

CREATIVITY FORWARD: A FRAMEWORK THAT INTEGRATES DATA ANALYSIS TECHNIQUES TO FOSTER CREATIVITY WITHIN THE CREATIVE PROCESS IN USER EXPERIENCE CONTEXTS

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Abstract. The latest technological advancements allow users to generate a large volume of data related to their experiences and needs. However, the absence of an advanced methodology that links the big data and the creative process prevents the effective use of the data and extracting all its potential and knowledge in this context, which is crucial in offering user-centred solutions. Incorporating data creatively and critically as design material can help us learn and understand user needs better. Therefore, design can bring deeper meaning to data, just as data can enhance design practice. Accordingly, this work raises a reflection on whether designers could appropriate the workflow of data science in order to integrate it into the research process in the creative process within a framework of user experience analysis. The proposed model: data-driven design model, enhances the exploratory design of problem space and assists in the creation of ideas during the conceptual design phase. In this way, this work offers an integrated vision, enhancing creativity in industrial design as an instrument for the achievement of the proper and necessary balance between intuition and reason, design, and science.

Keywords: big data, creative process, creativity, data-driven design, design, methodology, user experience.

Introduction

Data generation increases exponentially, and by 2025 (Reinsel et al., 2018), the worldwide data capacity is estimated at 175 zettabytes, with more than half of the data hosted in the cloud corresponding to connected devices. With the projections as of 2025, each person will interact with a connected device about 4800 times per day, which means one interaction every 18 seconds. Due to the increasing ubiquity of data and trends in data dissemination (Lycett, 2013), both third-generation new product development (NPD) (Bødker, 2006) and digital service designs are showing an upward influence by data (Mortier et al., 2014). Data are increasingly valuable but also more complex to understand and translate into knowledge.

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This process of knowledge extraction is known as knowledge discovery in databases (Han et al., 2012; Zaki & Meira, 2014). Given the apparent evidence about data's ability to conceal valuable information, research into model identification techniques for data analysis is needed to extract their full potential. To this end, several data processing technologies are becoming increasingly widespread due to their effectiveness and success in everyday products and services; these include artificial intelligence, machine learning, deep learning, and data analysis, among others.

As the science of data advances as a field (Cao, 2017), its utilization using available data sources for application to real cases is often unclear. Most existing data analysis models are technological or business in nature, but non-existent in the creative realm, where they are going unnoticed, and designers need to consider this ever-growing flood of advances and data. The design has the opportunity to address data access by creatively and critically, incorporating it as design material into professional practice. Sanders and Stappers explain that traditional design methods are also changing (2008), but could still be advanced and adapted to the current context by developing into methods that can integrate and effectively use massive amounts of data to support creativity and knowledge discovery in the creative process. The use of the data during the design process can be found to explore particular phenomena remains an emerging and recent trend (*e.g.* Speed & Oberlander, 2016; Bogers et al., 2016; Giaccardi et al., 2016; Feinberg, 2017).

This study is a further exploration of that conducted by Quiñones-Gómez (2019). The purpose of the work presented is to provide a framework to use the data as design material in the NPD based on user experience attributes. In this sense, it is aimed at making value creation operational in the creative design process by increasing combined creativity, involving the creation of new ideas through the exploration of unknown combinations of known ideas (Boden, 2004), leading to an epistemic model that conceptualises the management of big data as a user-friendly system, where the workflow of data science can be adapted to a process of design research and development. The data-driven design model (DDDM) presented by Quiñones-Gómez (2017), can be applied as an advanced model in comparison with more traditional to obtain new visions and strategies in the NPD, services, and systems where data stimulate and support creativity. So, designers can appropriate the data to foster their creative capabilities in hypothesis formation, particularly at the earliest stages of the creative process with the generation of ideas.

The following sections are intended to explore and provide initial evidence to support the following research questions so that further studies can be planned if the initial results are promising:

1. Would it be possible to use the data, with the same competence as in other areas, to gather relevant information that can be included in the design process, *i.e.*, could these data be correlated with typical behaviours of design cognition and design creativity to enhance the creative process?;
2. Can the data be integrated into the first stage of the creative process through a new methodology to obtain a richer understanding of the field under investigation and serve as an inspiration to encourage the generation of ideas that can be considered more creative and innovative?

1. Research strategy and review of evidence in the field

In order to question traditional creative processes and data analysis methods and their possible integration into a common framework, we use an approach known as problematisation (Nicholson et al., 2018); through the development of research questions, questions the theories and concepts of existing literature. The specific objectives of this approach are to extend and challenge the current thinking in this field and thereby designing meaningful connections, which would lead to new ways of acquiring knowledge. Such an approach need not necessarily involve a revolutionary or innovative approach since in many cases, it is merely a matter of questioning specific hypotheses in intellectual theories or practices (Sandberg & Alvesson, 2011). Therefore, it is intended to highlight the gaps in traditional procedures and to develop our contributions in the area of the creative process and big data. For the study of the existing literature and the detection of gaps, the following databases were investigated: *IEEE Xplore*, *Scopus*, *ScienceDirect*, and *Emerald Insight*, identifying more than 100 methodologies and related processes to date. Understanding a problem and the requirements of the solution are necessary to form ideas and arrive at a solution (Wallas, 2015). It implies having greater comprehension of the domain of knowledge (Amabile, 1983). This strategy allows us to know the current panorama of the existing literature, allowing us to question it since it highlights the gap between the creative process and the science of data and the contribution to knowledge in this document by establishing a bridge between both concepts through a new model. As mentioned by Pérez et al. (2002), it is essential to implement new approaches in conducting the creative process.

Based on previous work and existing literature in 1994, it is described by Boden (1996, pp. 75–117) as a creative process “the exploration and transformation of conceptual spaces”. One conceptual space is a knowledge network, which is connected by associations between knowledge groups (Gabora, 2000). In the creative process, existing but unrelated knowledge structures are formed (Ward et al., 1997). The exploration of conceptual space is related to the investigation 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. Each activation of the knowledge groups differs according to an increasing gap from the originally activated knowledge group (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 involves setting up a new association, a new combination, creating a new knowledge structure, namely: a new idea. The creative act occurs when a connection is made between the space of the problem and that of the solution by identifying a key concept (Dorst, 2017), as defined in the DDDM and which we will see in the following sections, identifying in this work the big data as the bridge between these two spaces.

2. Creativity

The body of literature on creativity is too broad to discuss in depth. Many definitions of creativity can be found in the research literature; it is a multifaceted term with more than 60 different definitions in the field of psychology alone (Taylor et al., 1974; Amabile, 1996). Boden (2004) has laid the foundation for many of the views on creativity. Creativity, as such, stands for one of the highest human cognitive skills (Taylor, 1959). Although the first definitions of creativity generally considered this capacity as a specific attribute of the individual (Guilford, 1967), currently the concept of creativity has evolved and is defined as an interaction between the capacity, the environment and the process of producing a tangible product that is both new (Shah et al., 2003; Sarkar & Chakrabarti, 2007, 2011) and useful (Lozano, 2008; Sarkar & Chakrabarti, 2007, 2011; Srinivasan & Chakrabarti, 2010), and which is situated in a social context (Plucker et al., 2004). Since it is a complex and multidimensional concept, its understanding constantly changes according to the socio-cultural environment that surrounds us (Mellander et al., 2014, pp. 23–30). This means that definitions of creativity evolve and fluctuate over time. Part of the literature on creativity (Burnett & Haydon, 2016; Davies, 2006) is devoted to the modelling and representation of the creative thinking process on which the generation of ideas is based. Several researchers (Osborn, 1979; Chakrabarti & Bligh, 1994; Candy, 1996; Cross, 1996; Shah et al., 2003) pointed out that the generation of many ideas has the potential to produce more and even better ideas. This is a process made up of some mental activities that people do when they are creating something, from identifying a problem, through the acquisition of knowledge, to the generation of an idea and its application. In light of the research work conducted on creativity, here is an illustration of how bringing together both creative domain data sources and hedonic psychophysics in combination with strong data analysis techniques has the potential not only to overcome creative obstruction but also to stimulate it into a system that can produce high quality and innovative creative outcomes.

The diffusion and democratisation of digital technologies have had an impact on the dissemination of the creative act, generating an unprecedented number of elements in the digital realm available for creative action and reaction (Moran, 2010). From an industrial economy, which valued manufacturing work and standardised memorisation of procedures, the economy of developed societies is moving towards a creative economy, which values creativity at work (Pink, 2006; Mellander et al., 2014; Burnett & Haydon, 2016). It is, therefore, imperative to study and expand on new methods and new technologies specifically designed to stimulate creativity, constituting the foundation stone of this study.

3. Collaborative technologies for creativity

Today, the objects with the greatest design complexity are intelligent objects. We have a huge range of devices that have internal computer technology and are partially or totally connected through the Internet, making objects or people identifiable, locatable, addressable and/or controllable, allowing us to complete our tasks and generating huge amounts of data and changing the way people process information, behave and socialise. The ability to provide relevant and timely data involving the products can be used to generate a more holistic and

accurate perception of the usage environment and user experience. It is acknowledged that creativity in these times of digital transition represents potentially among the most valuable and distinctive human skills required to foster and promote strong human-machine collaboration to its full potential (Corazza, 2017). Indeed, in any given field, creativity allows humans by generating novel and useful ideas (Amabile, 1988), harnessing the opportunities raised by digital technologies. In this digital context, creative thinking is understood as a distributed phenomenon in an environment where digital technologies in the creative process exist as an integral basis (Literat & Glăveanu, 2018). The central question that emerges from these considerations is how technological evolution is influencing the design and creative capabilities of the next generation of designers and processes. Understanding how technological advancements impact the creative process is, therefore, essential to design research aimed at developing a suitable model for the next generation of designers representing key players over time.

In the field of creativity, technological developments are offering great opportunities (Frich et al., 2019). Indeed, creativity is the basis of disruptive innovation and continuous reinvention (Varshney et al., 2019). Given the limitations of human creativity resources, it is essential to develop technologies for greater creativity, whether operating autonomously or in collaboration with people or tools. Lubart (2005) envisions a collaborative environment with computers, where the computer is involved as a trainer: computers have the potential not only to assist the creative process of providing information in diverse manners so that individuals might give creative insights but also to be used as a catalyst in setting into motion the creative process. Based on this context, we understand a possible collaboration of technology with creativity in our work, allowing the support and management of information to enhance the creative process. In previous research (Quiñones-Gómez, 2017, 2019), it has been established as a result of a designer's cognitive activity as the processing of data as well as the processing of information related to it. Accordingly, having a computational data analysis system (which includes all available data) allows every potential solution to be identified quickly and reliably, enabling knowledge structures to be formed, *i.e.*, new ideas, establishing a collaborative context between computer and designer.

4. Data in the design process

As data science evolved rapidly over the past few years, big data is currently in use across several sectors (health, agriculture, education, industry, finance, security, marketing, *etc.* except for design). Using predictive analysis techniques based primarily on statistical methods, all data and information provided are used to foresee potential scenarios based primarily as a result of the use of broad samples of data reflecting mainly, if not the entire population (Gandomi & Haider, 2015). However, it is unclear whether the contribution of designers remains well-defined and a significant impact of technologies of comparable magnitude that result in substantial products and services (Yuan et al., 2018). Hence, the ongoing research brings us at the stage where data emerges as a valuable tool for creativity as designers' means. Based on empirical analysis, subjecting individuals to a greater volume of information serves as a creative stimulus (Casakin & Goldschmidt, 1999; Goel, 1997).

Moreover, unprecedented opportunities have also arisen for the modelling and analysis of human behaviour through the methods of data science (Barlacchi et al., 2017; Lazer et al., 2009). In this way, data provides valuable information for designers, leading to better outcomes by optimising timing and resources within the design process. According to Prendiville et al. (2017), through the application of processes of interpretation, visualisation and persuasion, the design ensures data turns the abstract and intangible aspects of data into human-centred services providing both social and economic significance. Data-based models are used in engineering both with the analytical objective of predicting the value of a variable and with the descriptive objective of understanding and discovering patterns in the available data (Anand & Buchner, 1998). Geng et al. (2012) have also made use of data in design engineering to extract information and include it in the development of new solutions (Wickel & Lindemann, 2015; Lützenberger et al., 2016; Agard & Kusiak, 2004; Ma et al., 2016; Song & Kusiak, 2009). More recently, Pajo et al. (2015) have proposed a method to extract information about current and future customer needs from social media.

Big data are fundamentally big datasets, made up of structured, semi-structured, and unstructured data that can be processed and analysed to reveal patterns and trends (Hazen et al., 2014). Growing levels of digitisation increase the demand for greater data evaluation in terms of velocity, efficiency, and accuracy (Cao et al., 2019; Xu et al., 2016). Moreover, with the evolving status of data and the merge of data sets, it will create more and more options in a variety of contexts and domains (Akhtar et al., 2016; Caputo et al., 2016). To address the integration of data into the creative process, it is possible to highlight the variation between two major types of data processing: batch processing (Affetti et al., 2017; Casado & Younas, 2015; Grolinger et al., 2014), and real-time processing (Casado & Younas, 2015; Li et al., 2018; Wan et al., 2017). Historical data from the past is accepted by batch processing of big data analysis to inform future actions, strategies, and plans (Chen et al., 2015; Kitchens et al., 2018; Nunan et al., 2018; Yang et al., 2020). The processing with these two scenarios corresponds to both structured data (batch processing) and unstructured data (real-time processing):

- Structured and semi-structured (quantitative) data: For the data gathering, connected Internet of things (IoT) devices are highly valued, establishing a consistent framework merging virtual and physical data points (Uckelmann et al., 2011). In its condition as a data point, IoT can gather a range of user, transport, temperature, transaction, and global positioning system information, derived from a variety of sensors (Akhtar et al., 2019);
- Unstructured (qualitative) data provides user insight hitherto unavailable through structured data sets, social media usage, and user clickstream data along with keyword searches on search engines are resources that provide real-time insight into consumer thinking.

Creativity is understood not only as of the result of information about learning but also as using knowledge to produce something that can combine prior knowledge with the creation of something else: from the solution of different kinds of problems to the presentation of innovative ideas. The “ideas” to be combined can be from arbitrary sources, such as text, image, audio, or video (Han et al., 2016). Consequently, the potential opportunities offered by exchange and collaboration with data science environments should be explored. Such opportunities can be an incentive and a guide for the creative process, making it more stimulating and productive. Additionally, D’Ignazio’s and Bhargava’s research (2016), on creative

data literacy incorporates a range of tactics aiming towards supporting growth in creativity-oriented data competence.

A research study by Sio et al. (2015) has well illustrated the use of data, with findings showing that data stimulate creativity within the very first phases of the design process (it consisted of giving examples related to the objective of the research), permitting every individual a more in-depth exploration of the design problem. Speed and Oberlander (2016), provided a theoretical approach to categorise different data approaches by “designing from, with and by data” (Figure 1). In our study, we identified quantitative data as concrete data and qualitative data as abstract data. In the design process, theoretical data can aid the designer in developing new concepts, just as concrete data can be used to define, improve, or add value to design.

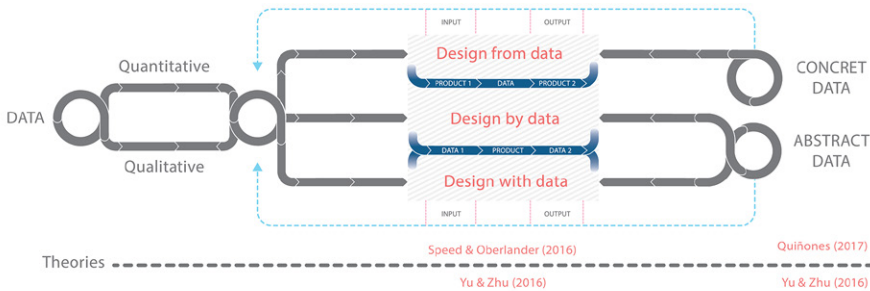


Figure 1. Data within the design process (source: created by author)

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. The creative and design processes will portray different realities. Based on preliminary work and existing literature, it is adopted the following statement: (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 because of the integration of big data into the creative process (Figure 2).

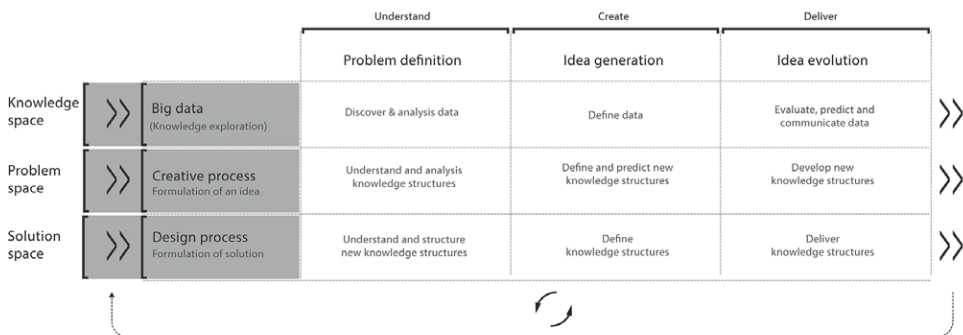


Figure 2. Big data and creative process and design process framework (source: created by author)

The integration of big data, as shown in the Figure 2, is going to turn into a growing practice in design, transforming the way we design and promote knowledge discovery in databases. The generation of ideas and value creation from big data depends on supporting decisions with new knowledge generated from data analysis; however, data analysis is only possible with a set of data science knowledge.

The purpose of the idea generation phase is to devise as many creative solutions as possible that fit the requirements defined by the design problem. There are estimates that 70% of the cost of a product is, in fact, determined within the framework of the conceptual design (Pahl et al., 2007). Dealing with the first phase successfully is fundamental, and many have been the investigations that have studied the cognitive process during the idea generation phase during the creative design process (Chan, 1990; Christiaans & Dorst, 1992; Hybs & Gero, 1992; Adams & Atman, 1999; Dorst & Cross, 2001; Kruger & Cross, 2001). An exciting observation is the great influence of abduction in the initial phase of design (Kolko, 2010; Dorst, 2011). Therefore, after a period of the abduction of the senses, data becomes a source of inspiration, in order to explore and use data as a resource of generative design of ideas, where the abductive perception is necessary to create new appropriate connections, resulting in novelty and variety (Quiñones-Gómez, 2019). The resultant is that creativity increases and more chance to design an innovative concept.

Even considering the absence of relevant studies relating to creativity and big data, the results suggest that this crossroad will create a new scenario (Figure 3), where big data will be a tool to stimulate creativity, enhancing the creative process. Consequently, it was established that there might be five areas (Quiñones Gómez, 2018) where big data can be effectively applied in the creative process, firstly, during the phase of searching for inspiration and ideas, to obtain more classified information as well as to comprehend the contents better and facilitate

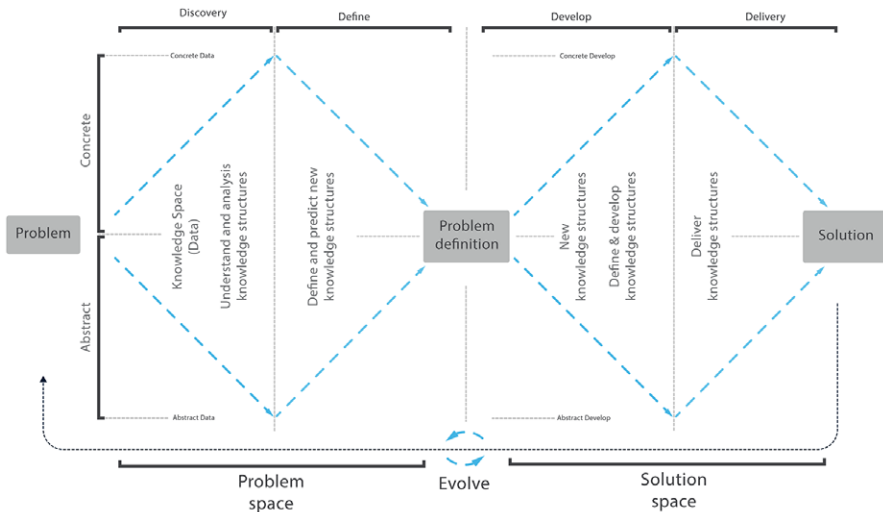


Figure 3. Data-driven design model process (source: created by author)

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 to be attained and enables better and easier chance of the alternatives selected to work with. Thirdly, this crossroads 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.

5. Analysis based on data

Being digital means that we can easily track activities in our daily lives and our interactions with the physical world, thanks to digital interfaces that simplify the task of data collection, the biggest challenge being the interpretation of the data and the meaning derived from it. Poor quality, non-representative, or poorly analysed data can lead to erroneous conclusions. All decisions and results will be considered to be by quality as long as they are based on qualitative data.

The suggested design methodology integrates the theory of data mining (Zhu et al., 2016a, 2016b), an approach based on the systematic discovery and examination, by automatic or semi-automatic systems, of huge volumes of data in order to discover significant trends and relationships, and then to introduce the results into the workflow of the creative process. Data mining tools allow designers to filter big data, discover hidden data, reveal new relationships and patterns, and extract anticipated, and useful information involved in large datasets. Data mining algorithms such as clustering and decision trees have been used in the design of numerous products. Data science allows you to explore the interrelationship of design variables and to establish design rules by applying the data-driven design method facilitating creative leapfrogging.

According to Kitchens et al. (2018), it is necessary to adopt a more holistic approach to further research, integrating multiple sources of structured, semi-structured, and unstructured data that will enhance competitiveness and decision-making, fostering creativity and innovative solutions. Big data has the potential to add value based upon the types of data collected; therefore, more volume means more possibility for comprehension (Targio Hashem et al., 2015). There are other characteristics that are based on this; for example, in the opinion of Targio Hashem et al. (2015), there are 4V's of big data that describe as volume, variety, speed, and accuracy. Volume represents both the amount of data produced and the corresponding mass quantities collected. Variety refers to both differing data forms received as well as the very diverse sources involved (Erevelles et al., 2016). IoT, in this context, plays a vital role, supplying data from a broad spectrum of interconnected artefacts (Akhtar et al., 2016). Velocity refers directly to the speed of data generation and collection, influencing the promptness of data analysis for strategy development (Ahmed et al., 2017). Value is about insight and the process of discovery, focusing on the acquisition of hidden knowledge. By

collecting data from different sources, designers have the potential to improve the generation of data-driven insights in the context of data analysis (Ghasemaghaei et al., 2016).

In the tabled model, the data can be integrated into different ways resulting in different types of knowledge:

- Descriptive knowledge focuses on understanding what happened in the past and is mainly related to structured and semi-structured data. Generalised descriptive knowledge uses historical data to identify patterns of trend information. This is the most common type of knowledge generated in products and companies (Ghasemaghaei et al., 2016). An illustrative view helps the designer to understand the current situation better so that developments can be more evident;
- Predictive knowledge contemplates future scenarios and can generate predictive and prescriptive visions that optimise designs and is related to unstructured data. Additionally, some companies have started using cloud-based services to obtain knowledge from large amounts of heterogeneous data quickly.

Thus, in this document, the main learning from the theory is used towards a better comprehension regarding the key role of big data in knowledge generation driven by the organisation in which the figure of the designer will need to be included to extract this knowledge as design material within the course of the creative process. For example, companies that collect a large amount of consumer data, both transactional information on the use of connected products and social media (structured, semi-structured and unstructured data), maybe more able to discover new patterns in relation to the needs and preferences of their consumers, compared to those who only consider a single source of data. Unlocking the hidden knowledge of consumers allows a better understanding and prediction of consumer behaviour and continuous response by consumers to changes in the market context (Erevelles et al., 2016). Thus, it is an opportunity for designers to enhance the learning process by tracking and monitoring new feeds from a variety of channels. On the other hand, it would be possible to use simple techniques such as drawing graphs to discover patterns in the data, use regression to understand the correlation between different variables, or visualise it to understand the data better (Pusala et al., 2016). Processing different types of data and their correlation is critical to the process, as it may help us in discovering new relationships and patterns in the data. In particular, the collection of various types of data (*e.g.*, numerical data, measurements, photos, text, and images) increases the possibility of identifying new and non-obvious data patterns (Dong et al., 2018).

The generation of descriptive information can enhance the ability to develop new products or expand existing product lines properly. It would also be possible to generate predictive knowledge. For example, using data mining tools to predict the success of NPD after analysing the historical experience of users, as well as online consumer opinions about products and services. As well as analysing the data in real-time, they enable a clear picture of consumer preferences for specific product features to be generated promptly.

6. Unlocking methods for data

This research aims at providing pragmatic perspective on the DDDM with relevance to design professionals in terms of the user experience usability attributes. User experience is the key to unlocking great data. Sometimes it happens that we designers have nothing but our

own competition and, of course, a variety of inconclusive tests, interviews, and surveys to test our assumptions. A further factor is that the user's actions are often substantially altered compared to the information that the users subsequently report. But as previously noted, in terms of design methods, traditional tools do need an evolution, because more in-depth knowledge of users' feelings and perceptions cannot be obtained through generative methods of user experience research. Accepting that the old research methods are limited (Razmi, 2018; Quiñones Gómez, 2018), the best alternative to evolve lies in data.

User experience design for NPD, services or systems that provide meaningful and relevant user experiences; involves the design of the entire product acquisition and integration process, including branding, design, usability and function aspects (Interaction Design Foundation, 2019), so far, this contribution has been mostly reduced to testing assumptions, but the big data extracted from the user experience can change everything. The major advantage of using big data is that the data is complete, diverse, and most importantly, generated by the users themselves, without interfering with their routine or influencing the experience. Today, data can be easily obtained on a wide variety of aspects; screen interaction views, average time spent on a single feature, clickable features are just a few of them (Everly, 2018). The involvement of big data in user experience research is enabling designers to see patterns and algorithms in large amounts of data because one of the crucial parts of user experience design work is predicting and helping users access desired goods or services when or even before they think they need them. We need to have hard empirical data to support our user experience solution proposal. Designers have the opportunity to see beyond the so-called big data in an Excel sheet; they can involve human intuition driven by elements such as psychology, ethnographic studies, and user research, being able to explain big data with much more context.

7. Data-driven design model application framework for evaluating usability attributes

Connected to each individual, IoT's personal data offers a valuable tool to inform and evaluate the creative process. It changes the way research is conducted, relying increasingly on data as a starting point to help identify relevant needs and challenges (Apple.com, 2019; Bourgeois et al., 2014; Handte et al., 2016). There is a growing interest from the design research community in understanding how product and interaction designers can engage with sensor data and how sensor data can be incorporated into design processes, *i.e.*, how data can be used as creative "design material" (Dove & Jones, 2014; Speed & Oberlander, 2016).

User performance metrics are an essential part of usability evaluation (Tullis & Albert, 2013). Using big data, in this case, can help achieve more reliable results in measuring the performance of a product in a phygital environment (an environment where physical and digital coexist synergistically), due to the ability to gather the variety of usage parameters in the real environment. It is essential to add that the analysis of big data in the creative process is not intended to replace existing subjective methods for usability evaluation, but rather to augment them. This section proposes a pragmatic approach to understanding how analysis of actual user data can contribute to the evaluation of subjective usability attributes,

to encourage creativity in the design of new solutions by presenting a new framework supported by DDDM.

The correct selection of variables and attributes for the analysis is fundamental in using the data. In this case, the classification of attributes proposed by Orlovska et al. (2018) is expected to analyse the attributes and divide them into three main groups: User performance, system performance, and user perception. The classification of the attributes is shown in Figure 4. Structured and semi-structured data can support user performance and system performance attributes. However, user perception attributes are supported by unstructured data, which allows measuring user emotions or similar cognitive feedback through the appropriate hardware. Via the analysis of structured and unstructured data users' activities, including the corresponding individual affective reactions, can be identified and analysed.

We identified the extraction and analysis of data framed in two different scenarios (Figure 5): first, if it is a digitised product, the usability and performance record is recorded in a log file, and we can analyse and classify its information based on the attributes defined above.

Log files that map the user interaction can, therefore, also map and record the behaviour of the user and the machine in general. For example, Landauer et al. (2018), used log file data on user activity to facilitate the identification of repeated or sporadic actions. Within this development trend, the increasing dissemination of applications increased the importance of log files for troubleshooting code, as well as for monitoring user behaviour (Krieter & Breiter, 2018), which is also an important factor in guiding the development of future features with less effort from developers (Ferre et al., 2017). Since each log refers to a product and a user, this allows for both individual quantitative analysis and analysis of the entire population by correlating data from the product as the whole pool, leading to improvements with a greater

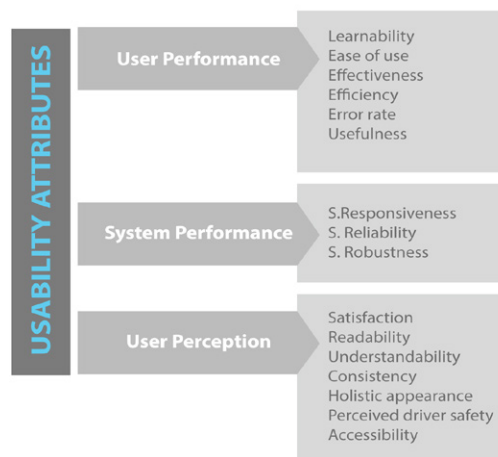


Figure 4. Usability attributes (source: created by author)

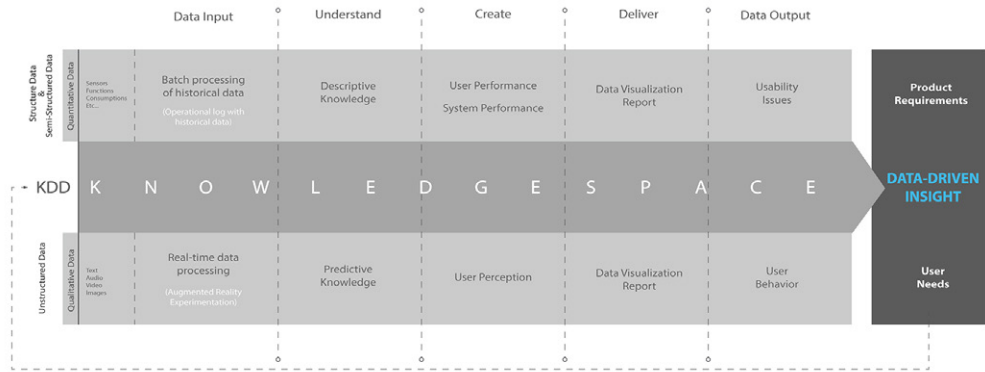


Figure 5. Data transformation flow into design material (source: created by author)

overall impact. Log files have also been found to contain relevant data on the usefulness of new technologies and their effects on users. Secondly, it is possible to analyse this pre-production experience in virtual augmented reality experimental environments, creating a virtual environment where the user and the product studied generate a huge amount of information interacting with the product. This environment can be formed by a product/user or by a virtual environment such as the digital twin.

After that, the classification of all the information extracted from logs, data mining techniques can be applied in order to extract useful information from the data and its subsequent interpretation to integrate it as insights into the creative process. Either approach provides data that is generally unstructured, *i.e.*, numerical, needed for quantitative analysis. However, for the study of the attributes related to the user's perception, a qualitative analysis will be necessary based on unstructured or semi-structured data, which can be extracted from the affective reactions generated by users and their behaviour, from images, texts, *etc.* Unstructured data also offers real-time analysis, unlike structured data, which is mainly based on historical data from existing users and only reports on past events.

The ability to collect data on how users use a product helps to identify problems that can be improved, detect trends and patterns, define people, the most used functions, and the most stressed elements of the system, as well as opportunities for innovation. The consideration of human aspects in the design process is vital in design. Only in this way can we understand how things work, the forces that cause particular conditions, and where to look to discover the underlying causes. The larger the sample and the more data obtained, the more representative the findings. Thus, since the data-driven design model (DDDM) is a process in continuous development, future system updates with considerable improvements or new functionalities are feasible based on the iterative analysis and design of the product. Moreover, considering digital environments, all these actions are easy to execute and scalable thanks to the use of cloud-based hosted systems that most of the connected products use today.

Discussion

The digital transition in the current context of Fourth Industrial Revolution is creating new motivation for commitment and the need for further technical skills that can enhance creativity in the field of design. This information and the framework presented is fundamental for designers and the creative class in general in order to empower the next generation of creatives to enhance all stages of the design process by developing tools to master the changes brought by the digital transition and the creative economy.

In these circumstances, design research needs to understand the impact of digital technologies on the creative design process, to update the toolbox at the conceptual stage in order to facilitate the creative potential of individuals in achieving the best performance at each stage of the process, as well as to address new technological challenges that generate a positive impact and innovation. The ever-evolving digital landscape will constantly demand an increased awareness of the technological, as well as social and cultural opportunities that could enable or inhibit creativity.

Based on the research questions addressed initially, along with the research conducted, it is possible to summarise as follows: Can data support creativity? Based on both professional and research experience, and on the knowledge of experts, it can be said that it is possible. There are still many questions about how companies and designers can achieve that perfect mix to integrate new processes, but the benefits of doing so are clear, resulting in benefits for the creative class and for companies in addition to faster growth.

Contributions

The overall objectives for this work were three:

Firstly, through gap-finding and problematisation, we provided a general framework for the evolution of the creative process and the integration of big data into the creative design process. The development of related research and design methods that conform to these principles is under-explored and requires further attention. This is a research gap at the intersection of design and research methods and data management and analysis.

In the second place, an attempt is made on identifying, extending, exploring, and understanding the involvement of structured, semi-structured, and unstructured data into the processing of big data in the framework of the proposed DDDM, where usability is studied.

The last contribution is to provide interdisciplinary literature that highlights the gap between the science of big data and the creative process, highlighting both the challenges of the industrial designer and the profession of design as a whole. Such contributions provide a valuable contribution to enhancing debate and understanding of the potential use of new technologies in creative activities today.

Our approach to problematisation and gap detection has significantly contributed to highlighting the main differences between traditional and more advanced methodologies, both in the creative and big data fields, and the nature of the data offering different possibilities in the extraction of knowledge related to the product, the user and the resulting opportunities.

Conclusions

An approach based on the integration of real user data analysis techniques at the initial stage of the creative process during the exploratory design is presented in this article. We found that the data can feed into existing usability structures. In this proposed application environment, the method can increase the detection of usability problems, allowing the measurement of their magnitude by grouping users with similar behaviour, thanks to big data. The data alone does not provide any value; the data analysis techniques will help us interpret the data to make better user-based design decisions to provide the best possible experience. As a final step in data analysis, data visualisation is critical to encourage creative thinking. When information is presented visually, it takes shape, allowing us to easily gain insights that would be difficult or impossible to extract from the same data presented textually or in other formats. In most of the current data interpretation systems, data representation, and algorithms are done in a way that is complex to interpret and extract information useful to the design process. An effective data representation can speed up and encourage the creative act by helping us to establish relationships, detect trends so that we can make the best design decisions. For example, using visual representation techniques such as data visualisation or data storytelling. By facilitating the recognition of user needs and behaviours. It is essential to mention that data visualisation itself in no way constitutes the objective, but only support.

In this research, it is illustrated how data science workflow can be adapted to a design research process. From the results, we observe the transfer of designers' creative skills to hypothesis formation related to data collection and the use of their design perception skills to synthesise data exploration in design research. The DDDM framework presented in this document aims to clarify the role of this technologically advanced data-driven model by highlighting the involvement of data in the initial phase. A key element of designing with the data in this model is the ability to iterate in a continuous design process. The use of automatic learning and data mining algorithms allows the discovery of correlations in the data, the identification of trends and patterns, as well as the prediction of results in a relatively short time compared to human analysis, speeding up the process significantly. It is necessary to state the following about the integration of data in the creative process: the tendered model does not intend to compete with man in creativity, but to establish a collaborative design environment. New emerging data-driven models, including using data mining and machine learning, are therefore increasingly needed, according to the literature that increasingly examines them as enablers for product, service, and system innovation.

Based on these findings, the creative process can effectively be supported in terms of providing information to help designers produce creative ideas in a collaborative environment with computers and digital tools. Furthermore, the results suggest the need to develop novel concepts and frameworks to support new ways of understanding, describing, and working with "big data" as well as the technologies associated with it – the conclusions of this research shows how a design practice in this new technological context faces multiple challenges. Key points include the high level and sophistication in technology, lack of education/experience of the designer is working with it, insufficient frameworks and collaborative tools between data experts and designers, as well as the rather elusive properties in technology. The intention is to provide the designer with a knowledge base plus a knowledge management strategy.

Data-driven design implies that the data being used determines design decisions. The outcome of the data analysis may not be clear or decisive, but it can contribute to the iteration of the design process and encourage creative leapfrogging. In this context, the creative class may offer a different perspective on interpretation and hypothesis formulation when interpreting the data. We believe that the variety of structured, semi-structured, or unstructured data from various sources feeds the creative design process by providing a variety of possible ways to address a problem, and in the context analysed, improve the end-user experience. The results of this work, therefore, support Manzini's call (2015) for the generation of theoretical abstractions that can enable designers to work with increasingly complex and rapidly changing technologies such as those presented in the practice of this work.

Therefore, the results can be considered a formalisation of the empirical evidence on the use of data models in early design, framed in the current literature on creative processes and user experience analysis. This paper has not been aimed at providing an overview of all possible applications of the DDDM, but rather to establish a reference framework further to investigate this model's potential contribution in product innovation and enhancing creative idea generation. Last but not least, to promote state of the art and the state of practice of data-based design, while providing guidelines for designers and the creative class generally, to gain an understanding with respect to the contribution of data in knowledge generation and a deeper understanding of user needs.

Further studies

Although it is necessary to transform user information and knowledge as part of globalisation and technological change, it is important that organisations effectively meet new and changing needs and stimulate consumer creativity using digital products. When addressing issues such as this, it is important for designers not only to evaluate the data generated by these products regarding the user experience but also to integrate it as part of the NPD process. In subsequent studies, it is intended to evaluate, according to the proposed framework, the data generated in a digitised product for the evaluation of the user experience, and to identify the characteristics that would improve the final result, as well as those variables related to functionalities or improvements of the product, enhancing the innovation and creativity of the process.

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