CERN IdeaSquare Journal of Experimental Innovation, 2018; 2(2): 32-38
DOI: https://doi.org/10.23726/cij.2018.736

ORIGINAL ARTICLE

Supporting the creative process from data

Juan Carlos Quiñones Gómez[1]

[1]University of Málaga, (EPS), Dept. of Mechanic Engineering and Fluid Mechanics, C. Doctor Ortiz Ramos, Campus de Teatinos. 29071. Málaga (Spain).
*Corresponding author: juancarlosq02@gmail.com

ABSTRACT

Data and information being generated by a wide variety of sectors are increasingly used to predict future situations, spreading through complex networks operating simultaneously in multiple markets, geographical, social and cultural contexts. However, this influence of data is going unnoticed in design development. Increasing demand for products/services utilising data and/or generating data involves defining new ways of operating in which new methods, practices and tools are important and can create a higher level of data integration in the creative process, being this the basis of the Data Driven Design Model presented in this paper.

Keywords: Big data; creativity; creative process; design development.

Received: April 2018. Accepted: December 2018.

INTRODUCTION

Technological advances are leading companies to face a recent set of business challenges based on digitalization and thus generating unprecedented levels of competition. Customer demand is focusing on individualization, i.e. on-demand service delivery, and is currently combining physical products with digital services. As a result, they are forced to improve their conventional design processes, requiring the use of more efficient and up-to-date development methods. Big data is driving business development further (Mayer-Schönberger, Cukier & Iriarte, 2013) and decision-making automation challenge. More information about their customers' emotions is also being gathered, leading to a growth in sentiment analysis (Liu, 2012). It is, therefore, necessary for companies to develop their data management capabilities accordingly so as to actively identify and managing data value, providing a tool to improve control over the dynamics within organisations and societies (Ratti & Claudel, 2016).

Today we have a massive range of devices, which boast both internal computer technology and a partial or total connection to the Internet, with individuals interconnected to systems through sensors that continuously collect digital data about the physical world (Lycett, 2013). This situation allows objects and people to become identifiable, trackable, manageable and/or controllable making possible a regularization of the data impacting more and more on our lives (O'Neil, 2016). Additionally, numerous projects already have the ability to encode data on the physical and tactile properties of objects, both in static (Stusak, Schwarz & Butz, 2015) and dynamic (Taher et al., 2017) forms. In turn enabling the completion of our tasks and generation of large amounts of data at an unprecedented level of granularity (Ciuccarelli, Lupi & Simeone 2014). Velocity, variety and volume are the three fundamental aspects of big data (Chen et al., 2012, Kwon et al., 2014), so existing methodologies need to acquire these qualities to an equivalent level. They must evolve and give rise to faster processes that allow for a more iterative and flexible development.

The aim of this work is to discuss the data-driven design model (DDDM); it has potential to increase knowledge in the first phases of the process of creative development based on big data, bridging the gap between the problem and the solution, where the creative act takes place. This discovery of data early on allows for far greater stimulation of creativity compared to traditional models, by promoting faster development times and innovative solutions. In addition, data interpretation makes it possible to monitor and predict design changes that could become difficult in the future.

THEORETICAL BACKGROUND

Empirical findings within this work are based on the fact that there is no consensual agreement on how creativity and the creative process itself should be understood, even after a century of research (Wallas, 1926; Guilford, 1950; Osborn, 1979; Amabile, 1983; Boden, 1994). With the passing of time, there has been an evolution in the creative process. The result is not thought to come about just because of a single event at one moment. It normally happens when several factors combine over a longer period. The main differences between the theories lie in the proposed mechanisms, which combine two previously unconnected contents.

Fig. 1: Definition of creativity

Figure 1 outlines the result of the study (Quiñones, 2018) of several different creative and design processes. The final outcome shows the two most typical parts which appear as summaries in the definitions by Mayer (1999) and Runco & Jaeger (2012). A fuller, more coherent and current perspective of creativity is outlined, thus enabling us to comprehend its impact on how the creative process is perceived and constructed.

The creative process has been described by Boden in 1994 as "the exploration and transformation of conceptual spaces". A conceptual space is a knowledge network, where knowledge groups are connected to each other by associations (Gabora, 2000). The creative process involves the formation of new knowledge structures which already exist but are unrelated (Vaid et al., 1997). The exploration of conceptual space is related to the exploration of knowledge groups. This exploration is initiated by some stimulus (e.g. visual, auditory, etc.), either consciously or subconsciously perceived, which activates one or more knowledge groups in the conceptual space (Santanen et al., 2002). When a knowledge group is activated, it simultaneously activates other related knowledge groups, and so the exploration process continues. The activation of knowledge groups deviates as the distance from the originally activated knowledge group increases (Gabora, 2000). The process of transformation, or formation of new structures, takes place when two or more previously unrelated groups of knowledge give rise to a potential solution applicable to a new domain (Gabora, 2000; Santanen et al., 2002). Transformation leads to the formation of a new association, a new combination, and the construction of a new knowledge structure, namely: a new idea.

Some researchers (Osborn, 1979; Chakrabarti and Bligh, 1994; Candy, 1996; Cross, 1996; Shah et al., 2003; Chakrabarti, 2006) argued that generating many ideas would increase the possibilities of producing better ideas (diverge). The idea-generating process is understood as a divergent process.

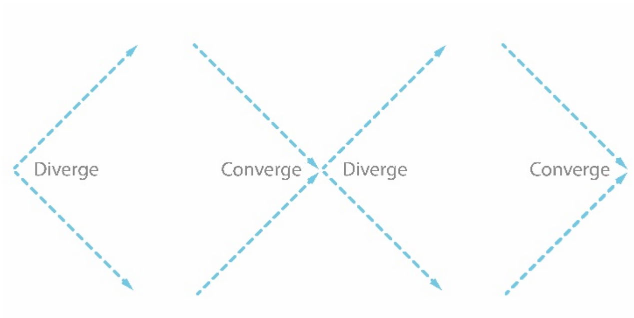

Fig. 2: Diverge & converge: double diamond model

Designers tend to use a wide range of information in the early phase in order to decrease abstraction by means of a growing number of conditioning factors (Bouchard et al., 2008; Bonnardel & Marmèche, 2005). They include a large quantity of information to be subsequently categorized and synthesized (converge) under design solutions (Bouchard et al., 2008). Generally, a double diamond model represents this process (Fig. 2). For the process to be successful, convergence is crucial. Therefore, the cognitive activity of the designer is like data or information processing in this respect. For this reason, a computational tool for data analysis (which includes all available data) helps ensure that all possible solutions can be considered quickly and reliably, as well as enabling the formation of new knowledge structures, i.e. new ideas. Kurtoglu et al. (2009) states that the increment of solution principles and components in their knowledge base improves the degree of variety and novelty, where the knowledge base as a computational tool was used to generate conceptual design solutions. The use of data will allow us to deepen the spaces of knowledge to improve the creative process, through a process based on big data: it means society's ability of making innovative use of information either to obtain useful information or goods and to provide meaningful services. (Mayer-Schönberger, Cukier & Iriarte, 2013). In addition, AI data management allows us to collect and process large amounts of data, “obtain better results and make faster decisions in a more systemic and organised manner” (Solares, 2017).

Data science has matured considerably in recent years (Cao, 2017) and big data is now being used in a number of areas (healthcare, agriculture, education, industry, finance, security, marketing, etc. except for design). Data and the information it provides are used for predicting potential scenarios, through techniques of predictive analysis based primarily on statistical methods, using large samples of data representing most, if not all, of the population (Gandomi & Haider, 2015). Designers' contribution is not yet fully determined and whether there is a positive translation of technologies of such magnitude into valuable products and services (Yuan et al., 2018). Therefore, the current research leads us to the point in which data appears as a new chance for creativity as a resource for designers.

Empirical analysis indicates how exposing individuals to more information inspires creativity (Casakin & Goldschmidt, 1999; Goel, 1997). Data can reveal information, which is highly valuable to designers, improving results, as well as optimising time and resources in the design process. Prendiville et al. (2017) state that design drives data through processes of interpretation, visualization, and persuasion into converting both the abstract and intangible nature of data into human-centered services with social and economic value. “Data should become the new steel” (Semmelhack, 2013), a resource on which to build, to “make products and services better and updated, altering the traditional lifecycles to more of an ongoing flow, a kind of living relationship” (Biron, et al, 2016). Deeper exploration of the problematic space will lead individuals into generating ideas of high novelty and quality, enabling further development of those with the greatest potential. Therefore, the long-term objective is to provide designers with an updated model that contemplates technological advances and helps them generate better ideas by stimulating their thinking process.

METHOD AND DATA

The structure of the research was carried out following the recommendations of vom Brocke et al. (2009). Thus, for the determination and identification of studies relevant to the present analysis, a four-step process has been followed. First, a keyword search was conducted using five publishing databases (CiteSeerX, ACM, AISeL, EBSCOhost and Emerald Insight) in addition to Scopus and Google Scholar. The aim of this bibliographic review was to identify common aspects and to obtain a current and revised definition of the term creativity (see Fig. 1). The terms "creative process", "big data" and "design methodology" were also included.

In the second step, it was necessary to carry out a manual search in the main related journals. The objective is to include highly relevant studies, as well as obtaining more specific contexts on the term's creativity and creative process, given their generic nature. Thirdly, research was carried out in the reference sections of studies of interest. Each paper, abstract and keyword that appeared in the first 100 search results was carefully examined on an individual basis. It was thus discovered that in most cases the notion of creativity is closely linked to concepts such as innovation, novelty and originality. Conversely, big data is more related to cutting-edge technology results along the lines of AI (Artificial Intelligence), IoT (Internet of Things) or ML (Machine Learning) along with terminology such as computational creativity, which appears much less in search results. Therefore, when specific keywords related to our initial concepts were assigned, the scenarios with a greater or lesser degree of creative process were seen, in terms of determination and evolution, as a main object of research.

A backward and forward search was used for the result search and Webster and Watson's (2001) guidelines were followed. The majority of publications deemed most relevant are those which mention creative processes, i.e. creativity, large data or design methodology as well as associated keywords, in the title, abstract or keyword. This analysis has identified an excess of 100 distinct creative and design processes. Moreover, major comparisons of roughly half of them are clearly shown in the studies of this paper and they have been selected for their great effect on research or resulting from the relevance of the author. Following the guidelines of Vom Brocke et al. (2009), the literary review is the basis for carrying out additional research. The fourth part includes large data, and literature concerning design methodologies from nowadays and the recent past.

RESULTS

The creative and design processes will portray different realities. On the basis of preliminary work and existing literature, it is adopted the following statement (Quiñones, 2018): (1) Creative process: a cognitive process resulting in the formulation of an idea. (2) Design process: a work process resulting in a proposal for a product or process. Furthermore, the results of this research revealed that novelty and variety are directly related to the levels of abstraction of new conceptual spaces as a consequence of the integration of big data into the creative process (Fig. 3). It infers that there is a greater possibility of designing an innovating concept. This conclusion becomes especially important when it is observed that designers do not use an adequate number of rules and mechanisms in design; which can make them lose a meaningful degree of novelty. Such an approach requires the need to support designers with knowledge of rules and impacts on design.

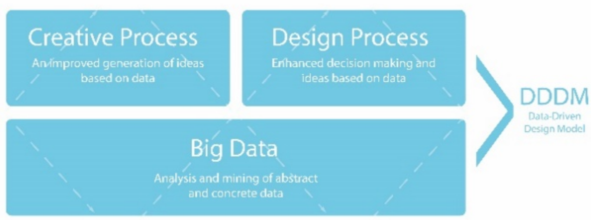

Fig. 3: Creative process and design process integration with Big Data

There are obvious similarities in both the creative and design processes, according to the research carried out these can be embodied in: problem definition, idea generation and idea evaluation (Fig. 4). The problem definition phase is present in all creative process models. After this, we concentrate on the fundamental elements that have the greatest relevance for creative process development in the future. As a result, we get a broad understanding of the early phases of the creative process. Before idea generation for problem solving is possible, it is first essential to fully comprehend the problem itself, and understand the parts of the ideal solution (Wallas, 1926). Delving further into a precise area of knowledge is needed to achieve it (Amabile, 1983).

In the design practice, big data integration, as shown in Fig. 4, will become a more frequent activity, which will transform the way we design. This brings us to the critical point where data emerges as a new medium for creativity. In spite of that, very few results have shown relation between creativity and the use of big data. Existing research into the effects of using examples in design processes has not been conclusive, leading in some cases to the design fixation effect due to the presence of related examples (Chrysikou & Weisberg, 2005; Jansson & Smith, 1991). However, some more conclusive studies have shown how the existence of examples is a source of inspiration in the processes of generating design ideas (Helms, Vattam and Goel, 2009). Whether exposure to a large amount of data is useful or not is difficult to judge by the coexistence of the positive and negative effects of the examples. In this regard, it is important to note that there is still no current model that can explain how and why data can affect design processes. Therefore, the study presented acquires greater relevance at this point. Understanding the impact of data on design processes leads to an effective use of them to drive innovation and creativity across of design practice. In addition, the analysis of external information generated by users will enrich our understanding to reach better solutions to certain problems and, therefore, improve people's quality of life through new designs.

The use of data was also closely illustrated by the study conducted by Na Sio and Kenneth Kotovsky (2015), which shows that there is evidence that data stimulate creativity in the early stages of the design process (it consisted of giving examples related to the aim of the research), allowing individuals to further explore the design problem. Speed and Oberlander (2016) have recently presented a theoretical framework for distinguishing "designing from, with and by data" to categorize existing data approaches.

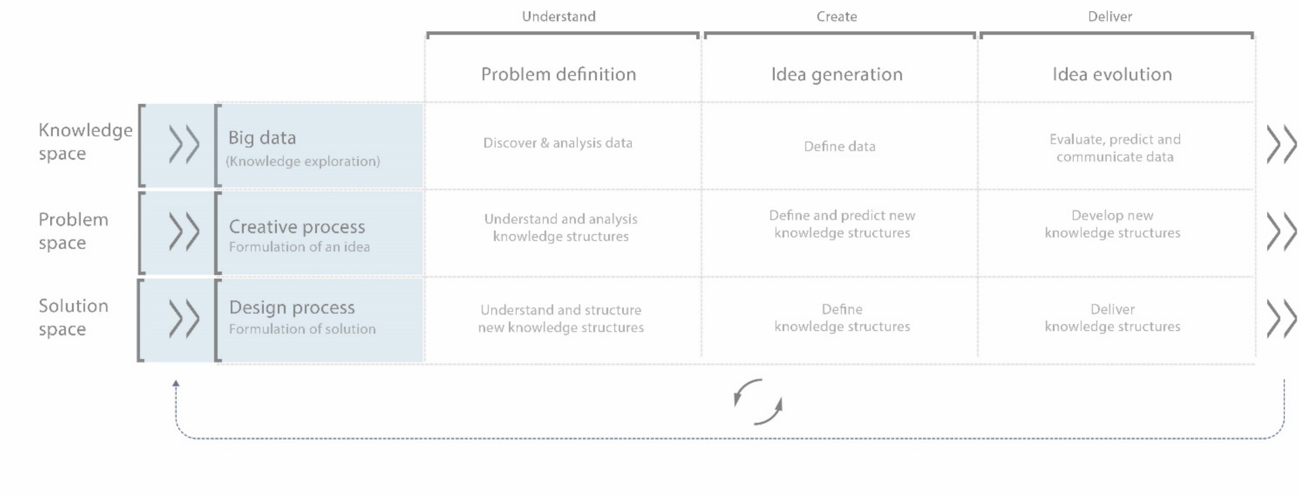

Fig. 4: Big Data and creative process and design process framework

Even taking into account the absence of relevant studies relating creativity and big data, the results suggest that this crossroad will create a new scenario where big data will be a tool to stimulate creativity, enhancing the creative process. Consequently, it was established that there might be five areas where big data can be effectively applied in the creative process. First, during the phase of searching for inspiration and ideas, in order to obtain more classified information as well as understand better the contents, and facilitate the creative process in the initial stage. Secondly, by offering innovative and creative solutions allowing the process to feed back into itself constantly with those solutions and results which evolve through the DDDM (Fig. 5) to be attained, and enables better and easier change of the alternatives selected to work with. Third, this crossroad between creativity and science provides the creative class with a greater intelligent experience to evaluate which creative outcomes are most effective with the greatest degree of innovation. Fourth, data brings its qualities, volume, velocity and variety to the creative process, by offering advances in agile design and simplifying the design process. Finally, bearing in mind that the creative process is the basis for the development of new solutions, it can be adopted in multidisciplinary sectors in order to reach innovative results. Data analysis used in the creative process provides a gateway to action, supporting strategic and operational decisions. In addition, it should be noted that the development of creative processes, tools and methodologies as well as their use by designers need to be considered a key value for leading innovation and improving business competitiveness.

This research is focused on the more specific DDDM model proposed by Quiñones (2017) supported on the double diamond model (The Design Process: What is the Double Diamond?, 2015), with the objective of presenting a more accurate approach. On this DDDM, two different classes of data can be present in the design process: (1) Concrete data, based on the procedure of pre-existing data sets; (2) Abstract data, that is existing information processed in other ways with predictive analytics to predict situations and gain deeper insight into the data. While abstract data may be used to generate new perspectives and concepts, concrete data can support or define design. Relying on this analysis, it is assumed that while big data sets may improve design, design can offer further comprehension of data. The hypothesis which underlies this study lies in this statement. In the initial phase, DDDM makes it possible to go into much further detail, thanks to big data in an infinite number of existing knowledge groups. Consequently, this favours the creation of new knowledge matrices. However, as Restrepo (2004) identified in his empirical research, frequently happens that designers completely ignore other external sources of information when developing their ideas. Thus, the abundance of data provides designers freedom to study other knowledge structures and perspectives or analyses as they focus on certain aspects of the process without ignoring the main standpoint, facing the design fixation problem; which has a negative impact on the initial phase due to dependence on the use of familiar methods.

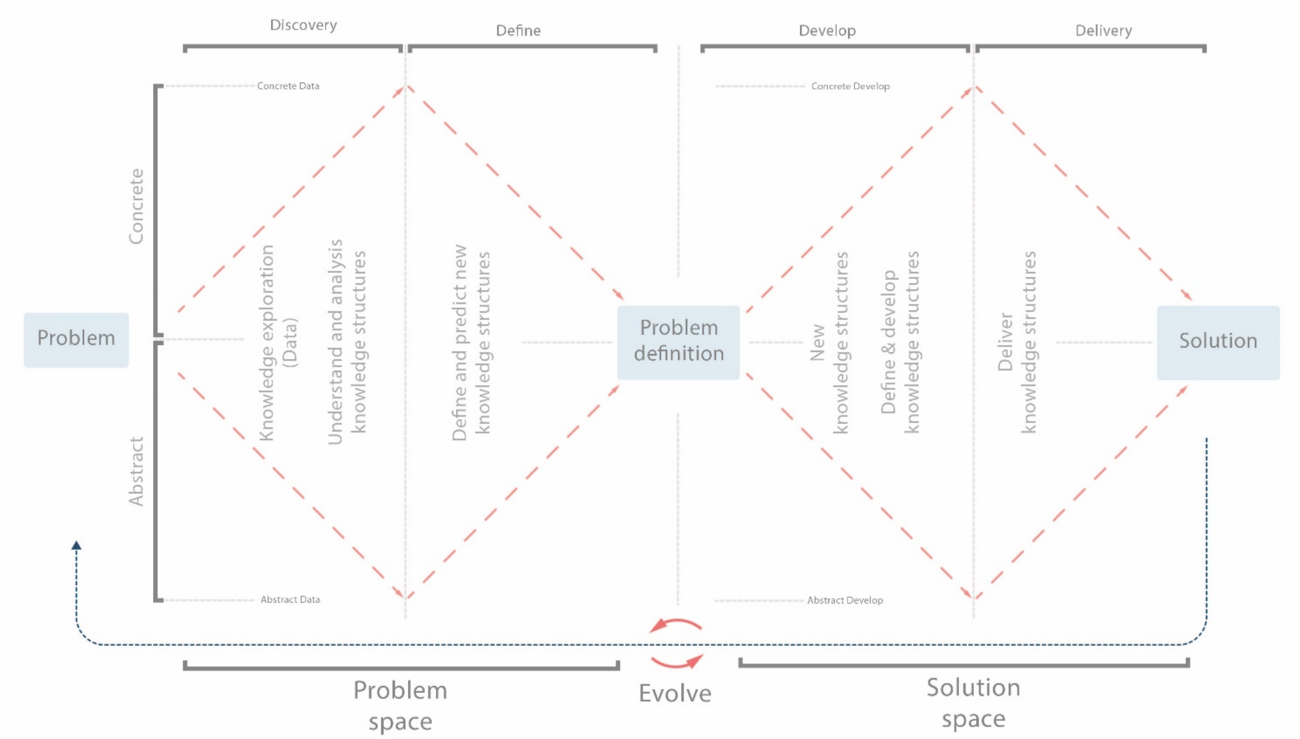

Fig. 5: Data-driven design model process

DISCUSSION AND CONCLUSIONS

The DDDM is intended to enable a more efficient design process as well as a way of understanding the influence of data. These new procedures show the need for advanced models as opposed to traditional ones. Traditional processes can be very suitable for "traditional" products, which are often the majority. However, the most innovative and ambitious projects tend to rely more on unknown technologies and address increasingly risky markets (Ulrich and Eppinger, 2012). Therefore, these new projects face difficulties and new challenges that require more efficient tools to make the process more "adaptive", "accelerated" and "agile" (Cooper, 2014), thus allowing companies to be more competitive. The most important contributions of the DDDM are highlighted below:

- Makes it possible to focus on the user's real behaviour regarding the product.
- Through the data input in the model, it is possible to understand exactly what is happening in the real situation without affecting the user's experience.
- It can predict needs and future behaviour, helping identify future scenarios or support a product development.
- Data emerges as a new medium and an instrument for creativity.
- Makes the process clearer, since the data used in the process are real data.
- The iteration of the model makes it possible to establish priorities and give order to ideas to be developed. Keeping the development process dynamic and adaptable.

Regarding to traditional processes, the integration of big data implies an advance with a holistic approach for the creative process and the development of the designer's profession, by learning more about other disciplines procedures (Rogers, 2013). As well as data best practices, know-how, tools, methods, etc. as a growing area as data science (Cao, 2017), data should not stay a domain merely for experts. Despite data's growing prevalence, the key role of creativity cannot be understated, and its focus should be on strengthening design.

The long-term research goal is to provide designers with computer assistance to help them generate more ideas by stimulating their thinking process. To verify the contribution of the model presented, it will be necessary to carry out research moving in several directions. A first step is to involve research professionals in design and design practice to ensure the proposed approach and validate the influence of data on the creative process. This paper's findings could be tested in real-life setting with additional work, involving multiple entities collaborating as in IdeaSquare with multiple teams of CBI students, integrating the data-driven design model integrated into their learning process. Experiments will also be carried out in collaboration with companies related to the production of connected products and/or devices, in order to test their influence not only from the point of view of new product development but also as a growth tool for companies.

REFERENCES

Amabile, T., & Kidd, R., 1983, Social Psychology of Creativity, Springer US, New York.

Quiñones Gómez, J.C., 2017, The Growing Influence of Design Data in the Design Process through a Methodological Development, International Conference 4D · Designing Development Developing Design, Kaunas, pp: 178-187.

Quiñones Gómez, J.C., (in press), 2018, International Joint Conference on Mechanics, Design Engineering & Advanced Manufacturing (JCM 2018), 20-22 June, 2018, Cartagena, Spain.

Biron, J., Follett, J., 2016, Foundational Elements Of An IoT Solution. Sebastopol: O'Reilly Media, Inc. Retrieved 20 July 2017, from http://thingworx-dev.vuforia.io/wp-content/uploads/2016/05/WP_oreilly-media_foundational-Elements-of-an-iot-solution_978-1-491-95097-5_EN.pdf

Boden, M., 1994, What is Creativity? Dimensions of Creativity. London: MIT Press.

Bonnardel, N., Marmèche, E., 2005, Towards supporting evocation processes in creative design: A cognitive approach, International Journal of HumanComputer Studies Computer support for creativity, 63(4-5), pp:422-435.

Bouchard, C., Omhover, J.F., Mougenot, C., & Aoussat, A., 2008, TRENDS: A Content–Based Information retrieval system for designers, Proceeding of Design Computing and Cognition DCC'08, Part 7, pp: 593-611

Brocke J. V., Simons, A., Niehaves, B., Reimer, K., Plattfaut, R., & Cleven, A., 2009, Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process, ECIS 2009 Proceedings, 161.

Candy, L., 1996, Understanding creativity: an empirical approach.Proc. Creativity and Cognition, pp:45-54.

Cao, L., 2017, Data Science: A Comprehensive Overview, ACM Computing Surveys (CSUR), 50(3), pp: 43-42. http://doi.org/10.1145/3076253

Casakin, H., & Goldschmidt, G., 1999, Expertise and the use of visual analogy: Implications for design education. Design Studies, 20 (2), 153-175. http://dx.doi.org/10.1016/s0142-694x(98)00032-5.

Chakrabarti, A., & Bligh, T., 1994, Functional synthesis of solution concepts in mechanical conceptual design. Part I: knowledge representation. Research in Engineering Design 6(3), pp: 127-141.

Chakrabarti, A., 2006, Defining and supporting design, 9th International Design Conference DESIGN 06, Dubrovnik, pp: 479-486.

Chen, H., & Chiang, R.H.L., Storey, V.C., 2012, Business intelligence and analytics: From big data to big impact, MIS Quarterly, 36 (4), pp: 1165-1188.

Chrysikou, E. G., & Weisberg, R. W., 2005, Following the wrong footsteps: fixation effects of pictorial examples in a design problem-solving task. Journal of Experimental Psychology: Learning, Memory, and Cognition, 31(5). http://dx.doi.org/10.1037/0278-7393.31.5.1134.

Ciuccarelli, P., Lupi, G., & Simeone, L., 2014, Visualizing the Data City, Springer International Publishing, Cham.doi.org/10.1007/978-3-319-02195-9

Cooper, R. G., 2014, "What's Next? After Stage-Gate", Research-Technology Man., 57 (1), pp: 20-31.

Cross, N., 1996, Creativity in design: not leaping but bridging. Proc. Creativity and Cognition, pp: 27–35.

Gabora, L., 2000, Toward a theory of creative inklings, In (R. Ascott, ed.) Art, Technology, and Consciousness, Intellect Press, pp: 159-164.

Gandomi, A. & Haider, M., 2015, Beyond the hype: Big data concepts, methods, and analytics, International Journal of Information Management, 35(2), pp: 137-144.

Goel, A. K., 1997, Design, analogy, and creativity. IEEE Expert, 12 (3), 62-70. http://dx.doi.org/10.1109/64.590078.
Guilford, J.P., 1950, Creativity. American Psychologist, 5, pp: 444–454.
Helms, M., Vattam, S. S., & Goel, A. K., 2009, Biologically inspired design: process and products. Design Studies, 30 (5), pp: 606-622. http://dx.doi.org/10.1016/j.destud.2009.04.003.
Jansson, D. G., & Smith, S. M., 1991, Design fixation. Design Studies, 12 (1), pp: 3-11. http://dx.doi.org/10.1016/0142-694x(91)90003-f.
Kurtoglu, T., Campbell, M., & Linsey, J., 2009, An experimental study on the effects of a computational design tool on concept generation. Design Studies 30(6), pp: 676–703.
Kwon, N. Lee, B. Shin., 2014, Data quality management, data usage experience and acquisition intention of big data analytics, International Journal of Information Management, 34 (3), pp: 387-394.
Lycett, M., 2013, "Datafication": making sense of (big) data in a complex world, European Journal of Information Systems, 22(4), pp: 381-386, http://doi.org/10.1057/ejis.2013.10
Mayer, R., 1999, Problem solving. Encyclopedia of creativity, Vol. 2, pp: 437-447.
Mayer-Schönberger, V., Cukier, K., & Iriarte, A., 2013, Big data. Madrid: Turner.
Sio, U., Kotovsky, K., Cagan, J., 2015, Fixation or inspiration? A meta-analytic review of the role of examples on design processes. Design Studies 39, pp: 70-99.
O'Neil, C., 2016, Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy, Crown, New York, Crown.
Osborn, A. F., 1979, Applied imagination, Scribners, New York.
Prendiville, A., Gwilt, I. & Mitchell, V., 2017, Making sense of data through service design–opportunities and reflections. In D.Sangiorgi, Designing for Service, Key Issues and New Directions, Bloomsbury, London, pp: 225-236.
Ratti, C., & Claudel, M., 2016, The City of Tomorrow: Sensors, Networks, Hackers, and the Future of Urban Life, New Haven, London, Yale University Press.
Restrepo, J., 2004, Information Processing in Design (Design Science Planning), Delft University Press.
Runco, M.A & Jaeger, G. J., 2012, The Standard Definition of Creativity. Creativity Research Journal, 24:1, pp: 92-96.
Rogers, R., 2013, Digital Methods, Cambridge Mass, The MIT Press.
Santanen, E.L., Briggs, R.O., & de Vreede, G.-J., 2002, Toward an understanding of creative solution generation. Proceedings of Thirty-fifth Annual Hawaii Int. Conf. on System Sciences (HICSS '02), 8(1), pp: 221-230.
Semmelhack, P., 2013. Social Machines: How to Develop Connected Products That Change Customers'Lives. Hoboken, New Jersey: John Wiley & Sons Inc.
Shah, J.J., Smith, S.M., & Vargas-Hernandez, N., 2003, Metrics for measuring ideation effectiveness. Journal of Design Studies 24(2), pp: 111–134.
Speed, C. Oberlander, J., 2016, Designing from, with and by Data: Introducing the ablative framework. Proceedings of DRS 2016, Design Research Society 50th Anniversary Conference. Brighton, June 2016, 1, pp: 2991-3004.
Solares, C., 2017, Evolución del Big Data a Inteligencia Artificial. iLifebelt™. Retrieved 18 September 2018, from http://ilifebelt.com/evolucion-del-big-data-a-inteligencia-artificial/2017/04/
Stusak, S., Schwarz, J., & Butz, A., 2015, Evaluating the Memorability of Physical Visualizations, In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems - CHI '15. Association for Computing Machinery (ACM).
Taher, F., Jansen, Y., Woodruff, J., Hardy, J., Hornbaek, K., & Alexander, J., 2017, Investigating the Use of a Dynamic Physical Bar Chart for Data Exploration and Presentation. IEEE Transactions on Visualization and Computer Graphics 23, 1 (jan 2017), pp: 451-460.
The Design Process: What is the Double Diamond? 2015, Design Council. Retrieved 18 July 2018, from http://www.designcouncil.org.uk/news-opinion/design-process-what-double-diamond
Ulrich, K. T., & Eppinger, S., 2012, Product design and development (5th ed.), New York: McGraw-Hill
Vaid, J., Ward, T., & Smith, S. Creative thought, 1997, Washington, DC: American Psychological Association.
Yuan, M., Price, R., van ERP, J., Socha, J. A. O., 2018, Designing with meaninful data: Deep personalisation in the air travel context, Proceedings of DRS 2018, Design Research Society Conference, Limerick, June 2018, 4, pp: 1440-1451.
Wallas, G. The Art of Thought, 1926, Harcourt Brace, New York.
Webster, J. and Watson, R.T., 2001, Analyzing the Past to Prepare For the Future: Writin g a Literature Review, MIS Quarterly, 26 (2), pp:13-23.