus on individuals. In the context of AI factories, the larger the number of users and the richer and complex is the stream of data, the better the predictions of the machine on the behaviors of individuals. An even more advanced example is provided by AirBnB. Here the organization has to deal simultaneously with different categories of individuals: hosts and guests. Not only the learning loops do not suffer by this increase of complexity, but they also benefit by the integrated elaboration of data from both sides of the market.

Scope and abductions. Human-intense design practices also had significant limitations in scope. Products were designed for a specific industry, and with a specific target. And once the project design was completed, it was unlikely to be applied in a different context. A car was designed to be a transportation mean. Moving from there to entertainment services was unlikely to happen. And if so, it required the design of a new product. Limitations of scope were significant even within the same industry. Consider the example of design thinking at Intercontinental Hotels Group, previously illustrated. The solution developed by IDEO to address the need of short-stay travelers (marked by convenience) and the solution targeted to business travelers required different design initiatives, by different teams, and different brands of the same organization. The scope limitations of human-intense design pose significant constraints to the possibilities of abductions. The design brief marked the scope of the design space. Once the brief was defined and frozen, creativity could happen only within that space.

AI enables to remove limitations in scope. In the context of AI Factories, a design brief is fluid and can be reframed even after a product has been released. For example, we have seen how Netflix uses unsupervised learning, to find new patterns in customer tastes that were not set up at the outset of the process. These predictions are used to support abductions in imagining new movie series. This fluidity of scope in the design may enable the exploration of radically new design spaces. Consider for example AirBnB, which has expanded into “travel experiences”, by offering guests the possibility to take a horse ride on a beach or hire musicians. To enter this new industry AirBnB leverages the same AI factory that

powers the traditional hospitality service of AI. Similarly, Tesla leverages the learning loops embedded in its cars to complement its offering (transportation) with entertainment that passengers may enjoy during a trip. A breakthrough idea for a car manufacturer, enabled by the lack of limitations in the scope of AI-Factories.

Learning and iterations. Traditional design practices, finally, had relevant limitations in terms of learning. In fact, design-build-test iterations that fuel learning were confined within a project. Once the project was terminated, and the product was released, iterations were substantially discontinued. New learning that comes from the observation of real product use could only feed the development of future versions. Innovation happened episodically, in lumps. And as the context evolved new solutions became rapidly “old”.

AI drastically removes limits in learning. Note that AI factories are intrinsically iterative. They deliver through loops. As the case of Netflix illustrates, each time a customer accesses the service, the firm activates a problem solving loop. This loop not only leverages the most recent data and algorithms. It also offers a new opportunity to further learn. The algorithm, in particular, can direct the learning strategy towards improvements, i.e. towards refining its parameters to solve a problem better (e.g. showing a more appropriate movie cover to a specific user), or towards exploring new opportunities (e.g. proposing to the user a new movie category). This balancing act of exploitation and exploration, facilitated by reinforcement learning and double-armed bandit algorithms, occurs continuously, throughout the entire product life cycle. The implications in terms of innovation are significant.

First, *learning never ends.* The solution experienced by a specific user in a specific moment is not the same she experienced when the product was first released. It is the most advanced design so far. In a way, the solution is always “new”. This is enabled not only by the intrinsic flexibility of software-run experiences, which can periodically incorporate new releases designed by software engineers. In AI Factories, the whole learning loop (design – build – test) is automated. Which means a new product version is “released” every single time a customer accesses a service. Second, *learning is based on real use.* Whereas in the past,

learning occurred through prototypes, often tested in simplified or protected contexts, here the learning comes from the actual use of the product in the context as it is today. Third, *learning is person centered*. In the past, the experience offered to a specific person, was designed by leveraging learning from other people (e.g. insights coming from customers who used previous generation products or through other users who tested a prototype). Now insights leverage not only data from other customers, but also from the person herself. Fourth, every instance of delivery is an opportunity not only to continuously improve the design, but also *to conduct new experiments* and open up space for more substantial innovation. To this aim, learning loops are designed with a different logic than traditional products. The latter included only the features that were considered useful at the time of design. In AI Factories, instead, the designed loops are *overloaded* by elements whose utility is not fully exploited at the time of release. In other words, AI factories are explicitly designed with redundant affordances (Gibson 1977), as we saw in the case of Tesla, where sensors that will enable autonomous driving are used to train algorithms about the complexity and variety of real street contexts, even if most of their functionalities are still not currently available or where the internal pointing camera has been not actively delivery any feature for two years.

In summary, AI Factories incorporate and further empower the principles of design thinking: beyond being people centered, they are single-person centered; they facilitate creativity across segments, stakeholders and industries, enabling abductions beyond the scope which a product was initially conceived for; finally, they are intrinsically iterative, moving learning and innovation beyond development into the product life cycle.

4.3 *Design for Artificial Intelligence*

If AI empowers a more advanced practice of design, the opposite is also happening: design can empower a more effective, human-centered implementation of artificial intelligence. Think at the hospitality industry. Both Booking.com and AirBnB make intense use of AI, for example for personalized listing

and helping host making decisions about the price. Yet, Booking.com's innovation path is less driven by design, but, rather, by an intense use of A/B testing. At Booking.com features are therefore pushed "from the lab outwards" rather than "from the user-inwards". On the other side, AirBnB has design thinking in its DNA, as two of its founders, Brian Chesky and Joe Gebbia, are alumni of Rhode Island School of Design. In 2011 the company launched the Snow White project to bring human-centered design at all levels of the organization, and redesign competitive strategy. The project was led by Rebecca Sinclair, then Head of User Experience Research and Design, and a former designer at IDEO. "At the time, like a lot of tech startups, we called the website and the app 'the product' ", says Sinclair. But then "by practicing design thinking [...] we were looking at a journey [...], imagining our customers booking, and we saw that the moments that mattered most were offline. This offline experience — this trip to Paris or stay in a treehouse — is what they were buying from us, not a website or an app. That's when we started to say, 'the product is the trip' and began shifting our perspective". The result of this design perspective in driving innovation is evident not only by comparing AirBnB's user interface with Booking.com, but also in the capability of AirBnB to funnel AI towards the development of new business categories, such as Airbnb Experiences.

Microsoft offers another insight on the key role of design for the implementation of artificial intelligence. As Microsoft's CEO, Satya Nadella, stated, AI is the new "runtime" of its firm. Its operating model is now built around AI. This required the company to radically reorganize its IT and data assets, which had been dispersed across the company's various operations (Iansiti and Lakhani, 2020). Interestingly, the transformation was not led by an IT manager or IT experts. Rather, the whole initiative was driven by Kurt Del Bene, an executive with product experience, as he was the former head of Microsoft's Office business unit, and a team of leaders and engineers from product functions. Nadella indeed wanted the company operating processes and AI Factory to be designed as one designs products rather than IT infrastructures.

4.4 *Artificial Intelligence and Design Theories*

“Professor Simon ignores the possibility mentioned in my article that problem solving and problem finding might require opposite, or at least orthogonal cognitive strategies (and by ‘cognitive’ I mean not just rational, but emotional and motivational as well).” (Csikszentmihalyi, 1988b).

In 1988, in front of advancements in computer intelligence, and of the challenges that this posed to our understanding of cognition, Mihaly Csikszentmihalyi and Herbert Simon started a dispute on the true nature of creativity. Simon, in exploring the potentiality of a computer program called “BACON” that he and his colleagues had developed at Carnegie Mellon University, was supporting a rational perspective of cognitive processes (Simon, 1985), where creativity could be interpreted as a process of problem solving (and therefore, partly embedded into computers). In a following article, Csikszentmihalyi challenged this perspective (1988a): “Simon wishes to prove, namely, that creativity is nothing but problem solving”; Csikszentmihalyi instead proposed “problem finding as the hallmark of creativity”. Simon reacted to Csikszentmihalyi’s challenge by further reinforcing its position (1988): “I would claim that, just as finding laws that explain data is a problem-solving process, so *finding good problems* and finding relevant data for solving them *are problem-solving processes* of a normal kind” (italics by the authors of this article). The essence of the response by Csikszentmihalyi is in the opening statement of this section: problem solving and problem finding do have a different nature. He anticipated the evolution of design theories in the years to follow: on the one hand scholars who looked at design mainly as creative problem solving (in which the school of Stanford and the related frameworks of Design Thinking are rooted. Buchanan 1992, Brown 2008 and 2009, Martin 2009, Kelley and Kelley 2013). On the other hand, scholars who looked at design as a process of problem framing, or, more precisely, as sense making (starting from Krippendorff’s definition that “Design is making sense of things”, 1989. See also Krippendorff 2006, Verganti 2008 and 2009, Stigliani and Ravasi 2012; Jahnke 2013, Verganti and Öberg 2013, Norman and Verganti 2014, Dorst 2015).

In the last decades, the first stream (creative problem solving) has captured the larger share of attention in the development of theories. Although it also embraced the framing of a problem (as for example in

the double diamond model of Design Thinking), it was still theoretically rooted in the theories of problem solving laid down by Simon (in which problem framing, was still considered a rational activity of nested problem solving). This focus of theory development was justified by the fact that problem solving was complex and therefore required the most significant chunk of effort by humans. The current diffusion of AI is dramatically changing this scenario. Problem solving is increasingly embedded into the automated learning loops of the AI Factories, shifting the core of human design into framing and sense making. The theoretical consequences are substantial. First, for the theories of problem solving. Most of these theories (especially in the realm of Design Thinking) have been developed assuming that innovation problems are solved by humans. What happens when they are solved by machines? We already discussed, for example, that AI loops work by replicating simple “weak” rules; and that designers instead address complex problems as a systemic whole. Another example concerns the moral consequences of loops: they scale up exponentially and rapidly, creating unintended outcomes on a large scale, including the amplification of biases. How to provide designers with the right frames to capture the exponential outcome of their design ahead of time?

A second, an even more relevant, implication is that we need to change the theoretical lenses we use to understand the human activity of design: not only as problem solving (which is now increasingly conducted by machines), but also, and especially, as sense making. The role of designers in AI Factories is becoming to understand what problems makes more sense to address, next to design the learning loops, and then to drive their continuous evolution towards a meaningful direction. Just to mention a simple example put forward by Csikszentmihalyi in his discussion with Simon: an algorithm that has been created to solve a problem cannot refuse to solve it; it cannot pull the plug (unless this trigger is already incorporated in its code). A human can. It can avoid to design, if it does not make sense, morally, emotionally, or by intrinsic motivation.

Since scholars in the past had been focusing on problem solving, our understanding of design as sense making is still very limited. There is therefore an enormous (and intriguing) space ahead to be explored.

We predict that the most significant future theoretical developments in design thinking will come from a deeper investigation of problem framing and will leverage theories of sense making. Also, we predict that design will move closer to leadership, which is an inherent act of sense making.

5. Conclusions

Artificial Intelligence is not like any other digital technology. It does not just automate operations. It automates learning, which is the core of innovation. It therefore offers unprecedented opportunities to dramatically reduce the cost and time of developing a new solution. In this article, we have opened a window on the implications for design, by exploring the strategies of pioneering companies in AI: Netflix, AirBnB, Tesla and Microsoft.

The cases suggest that AI does not undermine the assumptions and principles of Design Thinking. Rather, by removing past limitations in scale, scope, and learning, it enables to further enact design in its core: it realizes the ultimate form of people-centeredness, with experiences that can be designed for each individual person, and continuously improved based on individual user data; AI may enhance creativity, by expanding the scope of the design space beyond product categories and industries; finally, it brings iterations and experiments at the core of the operating models of firms.

Yet, the design practice of AI Factories is radically different than what we used to know. We have introduced a framework to discuss this transformation and capture the nature of design in the new context of AI Factories. With the advent of artificial intelligence, a significant chunk of problem solving (mainly, what we used to call “development”) is transferred to algorithms. They keep innovating and searching for better solutions thanks to their learning loops. These algorithms think in a significantly different way than a designer: they think in terms of small dumb operations, which, however, when scaled up and iterated thousands or even millions of times, can address complex problems.

For managers, understanding the new nature of the design practice in the age of AI is therefore fundamental to avoid applying the right design principles (that remain untouched) to the wrong process (which instead is significantly different than the past).

For scholars, the implications in terms of design theories are also substantial. We need two new types of frameworks. First, we need to provide designers with new models that support them in their new task: not of designing solutions, but of designing the problem-solving loops that will develop the solutions. Second, and more relevant for the management of design and innovation, we need to strengthen our understanding of the strategic dimension of design: the definition of a meaningful direction. In AI Factories the human side of design increasingly becomes an activity of sense making (defining which problems make sense to address). This brings design closer to management, and in particular to innovation leadership. In a way, the disciplinary distance between design and management has started to shrink already two decades ago (see also Leister et al. 2002; Boland and Collopy 2004). However, in the past it was management theory that moved closer to design, in search for new frameworks that could support problem solving. Now instead, we expect design to move closer to management. And the distance will shrink on a new dimension: the dimensions of sense making. The space for contamination between the two disciplines, and in particular between design (with its theories of framing and critique) and leadership (with its theories of sense making and dialogic), is relevant; it is significantly untapped; and it promises to be one of the most fascinating journeys for innovation scholars in the years to come.

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