

## **The impact of Artificial Intelligence on Design Thinking practice. Insights from the ecosystem of startups**

### **Abstract**

*Design Thinking (DT) is spreading out in the managerial community as an alternative way to innovative products and services respect to the classical stage-gate model mostly linked to technology-push innovative patterns. At the same time few disruptive technologies – like Artificial Intelligence (AI) and machine learning – are impacting the ways companies manage their knowledge and activate innovation and design processes. What is the impact that AI is exerting on DT practices? What are the main changes that DT is undergoing? These questions are analyzed in this paper, where the aim consists in increasing the understanding of the transformation that is occurring in DT and more general in innovation practices. Through a qualitative case study analysis made on startups offering AI based solutions supporting multiple or individual DT phases, the article pinpoints few main changes: i) a facilitation in blending the right mix of cultures and creative attitudes in innovation teams; ii) the empowerment of the research phase where statistical significance is gained and user analysis are less observer-biased; iii) the automatization of the prototyping and learning phase.*

### **INTRODUCTION**

Design thinking (DT) has become a pervasive innovation approach that impacts organizational culture, the way companies engage users, and more in general the underpinning constructs that characterize the innovation process (Beckman and Berry, 2007; Martin, 2009; Brown, 2009; Cross, 2011; Liedtka and Ogilvie, 2011; Liedtka, 2015; Elsbach and Stigliani, 2018).

Born in USA thanks to a fertile union between the leading Stanford University and the design consulting company IDEO, the strategic intent related to DT consisted in creating a common ground where managers could understand how designers “reason” in their work flow, and designers could better align creativity to business and competitive rules (Cross, 2011).

Even without a unanimous consensus, extant literature related to the Innovation Management domain has pinpointed different founding principles inherent DT. Firstly, abductive reasoning (Martin, 2009) has been highlighted as a different pattern that hugely differs from deduction and induction. Here, the pattern consists in setting novel hypothesis inherent the problem-context challenging the dominant paradigms through the “what-if” and heuristics techniques. Moreover, rounds of iteration, the Human-Centered approach (Brown, 2009; Holloway, 2009), the “framing and reframing” of the problem-context (Drews, 2009; Dorst, 2011), the continuous interplaying between the “problem-space” and the “solution-space” (Dorst and Cross, 2001), as well as the ambiguous nature of the problem that usually DT is used for (Boland and Collopy, 2004; ) lay the

foundations for a different approach to innovation that overcomes the limits of the old and widespread “stage-gate” innovation process (Cooper, 1989; Ulrich, 2003).

Currently however, despite a consolidated nature, few transformative factors – mainly related to the advent of disruptive technologies – are dramatically impacting the way companies run and implement innovation practices and approaches (Liebowitz, 2001; Nemati, 2002) including DT (Cross, 1999). Specifically, families of disruptive technologies like Artificial Intelligence, Machine Learning, Big Data analytics, are enhancing not only customer relation management and marketing activities but even those activities related to R&D and the wider management of innovation processes (Observatory of Artificial Intelligence, Politecnico di Milano, 2018).

Looking at AI in particular, this is typically defined as the ability of a machine to perform cognitive functions similar to human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, and even exercising creativity. Examples of technologies that enable AI to solve business problems are robotics, computer vision, language processing, and machine learning. AI is indeed a multiple purpose technology: as a matter of fact, its domain mostly embraces multiple solutions and even heterogeneous methodologies to accomplish many tasks in relation to different organizational departments across many industries (Michalski, Carbonell & Mitchell, 2013). Chatbots and virtual assistants – for instance - are largely spreading out in industries such as banking and finance to support users in accomplishing easy tasks or in taking complex financial decisions as asset allocation and wealth management (Observatory of Artificial Intelligence, Politecnico di Milano, 2018). Furthermore, customer relation management and sales management are widely benefiting from AI to increase internal efficiency and respond better to user behaviors and pains.

But what about the role of AI in supporting DT? Which is the specific role that this technology is playing in supporting innovation practices driven by DT in businesses? And moreover, which phases of DT – intended as innovation approach widespread across multiple industries – are mostly benefiting from AI solutions? These questions are relevant to better grasp the close future of DT and how creativity – that has been for a long time considered a non-replicable activity of the human brain – will be enhanced, empowered or limited by the advent of this disruptive technology.

Framing DT according to the main phases rooted in the literature and identifying the emerging AI services and software solutions applicable to individual or multiple DT phases, the aim of the article consists in deepening the understanding of how the DT approach is currently shaken by radical or incremental transformations driven by disruptive technologies. To provide a structured answer to these research questions, the article proposes a qualitative analysis of a sample of the most funded startups offering services and tools where AI is applied to individual phases or to the whole DT

process, considering startups as proxy drivers to foresee the next changes on creative approaches and innovation practices.

The article is divided mainly into four sections: the theoretical background explores the literature referred to DT and identifies the model that will be employed for analysis; research design and case analysis report the startup sample used, and the ways in which this has been analyzed; the findings explain the original contribution of the article identifying how AI is modifying DT; finally, the conclusions depict the larger implications for the future of DT.

## **THEORETICAL BACKGROUND**

### *A model to frame Design Thinking*

In an early attempt to lay the foundation of a novel disciplinary stream connecting innovation and design, Brown (2009) defined DT as “*a discipline that uses the designer’s sensibility and methods to match people’s needs with what is technologically feasible and what a viable business strategy can convert into customer value and market opportunity.*” As stated by Micheli et al. (2019), this definition qualifies DT as both a process and an individual characteristic – that is a specific “sensibility” – explicitly linking design with business issues. Lockwood (2010b, p. 5) on the other hand states that DT is “*a human-centered innovation process that emphasizes observation, collaboration, fast learning, visualization of ideas, rapid concept prototyping, and concurrent business analysis,*” thus highlighting the application of professional designers’ work process to business issues. The scope and at the same time the outcome of the process guided by DT are nowadays indifferently related to products, processes and business models (Liedtka, 2011). Moreover, rooted on the “experiential learning” theory, emerging perspectives consider DT as a means that enables changes in organizational culture through a continuous use of different tools and principles (Elsbach & Stigliani, 2018).

If until some years ago scholars (Carlgren et al., 2016) had highlighted in DT a discrepancy between a theoretically depicted process and the practice, in few years a general consensus around the essential attributes and key concepts denoting DT has been achieved (Micheli et al., 2019). In a research that has leveraged an exhaustive literature review conducted analyzing leading scientific journals in design and management combined with a card sorting exercise run by design professionals, key principles, tools and constructs have been identified. Putting aside the outcomes of DT practice – mainly recognized as “creativity and innovation” as well as “problem solving” – principles like “user centeredness and involvement”, “iteration and experimentation”, “interdisciplinary collaboration”, “ability to visualize”, “holistic view”, “abductive reasoning”, and

“tolerance for ambiguity and failure” represent characterizing attributes that describe the essence of DT both as discipline and practice. These attributes tend to stretch and complexify the earlier representation of DT as a “double diamond” (Stickdorn and Schneider, 2010) where the main phases were generally identified as “discover, define, develop, deliver”. In this article – in order to connect AI solutions to their application for DT practices – the more detailed process articulation developed by Micheli et al. (2019) is used, thus recognizing the following essential phases:

- *team building and task management*, considered as a propaedeutic phase directed to arrange and involve employees from different departments and project stakeholders forming cross-disciplinary teams for the accomplishment of the creative activity;
- *sensing and empathizing*, where user analysis is run according to the different techniques of user observation, ethnographic research, shadowing and interviews, further collecting information and insights on the problem context and developing “empathy” with the user;
- *interpreting and framing*, where the design problem is bordered, framed and alternative views and insights are sought for achieving a problem reframing;
- *ideating and conceiving*, where multiple ideas are proposed to widen the solution space;
- *prototyping and learning*, to create tangible mock-ups or even probes to be tested to collect feedback and learning for triggering later iterations and refinements;
- *launching and measuring*, oriented to create an early market for the solution thus measuring with contextual KPIs the early stage performing dynamics.

*Team building and task assignment* in DT are governed by the involvement of cross disciplinary teams. As stated by the dominant literature (Brown, 2009; Kelley and Littman, 2009; Kelley and Kelley, 2013), innovation and creativity are fostered by cultural diversity and by the involvement of the multiple perspectives that cohabit an organizational context. These principles seem to be tightly connected with the innovation management literature that highlights how diversity of cultures and cross disciplinary ranges matter for the innovation effort (Basset-Jones, 2005; Cox and Blake, 1991; Gibbson and Gibbs, 2006; Dell’Era and Verganti, 2010).

*Sensing and empathizing* can be seen as triggering activities for an innovation project where creative teams try to grasp the traits and the borders of the problem-space (Dorst and Cross, 2001) by increasing the empathy with users involving them directly through different activities, ranging from passive observation to active participation for co-design. This phase seems to be linked to a consolidated stock of literature in innovation management that analyzes the different forms of engagement and the relations between user involvement and innovation outcomes (Jeppesen, 2005; Bosch-Sijtsema & Bosch, 2015; Heiskanen et al., 2007; Magnusson et al., 2003).

*Ideation and conception* can be considered as the core of DT, where brainstorming sessions alternate with more structured techniques for idea generation, like metaphorical games or collaborative sketching (Smith, 1998; Linsey et al. 2011; Shah et al. 2001). Sketching and visualization appear fundamental at this stage because they promote “creative discovery” and support reflection and discussion for decision making (Van der Lugt, 2005; Verstijnen, Ilse M., et al., 1998; Kavakli et al., 1998).

*Prototyping and learning* represent the phase where sketched ideas become mock-ups or probes, characterized by sprint-like approaches and rough prototyping techniques (Knap et al., 2016; Schrage, 1993). These are spreading into businesses thanks to *ad hoc* digital environments and 3D manufacturing systems that support the development of digital apps or early releases of tangible items respectively.

Lastly – before starting a novel iteration round – a first launch in an early market or lead-users context is necessary in order to start measuring the basic KPIs of the new product, service or business model. Thus conceived, DT tends to be tightly aligned to the domain of the lean entrepreneurship (Ries, 2011) where the blend of hypothesis and assumptions underpinning new ideas related to products, services or business models need to be tested to grasp new avenues for refinements and improvements (Bicheno & Holweg, 2000; Müller & Thoring, 2012).

Considering the scope of the article, the articulation presented is useful to depict a more detailed structure to which services and software offered by startups can be related.

### *The advent of a disruptive technology domain: Artificial Intelligence. Few evolutionary notes*

The birth of AI has been dated 1956 when different scholars and scientific personalities like Herbert Simon, John McCarthy, Claude Shannon, and Nathaniel Rochester took part in a congress dealing with the power of calculators and the specific applications of intelligent systems resulted from a scientific ferment occurred between the 30's and 50's. This interest for intelligent systems boomed in 1943 when McCulloch and Pitts proposed the use of computational models to simulate intelligence and the functioning of neuronal networks. After a while, in 1950, Alan Turing published for *Mind* – a relevant academic journal dealing with philosophy and psychology - an article entitled “*Computing machinery and intelligence*” where he proposed the well-known Turing test, according to which a machine should be considered “intelligent” if its behavior – observed by humans – is undistinguishable by that of humans themselves.

Some applications related to the math logic and the neuronal network thus flourished from that moment on: the field of AI received great attention and after a while the entire domain was

distinguished in two main paradigms, the “strong AI” and the “weak AI”. The former theorizes machines accomplishing tasks and taking decisions with the self-acknowledgement of their activities; the latter recognizes the ability of machines to take decisions (as playing chess for instance) without self-consciousness. In time, the majority of attention has been attracted by the weak paradigm, thus consolidating the theory that the activity of the human brain remains too complex to be reproduced by machines.

### *AI main applicative domains*

Looking at the current applications of AI algorithms, five classes of solutions – mostly connected to R&D, innovation processes and organizational learning – have been taxonomized (Observatory of AI – Politecnico di Milano, 2018):

- *intelligent data processing*, in this category solutions that deal with structured and unstructured data to extract information from raw data and take action on this basis can be found; here applications can include “pattern discovery”, where framing and connections between different types of raw data are established, and “predictive analysis”, where applications analyze data to forecast future events or phenomena;
- *virtual assistant/chatbot*, in this category software agents that can execute commands or accomplish requests through natural language interactions are included;
- *recommendation*, solutions oriented to guide user preferences and choices on the basis of information provided (as for instance platforms that suggest the purchase of a specific product or propose new movies to watch on the basis of the ones already watched);
- *image processing*, solutions where single images or videos are analyzed in order to extract precise information;
- *language processing*, in this category solutions that elaborate languages with the goal of content comprehension, translation, or the autonomous creation of documents using data or other documents as inputs are recognized.

Potentially, all of the above classes of solutions can be applied to specific parts or to the entire DT process. For instance, an AI pattern discovery application can be dramatically useful in increasing the understanding of the problem-space or an image processing app can boost the analysis of competitor products; furthermore, language processing software can empower the phases of user observation and analysis increasing the capability of the creative team to save transcripts, match them to different users and indicate overlapping parts and divergences.

In the real business world as well as in the literature, we still ignore the existing number and the impact of AI applications in DT. This is the literature gap at the interplay between DT and AI that this article aims to partially cover, thus motivating the undertaking of an exploratory research focused on startups that offer AI-base service for DT proposed in the following.

## **RESEARCH DESIGN**

### *Sampling and skimming process*

Because of the presented literature gap, an exploratory research based on case study analysis has been run (Yin, 1981; 2017; Shell, 1992; Miles et al. 1994; Einsenhardt, 1989). The inquiry has been conducted on startups offering DT services through use of AI.

Startups have been selected by Crunch base®, a data-base with more than 500.000 data points about new ventures, incubators, and investors. From this data-set a first skimming process using major tags directly or indirectly related to DT has been conducted<sup>1</sup>. This has resulted in an initial sample of 4266 startups, that has been further skimmed reading the description of activities run by startups with a result of around 2.100 containing those more closely related to DT.

An in-depth analysis has thus been conducted to have a more manageable sample. Finally, 494 startups have been extracted, 168 of which are strictly related to DT, and 80 employ AI to offer their services and applications. Among these 80, to run the final qualitative case analysis we selected the 20 most funded ventures.

## **CASE ANALYSIS**

An analysis in two steps has been performed on the overall set of 20 startups.

In the first instance, companies have been analyzed using mainly secondary sources of data, thus studying their offer through information found online to understand the phase covered in the DT process. This analysis has provided initial insights on how the process is transformed and given inputs about which startups could be interesting for a deeper analysis. Details of how start-ups have been categorized are provided in Table 1 below.

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<sup>1</sup> Different tags categories predefined by the data set have been employed in order to have a first significant sample. Three main tags clusters have been distinguished: i) “design related” (for instance: #UX Design, Web Design, Human Computer Interaction, Product Design, Mechanical Design, etc...); ii) “creativity and organization related” (for instance: #Collaboration; Innovation Management; Project Management; 3D Technology; etc...); iii) “others” (for instance: #Market Research; Application Performance Management; Data Storage; Information Services). The third category has been considered as residual but significant because some specific categories such as “Market research” or “Internet of Thing” could have hidden an interesting number of startups non expressively related to DT.

**Table 1.** DT phases coverage

Startup name  Phases of DT	DT phases covered					
	Team Building and Task Management	Sensing and Empathizing	Interpreting and Framing	Ideating and Conceiving	Prototyping and Learning	Launching and Measuring
<i>Veritone, Inc.</i>		***				
<i>Applifools</i>					***	
<i>Gamalon, Inc.</i>		***	***			
<i>Sentiance</i>		***				
<i>Eightfold</i>	***		***			
<i>Test.ai</i>					***	
<i>Eigen Tech</i>			***			
<i>Pymetrics</i>	***	***	***			
<i>Fetch.ai</i>			***			
<i>iGenius</i>	***	***	***	***	***	***
<i>HyperAnna</i>		***	***			
<i>B12</i>					***	
<i>Pixoneye</i>		***				
<i>Gooroo</i>	***	***				
<i>Appvance.ai</i>					***	
<i>Daisee</i>		***				
<i>ForwardLane</i>		***	***			
<i>DataRPM Corp</i>		***				
<i>AdMobilize</i>		***				
<i>Iguazio</i>		***	***			

To deepen this first outlook, 5 startups have been selected for further analysis to understand how their offer of services is approaching and covering the DT process. The 5 startups have been selected because of their representativeness of a specific cluster of offering; specifically one startup for each of the 4 mostly covered phases has been analyzed, that is one for *Team Building and Task Management* (covered by 4 out of 20), one startup for the phase *Sensing and Empathizing* (covered by 13 startups out of 20), one for *Interpreting and Framing* (covered by 9 out of 20), one for *Prototyping and Learning* (covered by 5 out of 20). Finally, the only company covering all phases has also been included.

This final sample has been searched mainly to understand: the offer of the company, the partial or general coverage of the DT process, the specific phases covered, the specific solution used for DT, and the main changes caused in the process. An outlook of this analysis is provided below in Table 2, while further details on the companies analyzed are provided in the annex to the article.

**Table 2.** Details of the 5 most representative startups (further detailed in the annex)

	Main categories of analysis				
	General description <i>(What does the start-up offer? To whom?)</i>	Partial or whole coverage <i>(Is the DT process covered partially or generally by AI?)</i>	DT phases covered through AI <i>(What are the single or more phases covered by the startup?)</i>	Specific solution <i>(What specific solution is provided to address the DT phase/phases?)</i>	Overall changes in DT <i>(What changes AI is providing to DT?)</i>
<p><i>Startup 1</i> <i>IGenius,</i> <i><a href="https://igenius.ai">https://igenius.ai</a>,</i> <i>founded in 2016</i></p>	<p>The company uses AI to build a human-friendly relationship between people and data. IGenius works for any business sector and with any type of data (CRM, marketing data, operations) mainly providing AI-based advisors for business intelligence.</p>	<p>Whole coverage</p>	<p>All</p>	<p>Software based on Natural Language Processing, Machine Learning and fast data retrieval.</p>	<p>Access and analysis of data is reinforced and made central throughout the creative process. Insights are provided handling quickly data diversity, providing statistical significance to ideas, scanning e-conversations to let ideas emerge, tailoring and even measuring stimuli for creativity.</p>
<p><i>Startup 2</i> <i>Sentiance,</i> <i><a href="http://www.sentiance.com">http://www.sentiance.com</a>,</i> <i>founded in 2012</i></p>	<p>Sentiance is a data science company turning IOT sensor data into rich insights about people's behavior and real-time context.</p>	<p>Partial coverage</p>	<p>Main: Sensing and Empathizing</p>	<p>Through using Machine Learning and behavioral modeling, users are observed in real-time in their context to learn about temporal routines and behaviors.</p>	<p>Building empathy with users becomes a direct unbiased process, without the intermediate personal interpretation of the observer. The understanding of users becomes much deeper and can happen in real daily situations, also supporting a more objective framing of problems.</p>
<p><i>Startup 3</i> <i>HyperAnna,</i> <i><a href="http://www.hyperanna.com">http://www.hyperanna.com</a>,</i> <i>founded in 2016</i></p>	<p>HyperAnna is an AI powered data analyst capable of analyzing any type of data within</p>	<p>Partial coverage</p>	<p>Main: Interpreting and Framing</p>	<p>The software generates key insights based on statistically relevant analysis, providing</p>	<p>Framing and interpreting problems and users' insights, but also access and analysis of data for</p>

	seconds by using natural language.			actionable insights within seconds to impact business decisions.	the discovery phase of the DT process are improved by AI.
<i>Startup 4 Pymetrics, <a href="http://pymetrics.com">http://pymetrics.com</a>, founded in 2013</i>	The company matches people to jobs, accurately and fairly, by measuring their cognitive, social, and emotional traits.	Partial coverage	Main: Team building and Task management	Customized Machine Learning and neuroscience are used to make the hiring process more efficient, but also to understand people's true talent for theirs and companies' best success.	Creativity and balance inside teams is made scientific and objective: through measuring and matching people cognitive and emotional traits, teams to deliver different types of tasks are enhanced, while time and resources for HR is greatly reduced.
<i>Startup 5 Applitoool, <a href="http://applitoools.com">http://applitoools.com</a>, founded in 2013</i>	Applitoools has developed the first cloud-based software testing tool that automatically validates all the visual aspects of any web platform.	Partial coverage	Main: Prototyping and Learning	Through AI powered visual testing, Applitoools revolutionizes the ways app and web platforms are tested.	Prototyping is made more efficient. Visual tests for web products become almost perfect for commercialization thanks to AI.

## MAIN FINDINGS AND DISCUSSION

The first analysis made on the overall sample has produced few relevant insights, useful to understand at a general outlook where and how the DT process is being transformed by AI. This is summarized in Table 3 where the twenty companies are further analyzed to identify the intensity of coverage for each DT phase by means of the specific AI applicative domains described in the previous paragraphs. This is useful not only to understand which phases of DT are mostly transformed, but also to identify which AI-based applications are currently experimented with this scope. Furthermore, three main insights are commented below, related to understanding the larger implications of the upcoming introduction of AI applications in parts or on the entire process of DT.

**Table 3.** *Low-Medium-High* intensity of coverage of the sample analyzed by DT phases and AI applicative domains

<i>AI applicative domains</i>	DT phases					
	<b>Team Building and Task Management</b>	<b>Sensing and Empathizing</b>	<b>Interpreting and Framing</b>	<b>Ideating and Conceiving</b>	<b>Prototyping and Learning</b>	<b>Launching and Measuring</b>
<i>Intelligent Data Processing</i>	<i>Medium intensity of coverage</i>  <b>3 startups</b> covering this phase/technology  (Eightfold, Pymetrics, Gooroo)	<i>High intensity of coverage</i>  <b>8 startups</b> covering this phase/technology  (Veritone, Inc., Sentiance, IGenius, Pixoneye, Gooroo, ForwardLane, DataRPM Corporation, Iguazio)	<i>High intensity of coverage</i>  <b>6 startups</b> covering this phase/technology  (Gamalon Inc., Fetch.ai, IGenius, HyperAnna, ForwardLane, Iguazio)	-	<i>Low intensity of coverage</i>  <b>2 startups</b> covering this phase/technology  (B12 Appvance)	-
<i>Virtual Assistant/ Chatbot</i>	-	<i>Low intensity of coverage</i>  <b>1 startup</b> covering this phase/technology (Gamalon, Inc.)	-	-	-	-
<i>Recommendation</i>	-	<i>Medium intensity of coverage</i>  <b>5 startups</b> covering this phase/technology (Gamalon Inc., Pixoneye, Daisee, ForwardLane, AdMobilize)	<i>Low intensity of coverage</i>  <b>1 startup</b> covering this phase/technology (Gamalon Inc.)	-	-	-
	-	<i>Low intensity of coverage</i>	-	-	<i>Medium intensity of coverage</i>	-

<i>Image Processing</i>		<b>1 startup</b> covering this phase/techno logy (AdMobilize)			<b>3 startups</b> covering this phase/techno logy (Applitoools, Test.ai, Appvance)	
<i>Language Processing</i>	-	Low intensity of coverage  <b>1 startup</b> covering this phase/techno logy (Daisee)	Low intensity of coverage  <b>1 startup</b> covering this phase/techno logy (Eigen Technologies )	-	-	-

The part of process that is mostly covered by current AI software solutions relates to the research part in DT, both in the initial stage to form teams (team building) and identify, read and interpret issues and user needs (sensing and empathizing, interpreting and framing), and in a later stage when research is mostly addressed at testing and verifying concepts (prototyping and learning). This is evident both in Table 1 and 3. Especially in Table 3, it is interesting to notice how the *Sensing and Empathizing* stage is the one mostly covered with AI, as at least 1 startup in our sample is proposing one of the applicative domains described to support innovation in this area. In these stages, AI is useful for many tasks previously mainly left to humans. For instance, AI is obviously supporting knowledge management and helping manage large amounts of data to make sense out of them in a way that humans might find quite difficult to handle: software can interpolate different types of datasets and data sources to reach insights with statistical significance way faster than before. Beyond this, many applications found in the sample propose AI as a better means to analyze and interpret users' behaviors by drawing statistical evidence from data coming from sources as social networks, websites of many kinds, sensors placed around cities, and in mobile phones' apps. In some ways, this suggests a new era for user observation and analysis, where AI is capable of providing a more scientific and objective strength to qualitative analysis, thus modifying a task long considered a subjective/qualitative input to the design process.

On the other hand, there is an area of DT, mainly connected to creativity and ideation, that remains hardly touched by machine-thinking despite the potential of current artificial brains to make unusual connections imitating the human mind. In our sample, this part of DT is hardly addressed, confirming that creative jobs are still the ones that will not be replaced by machines in the near future.

If AI is already well known for data and knowledge management capabilities, the analysis shows an upcoming trend based on new types of algorithms capable of improving, reinforcing and speeding up the hiring process in companies, also considering the psychological sides of people with the aim of creating the “perfect match” to improve and empower collaboration and creativity. This is currently applied to innovate team building and participation in the same organization, as well as in the collaborative relationship between companies and users.

More into the specifics of the smaller sample analyzed, few main findings can be highlighted in connection to the DT phases transformed.

In relation to *team building* and *task management* – a crucial phase for DT – AI is providing efficiency, helping develop mixes of people and cultures on neuro-scientific evidence about the intrinsic traits and attitudes of individuals. Thus, AI reinforces the collaborative and collective view of creativity by providing the right conditions to kick-start the process as an interdependent activity where different contributions bringing different angles tend to guarantee a holistic view for a design problem.

In *sensing* and *empathizing* the emotional side of users has always been considered a key to generate new solutions. This is therefore a crucial transformation that AI is enabling, allowing businesses and organizations to access statistical evidence on the emotional side of users, by investigating behaviors in-context and substituting the presence of any observer and subjective biases. The example of IoT sensors provided by Sentiance does just this: collects data and recreates user behaviors for analysis of specific moments and events, thus having companies and creative teams empathize without individual/observer bias. This is also one of the strongest transformations emerged: the emotional dimension in design is usually gained through field research and by performing interviews or direct observations. By definition, this used to include bias coming either from the context or from the subjective understanding of the observer. AI is now enabling managers and designers to access high volumes of less biased data on user behaviors, emotions, neurological and psychological responses, thus modifying the meaning of the empathic dimension of a design problem.

In relation instead to *interpreting* and *framing* – with reference to the case of HyperAnna – it is shown how much AI is becoming relevant for data analysis, both to blend different sources and to provide statistical evidence where this was too expensive to be achieved prior to AI introduction. Many tasks at the beginning of the DT process (i.e. market research and analysis) are conducted faster and with a lower effort, especially when it comes to integrating and interpolating data coming from different business departments and separate sources. This is an incredible aid to having statistically sound insights for idea generation, thus speeding up the process and making it more

efficient and even automatic in some parts. Tailored data and analysis are generated also scanning e-conversations, thus exploiting all moments of interaction and dialogue to start business ideation and thus providing the potential to run a design process in any working moment.

Lastly, AI is also automating for a great part the process of prototyping and learning for future iteration. Currently, this is still an evolving practice and it is mainly applied to web apps and platforms where AI-based solutions can automatically run user tests and visual corrections. Changes here are mainly about saving costs for companies, as clearly web platforms are a central touchpoint for any type of offer, whose test required many working hours at the risk of being never perfect. However, as AI grows in use it will probably also expand its application for prototyping of many more types of products and services beyond web platforms. For example, AI could simulate user behaviors and cognition previously studied through IoT sensors to run more effective virtual prototyping sessions, and then automatically iterate solutions for improvement on the basis of the results obtained, thus almost totally eliminating human presence in the final part of the DT process. Prototyping and learning is therefore one of the most interesting phases to keep monitored, as it could be extremely transformed by future applications of AI.

## **FUTURE REMARKS AND CONCLUSIONS**

As highlighted by the analysis of findings, AI is impacting DT in a manifold way. If currently the main effort of DT is connected and related to the “context of the (design) problem” – where human capabilities to frame and reframe the design problem seem to hardly matter –future attention with the diffusion of AI will be probably directed to the “context of the solution”. AI is indeed shrinking and accelerating the research phase shortening the time dedicated to this activity, integrating sources of data, connecting and processing data in few seconds. This is expected to shift managers and designers’ attention to dedicate more time and energy to activities related to ideating and conceiving, so as to say that creativity will be applied less to analysis and more to proposing new solutions (quite the contrary of the DT characterizing principles). Moreover, if design managers will be facilitated in hiring and selecting people with different personality traits and creative attitudes by AI, their work will consequently be more centered on guiding the phases of visioning and development of propositions. This is to say that instead of gaining leadership from the top, they will enter the creative process directly with new sensibilities and capabilities.

Lastly, it seems that AI entering the phase of prototyping and learning could lead to a future scenario where products and services are tested not by humans, but by robots or “intelligent agents” where designers test their solutions on virtual individuals characterized by realistic sets of preferences and emotions.

To conclude, it is important to stress how the attempt of this article to analyze the potential future implications of AI on DT through emerging seeds provided by successful startups is not immune by intrinsic methodological limits. For future research few recommendations are thus provided. First, the case analysis can be enriched by primary data taken through in-depth direct interviews. This additional activity could strengthen the concepts derived by the analysis of cases and identify new ones. Secondly, the startups analysis could complement the analysis made on incumbents that are commercializing apps and services supporting DT. Incumbents related analysis might provide a more exploitative view, where apps and services are being sold in the present to different businesses and industries. This analysis could offer a complete picture of the on-going adoption of AI solutions in DT practices.

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# ANNEX

## Description of startups analyzed

<p><b>1.</b> <i>Name of the startup: IGENIUS</i> <i>Year of foundation: 2015</i> <i>Place of foundation: Milan, Italy</i></p>	<p><i>Main claim</i> <b>Welcome to powerful simplicity.</b></p> <p><i>Website</i> <a href="https://igenius.ai/">https://igenius.ai/</a></p>
<p><i>Value proposition/Service package</i> The company uses AI to build a human-friendly relationship between people and data. IGenius works for any business sector and with any type of data using Crystal, an AI-based advisor for business intelligence thought for marketing. In the pipeline, the company is planning to apply the same principles and technology to other business areas like Sales, and more specific sectors like health care. The software is a <b>fast data retrieval system</b> that can fetch data from any channel in a matter of seconds and a scalable machine learning module that can elaborate a complex user request in real time.</p> <p><i>How the startup leverages AI</i> The core of the offer is based on Natural Language Processing, Machine Learning and fast data retrieval. By learning about multi-source datasets, a Machine and Deep Learning system creates the knowledge graph of a business, getting smarter with time at predicting needs and figures and automating tasks.</p> <p><i>Kind of outcome from the software</i> Crystal answers questions asked in normal language, providing statistically sound results crossing and matching data from different channels. It uses traditional types of visualizations, like bar charts, histograms, radar charts, and similar, and updates results and data in real time.</p> <p><i>Main clients</i> 20 thousand users active in 20 different countries and going from big organizations like Toyota to the restaurant nearby.</p> <p><i>Quotes from interview:</i> Quote from CEO: “We want to guide the shift of platforms in business intelligence (...) going toward applied AI. This is what today supports resolution of concrete problems, and that in our vision simplifies the relationship between data and people. We can interface in real time any dataset, interpreting information and making results available in normal language, this makes data analysis simpler, more effective and efficient, and frees access to data for anyone in the organization.” Source: <a href="https://www.startupbusiness.it/igenius-rivoluziona-la-business-intelligence-con-lai/95821/">https://www.startupbusiness.it/igenius-rivoluziona-la-business-intelligence-con-lai/95821/</a></p>	
<p><b>2.</b> <i>Name of the startup: SENTIANCE</i> <i>Year of foundation: 2012</i> <i>Place of foundation: Antwerp, Belgium</i></p>	<p><i>Main claim</i> <b>Powering the internet of You</b></p> <p><i>Website</i> <a href="http://www.sentiance.com">http://www.sentiance.com</a></p>
<p><i>Value proposition/Service package</i> Sentiance is a data science company turning IOT sensor data into rich insights about people’s behavior and real-time context. Its core consists in Interpreting daily activities in real-time and recreating a rich timeline of contextual moments and relevant behavioral profiles. Data collected through this method can be used to develop solutions in a wide range of fields, from health (i.e. for remote monitoring and assisted living) to commerce (i.e. to manage customer journeys or for contextual marketing) but also to support the</p>	

creation of smart city services by detecting activity patterns, predicting mobility flows and monitoring anomalies for real-time interventions.

*How the startup leverages AI*

Sentiance employs state of the art machine learning and behavioral modeling to apply AI in a range of ways: signal processing, transport mode classification, venue mapping, map matching, home/work detection, semantic time modeling, unsupervised learning of temporal routines and expected behavior, deep learning to predict expected events and moments before they happen.

*Kind of outcome from the software*

The technology is used by the company to produce different types of outputs, from personalized services to mobile apps and public services tailored on the specific needs of a user (i.e. a municipality providing a service for its citizens).

*Main clients*

Other businesses in various fields, from insurance to pharma, as well as public sector.

*Quotes from interview:*

Quote from Chief Business Officer: “We are able to detect and predict how people live their everyday life, and we do so by mining and analyzing smart phone data and data from connected devices. It’s our believe that it’s these types of insights that will enable you not only to manage your risks more effectively but also to turn the premise of insurance upside down from protection to prevention.”

Source: <https://www.youtube.com/watch?v=zLafSli9hu0>

**3.**

*Name of the startup:* **HYPERANNA**  
*Year of foundation:* **2016**  
*Place of foundation:* **Sidney, Australia**

*Main claim*  
**Artificial Intelligence for Analytics**

*Website*  
<http://hyperanna.com/>

*Value proposition/Service package*

The main offer is a software package called HyperAnna, an Artificial Intelligence powered data analyst developed to make natural language the main interface between human and machine. The software is offered to big companies to analyze any type of data in a multi-layered way and within seconds (4-10 seconds is the average time), opening this possibility to anyone in the organization without specialist language or skills needed.

*How the startup leverages AI*

AI is mainly used for data analysis. Anna is an AI powered data scientist with experience and solid knowledge on time series. Unlike descriptive summarization from other AI-based similar software (IBM Watson), Anna generates insights based on statistically relevant analysis providing actionable insights within seconds.

*Kind of outcome from the software*

The software provides insights through data analysis and traditional types of visualizations, like bar charts, histograms, radar charts. One of its most important features is to understand intention and context of a question also interpreting e-mail conversations.

*Main clients*

Large enterprises in the sectors of banking and finance in Australia, New Zealand, Hong Kong, Singapore.

*Quotes from interview:*

Quote from Head of Sales: “To be able to make a better business decision from the data that you’ve got is the true power of HyperAnna (...) normally business users don’t need to be trained on HyperAnna, they can just ask a question and get a response in plain English”.

Source: <https://www.sibos.com/media/video/sibos-tv-fintech-hyper-anna>

**4.**

*Name of the startup:* **PYMETRICS**  
*Year of foundation:* **2015**  
*Place of foundation:* **New York, USA**

*Main claim*  
**Matching talent to opportunity, bias-free**

*Website*  
<https://www.pymetrics.com/employers/>

*Value proposition/Service package*

Pymetrics applies neuroscience games and AI to reinvent the way companies attract, select, and retain talent, matching people with jobs: through 20 minutes of game play, Pymetrics measures candidates’ inherent cognitive and emotional traits (about 90 social, emotional, and cognitive ones) to determine which roles they are most likely to succeed in, and uses AI to compare their profile to that of a company's top performer. Pymetrics offers: neuroscience games to collect objective behavioral data, customized AI, bias-free algorithms.

*How the startup leverages AI*

Customized AI is used to provide custom, cross-validated profiles running and analyzing results of interviews and providing decisions for the candidates to be interviewed in person.

*Kind of outcome from the software*

Pymetrics is based on a platform, here neuroscience games are run and results recorded and analyzed by the AI software. The outcome is a report highlighting candidate’s traits.

*Main clients*

50+ enterprises are clients worldwide, from Unilever, to Accenture, Tesla, and so on.

*Quotes from interview:*

Quote from CEO: “The proprietary model building process not only leads the market in terms of predictive power, but also engineers bias-free algorithms - giving companies access to the best-fit candidates from a wide variety of backgrounds.”

Source: <https://www.hrtechnologist.com/interviews/recruitment-onboarding/making-talent-processes-more-efficient-in-conversation-with-frida-polli-ceo-at-pymetrics/>

**5.**

*Name of the startup:* **APPLITOOL**  
*Year of foundation:* **2013**  
*Place of foundation:* **Tel Aviv, Israel**

*Main claim*  
**AI powered visual testing and monitoring**

*Website*  
<http://applitools.com/>

*Value proposition/Service package*

Applitool developed the first cloud-based software testing tool that automatically validates all the visual aspects of any web. It uses AI to automatically run visual tests across every app, browser, OS and screen

size. In doing so, it captures visual differences via full-page screenshots, comparing them across every platform, and running those tests with every release.

*How the startup leverages AI*

Essentially, visual tests are made automatic drastically reducing the time to release any web application.

*Kind of outcome from the software*

Applitool integrates with existing testing environments to provide visual test coverage.

*Main clients*

Large enterprises worldwide.

*Quotes from interview:*

Quote from CEO: “Emulating human vision is a very complicated task (...) one thing that is unique about our computer vision technology is that it doesn’t require any calibration or tuning, it just works out of the box. What excites us so much is that we are changing the face of software engineering around the world.”

Source: <https://applitools.com/>