Univerzita Karlova

Filozofická fakulta

Ústav informačních studií a knihovnictví
Studia nových médií

Diplomová práce

Bc. Richard Kabilka

Algorithm driven graphic design

Algoritmizovaný grafický design

Praha 2020 Vedoucí práce: Mgr. Michaela Slussareff, Ph.D.

Poděkování:
Na tomto místě bych rád poděkoval za cenné rady a připomínky při zpracovávání diplomové práce Mgr. Michaele Slussareff, Ph.D, Mgr. Ditě Malečkové, Ph.D. a svým blízkým za podporu, trpělivost a koláče.

Prohlášení:

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V Praze, dne 28. července 2020

Richard Kabilka

Klíčová slova (anglicky):
Graphic design, artificial intelligence, algorithmization, automatization, visual creativity, graphics editor

Klíčová slova (česky)
Grafický design, umělá inteligence, algoritmizace, automatizace, vizuální kreativita, grafický editor

Abstract (in English):

The diploma thesis inquires into the use of A.I. – artificial intelligence in the field of graphic design. This thesis aims to describe the current state of A.I. use and algorithmization in graphic design and, based on the conducted study, to evaluate the potential of this type of tool and possible impacts on graphic design. The theoretical section will introduce basic principles and concepts of graphic design and its relationship with art and technology, based on professional literature and current research. Furthermore, it will describe the current possibilities and specializations of artificial intelligence. Findings from these two chapters will serve as a framework for critical evaluation of the currently available A.I. driven tools for graphic design. In the research section, a quantitative study utilizing a questionnaire will be conducted among the professional public and examine the opinions and experiences of Czech graphic designers with tools for design automatization. Its results will be used to test the formulated hypotheses utilizing appropriate statistical methods.

Abstrakt (česky)

Diplomová práce se zabývá využitím A.I. – umělé inteligence v prostředí grafického designu. Cílem práce je popsat současný stav využití A.I. a algoritmizace pro grafický design a kriticky, na základě provedeného šetření, zhodnotit potenciál těchto nástrojů a možné dopady pro oblast grafického designu. Teoretická část představí, na základě odborné literatury a dosavadního výzkumu v oboru, základní principy a pojetí grafického designu a jeho vztah s uměním a technologiemi. Dále popíše současné možnosti a zaměření umělé inteligence. Poznatky z těchto kapitol poslouží jako rámec pro kritické vyhodnocení aktuálně dostupných A.I. nástrojů pro grafický design. V praktické části bude realizován kvalitativní dotazníkový průzkum mezi odbornou veřejností, který bude zkoumat názory a zkušenosti českých grafických designerů s nástroji pro automatizaci tvorby designu. Jeho výsledky budou použity k vyhodnocení stanovených hypotéz pomocí vhodných statistických metod.

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0. Introduction

Automatization of work became a topic of mainstream discussion. The Future of Jobs Report released in 2016 by the World Economic Forum discusses the impacts of the fourth industrial revolution. As many as 65% of children presently attending elementary schools will work in jobs that do not yet exist (World Economic Forum, 2016). While the most prominent example of the possible future disruptions is arguably the driverless car, the shifts brought by automatization could affect all industries. David Autor describes how computerization have already largely replaced routine task intensive jobs between the years 1999 and 2007. On the other hand, abstract task-intensive jobs remained or increased with human knowledge being complemented by computers (Autor, 2014). Nick Srnicek, in the light of the imminent changes, argues for a post-work economy and introduction of universal basic income (Srnicek & Williams, 2016). Andrew Yang, the Democratic candidate for the president of the USA, made universal basic income, or the freedom dividend, as he titled it, a crucial part of his campaign (Yang, 2020). Although graphic design would seem like a field not very likely to be affected by automatization, an argument can be made based on the investigation of possible effects of A.I. on graphic design that even fields deemed as creative could be affected.

This thesis aims to describe the current state of implementation of A.I. and algorithmization in graphic design and, based on a conducted study, evaluate the potential of this type of tool and possible effects on the field in the Czech republic. The thesis is divided into several chapters. Trough exploration of the history of graphic design, identifying main topics of theoretical discussions, and defining its guiding principles, a set of intersections with A.I. will be defined. These intersections between the demands of graphic design and the possibilities of A.I. will then be investigated in terms of their fulfillment by existing tools and software. A quantitative study among the Czech graphic designers will be conducted, examining their practice, opinions, and experiences with this type of tool. The research part of this thesis provides a description of the implemented methodological procedures, description of the collected data, its statistical analysis, and finally, contextualization and evaluation utilizing previous theoretical findings, with a critical assessment of its limitations. Since this study will generate primary data, it could serve as an inspiration or as a comparison for future research.

1. Graphic Design

Artificial intelligence is affecting various fields of human activity. To evaluate automatization and A.I. driven tools in graphic design, this thesis must first define what constitutes graphic design by examining its history and its connection with related fields, with the main focus on art and photography. The concerns of designers identified as lasting topics of discussion will help us define relevant questions in the research section.

1.1 History

While practical emergence of proto graphic design could be traced as far back as the beginnings of human civilization and the invention of the first alphabets, theoretical concepts of modern graphic design began to emerge within the avant-garde movement and specifically in the Bauhaus school. (Armstrong, 2009). The evolution of these concepts will be summarized to provide the historical context of how graphic designers viewed themselves and the artifacts they produced. “It seems fairly commonplace that the way designers conceive of the nature and purpose of design will affect their practice.” (Galle, 2011, p. 1)

1.1.1 Avant-garde

Born from an era of upheavals, reacting to mass industrialization, and the first world war, the avant-garde movement tried to find new meaning in radical divergence from traditional conventions by experimenting with and discovering new visual forms. Inspired by the capabilities of machinery, their design was functional, minimal, ordered, and neutral. While being socially engaged, striving to reshape the chaos of a rapidly changing world. (Armstrong, 2009; Meggs, 2016)

The most prominent movement in advocating the embrace of the future was Futurism. Although F.T. Marinetti was primarily a poet, he used graphic design in a new and unexpected way, broke the rules of typography to better suit his vision, creating a modern typographic style called parole in libertá or “words in freedom” (Armstrong, 2009; Meggs, 2016). Breaking the traditional typographical flow on a page was already used before in poetry, most notably in works of Guillaume Apollinaire, but the futurists used these new techniques in a provocative and public way, that forced graphic designers to revise the basic concepts of typography. "He challenges us even now to embrace the future [...] to believe that entirely new forms are not only possible but imminent." (Armstrong, 2009, p. 20).

Inspired by the Soviet revolution, Alexander Rodchenko, one of the founders of constructivism, viewed the role of a designer as a catalysator of social change, creating objects of everyday use, like furniture, book and magazine covers, that would lead to a utopian society and by using new technology and mass production he was able to reach large audiences (Margolin, 1998).

The De Stijl movement started in 1917 in the Netherlands. Their visual vocabulary was inspired by mathematical structures and harmony found in nature, and characteristic by using only elemental geometric compositions and colors. While being concerned with the spiritually challenging post-wartime, their focus shifted to an applied art to the everyday objects, which would be, by following ideas of purified aesthetics, elevated to the level of art (Meggs, 2016). Affected by the horrors of war, striving for a utopian society, the constructivist and De Stijl movements sought pure geometric and harmonious order in graphic design and unification of human values and technology.

Walter Gropius founded the Bauhaus art school in 1919, and its innovative style became one of the most influential currents in product design and affected the development of modern graphic design and typography. "Gropius sought a new unity of art and technology as he enlisted a generation of artists in a struggle to solve problems of visual design created by industrialism." (Meggs, 2016, p345). László Moholy-Nagy, a Hungarian constructivist, came to the Bauhaus in 1923 and became the pioneer of photography in graphic design. He saw photographic images as impartial and objective and their use combined with text, the typhoto as "the visually most exact rendering of communication" (Moholy-Nagy, 1925, p. 38). While striving for impartial communication, his view of graphic design was built on anonymity, neutrality, and objectivity.

These ideas were further spread into the general public by Jan Tschichold and his "New typography." Design theories of Bauhaus and De Stijl were introduced to the printing industry and set a new standard for books, advertisements, and posters to deliver a clear message efficiently through functional design. (Meggs, 2016). "The method of new typography is based on a clear realization of purpose and the best means of achieving it. No modern typography, be it ever so "beautiful," is "new" if it sacrifices purpose to form." (Bierut, 1999, p. 47).

With the rise of nazism in Germany, many intellectuals left Europe and emigrated to America. The Bauhaus was closed in 1933, Moholy-Nagy opened the New Bauhaus in 1937 in Chicago, which was later transformed into the School of Design. The disruptive and idealistic views they developed were confronted with American business reality, and graphic design became a profession with formal methodologies (Armstrong, 2009; Meggs, 2016).

1.1.2 International

The Swiss design or the International Typographic Style was an influential design movement that affected designers both in Europe and America. It emerged in the 1950s and mainly developed in Basel and Zurich. Their conception of the design was a logical tool to conduit information, detaching it from the idealistic and eccentric notions of the avant-garde. The scientific approach in solving design problems lead to utilizing a complex mathematically constructed grid and creating new sans-serif typefaces. The grid was regarded as a way of creating a universal form of graphic expression. Karl Gerstner developed a typographic grid as a composition tool, capable of generating broad variability of layouts while keeping within mathematical constraints. "The creative process is to be reduced to an act of selection. Designing means: to pick out determining elements and combine them." (Gestner, 1964, p. 242). Further expanding the grid as the primary tool for graphic design Josef Müller-Brockmann sought to avoid the designer's subjectivity or propaganda. "Working within the grid system means submitting to laws of universal validity." (Müller-Brockmann, 1981, p. 277).

The Swiss design gained influence in America after World War II, and their approaches were used to create compelling corporate identities and visual-identification systems for large organizations. At MIT, a program was set up to provide professional design assistance with academic publications to improve their communicational value while committing to the grid's principles. Informational design pioneered, among others by Czechoslovakian designer Ladislav Sutnar, who emigrated to America in 1939, showed the necessity of a clear visual language when presenting complex information in large quantities. International events, large government bodies, and corporations increasingly relied on design systems to help them communicate information effectively while also managing to build brand identities. American designers expanded on European foundations and concepts with a less rigid and formal approach. (Armstrong, 2009; Meggs, 2016)

Paul Rand was one of the most prominent and influential graphic designers of this era in America. In the 1950s, Rand created compelling logos and brands for then expanding corporations, like IBM and UPS. (Armstrong, 2009) In Thoughts on Design, his 1947 book, he collected his principles and ideals of what constitutes good design. In his view, visual communication was the integration of aesthetic value and utility. Rand defended the role of the designer's individuality and its importance for the designed product. He emphasized the need for interdisciplinary knowledge so the designer would be able to improvise, interpret, and discover new techniques. Using symbols, abstractions, and analogies, designers can find a shortcut to the spectator's unconsciousness and simplify and intensify the message of their designs. Rand advocates for the use of repetition because of the emotional power visual rhythm can evoke in the spectator and to avoid symmetry and predictability as it does not offer any contrast. For Rand, the designer's role is to continually upgrade the visual culture while not forgoing the accessibility of the information his product should communicate (Rand, 2014).

1.1.3 Postmodern

By the 1970s, influenced by the pivotal time in America, with various social activist movements challenging the established views in society, many designers started breaking the international style, which dominated graphic design since the Bauhaus. The significant deviation from modernist design was in the liberation of form and methodology, by being intuitive and subjective, departing from rationality and objectivity. (Armstrong, 2009).

Katherine McCoy led the Cranbrook Academy of Art in Michigan while creating experimental and provocative graphic designs, exposing the audience to a multilayered, personal work, requiring evaluation and interpretation. “If design is about life, why shouldn't it have all the complexity, variety, contradiction and sublimity of life?” (Aldersey-Williams, 1990).

Several competing political values replaced the utopian ideas of modernism, mass culture was replaced with popular culture, egalitarianism by populism. (DeKoven, 2004). “In postmodernism, modernism's hierarchical distinctions between worthwhile ‘high’ culture and trashy 'low' culture collapse and the two become equal possibilities on a level field." (Poynor, 2003, p. 11). With the development of personal computers, designers became increasingly intrigued by streamlining and innovating graphic design (Meggs, 2016).

1.1.4 Digital

The rise of digital technologies profoundly changed all fields of human activity, including graphic design. The process of creating and printing design was simplified from a number of specialized steps and professions into the hands of one person operating a computer. The creative potential of graphic design was expanded with advanced software for image manipulation. World Wide Web created a unique platform for decentralized mass communication. These new opportunities also convey constraints in the form of industry-standard graphic software and web protocols.

Lev Manovich defines the characteristics of new media by five axioms that differentiate them from the old analog media: numeric representation, modularity, automatization, variability, and transcoding. "The logic of this new hybrid visual language [...] Is one of remixability: not only of the content of different media or simply their aesthetics, but their fundamental techniques, working methods, and assumptions." (Manovich, 2006).

1.1.5 Conclusion

Throughout the offered brief historical summary of graphic design, conceptions of authorship, universality, and social responsibility were followed. The avant-garde movement saw the role of graphic design in accelerating social change while abandoning the artistic ego, finding universal rules in abstract shapes, and using new print layout and photography technologies. The Swiss design school continued in the quest for universal visual language while focusing on the instrumental role of graphic design solely for communication, without the utopian notions of the avant-garde. Their ideas were then assimilated by the realities of America, proving as a powerful tool for corporations and institutions. The postmodern turned for a more subjective and artistic approach. With the digital revolution and expanse of the World Wide Web, the need for universal visual language for corporations and institutions was highlighted while providing possibilities for graphic designers to experiment, remix, and collaborate.

With new developments of A.I. tools, concerns about aesthetic value and the graphic designer's subjective contributions are accentuated. In the next chapter, the relationship between art and design will be explored.

1.2 Art

The scope of this thesis does not cover a discussion of aesthetic theory or philosophy of art. For this reason, notable views on the role of design and art will be explored in this chapter, emphasizing those relevant for later discussion on A.I. aesthetics.

1.2.1 Uniqueness

The debate on the relationship between art and design can be traced back to the beginning of the industrial revolution when mass production of goods stirred hostility of artists towards manufactured goods. One of the first products creating opposition from the ranks of the artists was wallpaper, diminishing the role of interior decoration. (Irwin, 1991) French architects Charles Percier and P. F. L. Fontaine wrote in 1812, "...the practice of seeing a multitude of art objects made by a mechanical routine, products made by templates, by moulds, which immediately throws discredit on the very kind. One no longer takes the trouble to distinguish the original work of art from the servile work of routine." (Percier and Fontaine, 1971, p. 12).

Walter Benjamin argues that the invention of mechanical reproduction and film had a significant impact on art in its traditional form. Traditional art lacks in its ability to exists in only one place at a particular time. Mechanical reproduction provides the accessibility of art for the masses, but reproductions are missing a vital aspect of the work of art, that Benjamin calls aura. Magical status of art whose process of creation was ritualized was transformed and politicized by the rise of fascism and communism. (Benjamin, 1970)

One of the earliest concerns about the changing characteristics of art was the role of artistic ego and the artifacts' uniqueness, later revolutionized by the avant-garde movement (see chapter 1.1.1) in contrast with the graphic design utilizing the new technologies of mass production.

The question of authorship is diminished in design. Design of common domestic products, such as a chair or a cup, is based on generations of small incrementations. The individuality of the designer is, in contrast with art, not important for good design. Fulfilling a function is the mere basics for good design. Therefore imitation of standard patterns and implementation of best practices is common in the design process (Nelson, 1979). Artist is usually involved in the material production of the artifact. The designer often only provides instructions to be executed by others (Potter, 1989).

1.2.2 Intention

In the early 19th century, artists concerned with the rise of applied art and industrial design defined pure art as the intention and purpose behind the artistic object. (Munari, 1966) The phrase "L'art pour l'art" (art for art's sake), credited to Théophile Gautier, French author, and art critic, depicts this notion. Adolf Loos, a modernist architect, wrote in 1908 in his Ornament and Crime "...art must be stripped of practical goals".

Graphic designers, in contrast, from Jan Tschichold to Paul Rand, throughout the history of graphic design (viz chapter 1.1), recognized their role as problem solvers, finding the balance between utility and aesthetic value. Rand believed that any object could be considered art, the critical distinction is the impact on the spectator "what determines the status of art is not genre but quality" (Rand, 1996). Trough visual communication, the graphic designer addresses the spectator while taking into account the realities of the audience, needs of the client or institution, and inside the constraints of accessibility of information, ideally creates something new and unexpected. (Rand, 2016).

Design theoretics such as Herbert A. Simon, Donald Schön, and Klaus Krippendorff explain what design should strive for in the broader sense. These concepts will be briefly summarized. Simon sees design as a problem-solving process, defining the "command variables" that represent the given constraints, and then by process of optimization arriving at the sought-after artifact (Galle, 2011). Schön criticizes his approach as only applicable to well-defined problems. Simon's proposed science of design fails in the realm of divergent and less explored situations. Schön argues that the practice of "reflection-in-action" should be implemented in the design. He describes it as "When someone reflects-in-action, he becomes a researcher in the practice context. He is not dependent on the categories of established theory and technique, but constructs a new theory of the unique case" (Schön, 2011, p. 68). Krippendorff takes a radical "semantic-turn", emphasizing the user of the product as the primary concern in the designing process, from "technology-centered design" toward "human-centered design." (Krippendorf, 2006, viii).

This notion of design in service for its users seems to be the prevalent idea. Michael Bierut, an influential contemporary graphic designer, critic, and educator, articulated, "It's the responsibility of designers to address the needs of human beings and improve their lives in whatever way we can" (Beirut, 2017). Bruno Munari in his book "Design as art" describes the role of a designer as an artist who responds to the human needs, with the aim of "bettering his living conditions and encouraging him to develop his taste and sense of beauty" (Munari, 1966, p. 26).

A graphic designer works not only for the recipients and users of their work but primarily for their clients. In a famous quote, Marshall McLuhan said, "Art is anything you can get away with". In graphic design, the client and users create tight boundaries. Arguably the most reliable sources to confirm this claim are professional graphic designers with extensive experiences from the business practice. Rand sees the primary motivation of a designer as "art in the service of business" (Rand, 2016, p. 233), the restrictive character of clients is also recognized by Beirut "Clients are the difference between design and art" (Beirut, 2010). Don Norman, the world authority in the field of usability and design, commented on the still ongoing debate between artists and designers "Art makes statements. Designs work." (Norman, n.d.). An artist sets goals for himself (Dorst, 2003). A designer needs to be able to find a compromise within given constraints of manufacturing, client expectations, budget, and consumer needs. The ability to communicate ideas, persuade, and use arguments is at all times relevant to design work (Potter, 1989).

1.2.3 Environment

In the late 1990s, a new artistic movement, later named by an American artist Joe Scalan as "design art", introduced works of art that used everyday objects and placed them in a gallery, much like Duchamp's readymades. "Design art could be defined loosely as any artwork that attempts to play with the place, function and style of art by commingling it with architecture, furniture and graphic design" (Scalan, 2001, p. 10). As Scalan points out, utility in an art object, a way for it to be used for a purpose other than pleasure, threatens its value by introducing the possibility of damaging it. Art is preserved, design is consumed (Scalan, 2001). Works of art are intended to exist in a specific infrastructure of galleries, museums, and art critic magazines (Roberts, 2018). With art being used as an investment and museums functioning on business principles (Kwon, 2002), artistic objects live in a protected environment, excluded from everyday reality. Designed objects are, in contrast, exposed to the everyday life of people that use them. Thorstein Veblen, an American economist, and sociologist introduced the concept of conspicuous consumption. According to one of its laws, beauty's most basic trait is the lack of utility (Veblen, 2009).

1.2.4 Conclusion

Graphic design, unlike art, does not concern itself with the uniqueness of artifacts, and even the authorship is put aside as the communication of a message is more important than its origination. The remixability of digital media and even more a possibility of an inanimate creator of design artifacts does not create a concern for the majority of graphic designers. In contrast with the protected environment of museums, design needs to withstand the variability of everyday life. The emphasis on human-centered design creates a need for developing methods and technology, enabling computers to understand the human world and understand their emotions and needs, even inarticulate.

1.3 Technology

The relationship between design and technology will be discussed in this chapter. While deciding if an object can be labeled as good design, we need to set the evaluation process into a broader historical context, social and technological restrictions of a given era (Nelson, 1979). As suggested in the previous chapter, good design is solving a problem within given constraints. One of those constraints is technology available at the moment. A majority of contemporary visual A.I. tools are aimed at working with photography from capturing it to its categorization, a particular focus will be given to the discussion of the technology of photography.

1.3.1 Domestication

Vilém Flusser, in one of his essays, "About the word Design" trough etymological analysis of the word describes the design as a place "where art and technology (along with their ways of thinking) come together as equals" (Flusser, 2013, p. 19). The relationship between art and design was discussed in the previous chapter, the other side of the bridge leading to technology needs to be explored further.

As design historian Barry Katz argues, "[...] it is the designer who domesticates new technology and makes it available for human use" (Katz, 1997, p. 453). Design's role is to make new technologies accessible and useful for people who do not necessarily need to understand how the technology operates. "The design of technology to fit human needs and capabilities is determined by the psychology of people. Yes, technologies may change, but people stay the same." (Norman, 2013, p. 259). Human psychology and rules of ergonomy are the reasons why items designed centuries ago can seem from the current point of view as a good design. The influence is not only one-directional. New technologies provide new opportunities for designers, by relieving material constrictions, or by inventing new tools.

1.3.2 Photography

One of the arguably most disruptive inventions for graphic design was photography. Its significance seems to be only amplified with each new wave of technological progress, from digitalization to social media. With the rapid advancements of mobile photography and the involvement of A.I. in its success, questions of its social and psychological impacts need to be discussed.

With the technology available in everyone's pocket, the obsession in taking massive amounts of redundant photographs becomes more and more apparent. In her collection of essays On Photography, Susan Sontag explains this by a misguided feeling of appropriation of the world, "photography makes us feel that the world is more available than it really is." (Sontag, 2005, p. 18). Furthermore, she describes modern society as image-junkies. Vilém Flusser in his approach absents the psychological motivations of a person and talks about the camera as an apparatus that uses the photographer to take as many pictures possible, to improve itself “we are manipulated by photographs and programmed to act in a ritual fashion in the service of a feedback mechanism for the benefit of cameras” (Flusser, 2016, p. 64). The similarity of Flusser’s apparatus and contemporary neural networks is uncanny. Creating a photograph that is properly exposed and color balanced is no problem with the help of current A.I. software, predefined categories of scenes such as portrait, landscape or even a family Christmas photo guides the person taking the shot, and the only decision he needs to make is when to press the button.

In the last book published before his death, Roland Barthes discusses photography with a sentimental approach, as an attempt to deal with the death of his mother. He defines two concepts present when interpreting a photograph. *Studium* is the information anyone from our civilization would see while looking at it, including cultural and historical context. And *punctum* refers to a detail, that creates a deep personal connection with the scene or person on the image. While looking at old photographs of his mother, trying to find one that would bring a complete image of her into his mind, Barthes finally found that photo, containing punctum which made him remember her “For once, photography gave me a sentiment as certain as remembrance” (Barthes, 2010, p. 70). It could presumed that everyone has an experience with this sentimental power of photography that is unique and subjective, as Barthes says, “I cannot reproduce the Winter Garden Photograph. It exists only for me. For you, it would be nothing but an indifferent picture, one of the thousand manifestations of the ordinary” (Barthes, 2010, p. 73).

1.3.3 Conclusion

From the discussion in this chapter, the role of design as an enabler resonates. The human-centered approach introduced in chapter 1.2 becomes even more significant when the relationship with technology is considered. As advances in computation provide immense amounts of data and analytical power, an intuitive interface and data visualization takes on a crucial role. One could argue that the domestication of A.I. is the next big challenge in design. New technology provides new tools for the designer and new platforms to design for. In turn, the designer makes technology usable in everyday life. While discussing the impact of photography in our lives, a need for a genuine human connection and sentiment was discovered. If A.I. is capable of simulating even the most profound human sentiments will be discussed more in chapter 2.3, but first, the definition of graphic design for the intentions of this thesis will be continued by exploring the basic principles of graphic design.

1.4 Principles

To be able to evaluate A.I. tools that are available at the moment, we must first define basic principles and best practices of graphic design and design process as described in industry-standard guidebooks.

1.4.1 Research

Before a designer starts to work on a final design, which in this era means turning to the computer and graphic software, an even more essential part precedes. An indispensable part of a designer's job is to put the visual product in context with various interrelated systems of the world. "Software tools provide models of visual media, but they don't tell us what to make or what to say. It is the designers task to produce works that are relevant to living situations" (Lupton & Phillips, 2015, p. 11). As described in chapter 1.2.2 the designer needs to reach his target audience while fulfilling the requirements of the client. This means the designer should understand demography, cultural differences, and have a general overview about the society. Evoking an emotional response in the viewer renders him more receptive to the message that is being communicated. Knowledge of the principles of rhetorics, signs, and metaphors expands the designer's nonverbal vocabulary. Collecting ideas and impressions throughout daily experiences provides the designer with an irreplaceable collection to refer to when working on a specific project. "Reading only about graphic design can be particularly dangerous" (Dabner & Swann, 2013, p. 11). Having a broad spectrum of interests is one of the necessities of a good designer.

RESEARCH TECHNIQUES

	Factual research	Visual research
Primary sources	Observation, interviews, questionnaires, focus groups	Photography, sketching, experimentation
Secondary sources	Articles, surveys, statistics, lectures	Exhibitions, magazines, work of other designers, films

Table 1: Research techniques

Research techniques can be divided into four categories. Factual research enables the designer to familiarize himself with the target audience, the product, or the company he designs for and its competitors. Visual research explores the mood and visual rhetoric relevant to the project. Both factual and visual research can be further divided by the type of used sources to primary and secondary research. Research of secondary sources is an exploration of preexisting materials. Primary sources are created as entirely new materials. Examples of primary factual research can be focus groups and observation. Secondary factual research is searching for and learning from already existing statistics and published articles. Primary visual research consists mainly of sketching and experimentation, and secondary visual research looks for inspiration in relevant works of other designers or exhibitions (Dabner & Swann, 2013).

1.4.2 Concept generation

Concept generation is the part of the design process connecting the research with final design work. It's goal is exploring possibilities and generating ideas. As flexibility and rapid development are crucial, one of the main tools for concept generation is sketching. "Temptation to turn directly to the computer precludes deeper levels of research and ideation" (Lupton & Phillips, 2015, p. 14). Sketching enables multiple iterations of ideas, allowing them to dig deeper into the visual rhetoric and exhausting the obvious solutions leading to original designs. The rugged nature of a sketch serves as a focus lens for the bearing idea, enabling the designer to present it within the team or to the client. When generated on a computer, sketches tend to evoke the final product and steer the conversation to details and polishing, making the discussion ineffective. Lateral thinking plays a large part in concept generation, brainstorming random associations unlocks new possibilities and ideas (Dabner & Swann, 2013).

Various studies covering the creative process behind sketching have been carried out, and their findings will be summarized. Trough an experiment designed to compare digital and analog tools for the ideation phase of the design process, the authors found that digital tools negatively affect the designer's ability to elaborate on creative ideas. "It would appear that whilst not causing reinterpretation, paper-based sketches, more than digital tools, can support the vital process of reinterpretation that generates new ideas." (Stones & Cassidy, 2010, p. 439). The previous study from the same researchers showed that in the specific task of working with typography, digital tools limit the designer's creative efforts. "The results suggest that not only was paper-based sketching more effective in producing more solutions than digital working but was also more effective in supporting one particular synthesis strategy." (Stones & Cassidy, 2007, p. 59). Another research conducted an experiment to review the problem-solving process graphic designers implement in their work. A strategy of subdivision into smaller manageable objectives was observed as well as an implementation of digital and analog tools for both routine and creative tasks. "creative tasks include gathering information, identifying constraints of the problem, understanding the requirements of design problem, sketching, and generating idea solutions." (Tan & Melles, 2010, p. 475).

While being irreplaceable in the design process, research and concept generation tends to be skipped or ignored by many designers. Reasons might lie in saving time (and money) or an inclination to start working directly on a computer where the designer automatically tends to limit his ideas to those he knows how to execute in the digital environment efficiently.

1.4.3 Composition

Composition is the visual structure of the design, the organization of different elements used. Its primary role is to guide the viewer, creating hierarchy, and emphasizing important information. The first mathematical formula used since ancient Rome, describing how to create a visually pleasing and engaging composition, is called the golden ratio. The Fibonacci sequence defines each number as the sum of the two preceding ones. This sequence can be used to describe the golden ratio mathematically. With the avant-garde movement came a more expressive approach to composition, described by Henri Matisse as the art of arranging elements to express feelings (Dabner & Swann, 2013).

Basic principles that can be used to compose elements are balance, consistency, contrast, proximity, repetition, and white-space. Symmetrical compositions use mirroring of elements, which evokes harmony and stability. Asymmetrical compositions are perceived more dynamically (Dabner & Swann, 2013). Deciding what type of composition to use requires, besides comprehensive research of the target group, defining the right tonality for each client, and a knowledge of the psychological theory behind visual perception.

Gestalt psychology suggests that the human brain actively analyzes and combines input from all senses and implements past experiences to create the resulting perception. This holistic character of perception leads to a grouping of separate elements to indicate related function and the creation of patterns, even where no prearranged pattern exists (Lupton & Phillips, 2015). Identification of figure (the main object) and ground (background, environment) is also done automatically by the brain and can be utilized to create interesting compositions. The mind's ability to see objects even from suggestions of incomplete shapes is called closure and is also used in graphic design. Textures can evoke the touching sensation, photography a specific scent (Dabner & Swann, 2013).

The point, line, and their interactions are the basic building blocks of design. While their use is tied to the printing technology, techniques developed for the physical environment remain heavily in use even in digital space. Groups of points can be used to create patterns, or to depict shadows and suggest volume. Interaction of lines can be used to express data visually in graphs and diagrams or to evoke motion and establish visual hierarchy (Lupton & Phillips, 2015).

To present content coherently, especially in a multipage publication, graphic designers rely on the grid. Grid is a pre-made structure that provides underlying rules which separate the blank area into columns and margins. It offers a starting point to the designer to create varied compositions with visual coherence across a series of pages. An understanding of the content and its significance is a necessary prerequisite. Presenting the material hierarchically, distilling information, allowing skimmed reading, and emphasizing essential elements enables the viewer to make sense of the content. Using the principles of composition with the help of an underpinning grid helps the designer control the pace and rhythm of presented content, creating focal points that carry the viewer's eye through the design and using variation that helps maintain his interest. An overall plan from a macro perspective is necessary while designing more extensive publications. Alongside the viewer, client, and content, understanding the medium and format influences design decisions (Dabner & Swann, 2013; Lupton & Phillips, 2015).

The environment and manner of consumption of design are one of the defining variables. Magazines are read in an entirely different way than books, and with digital content, the variety of screens and the short time available to persuade the viewer, pose a challenge for visual communication. Packaging of products considers the retail experience where it's competing with other goods. A different approach is taken when designing a billboard ad or a business card (Lupton & Phillips, 2015).

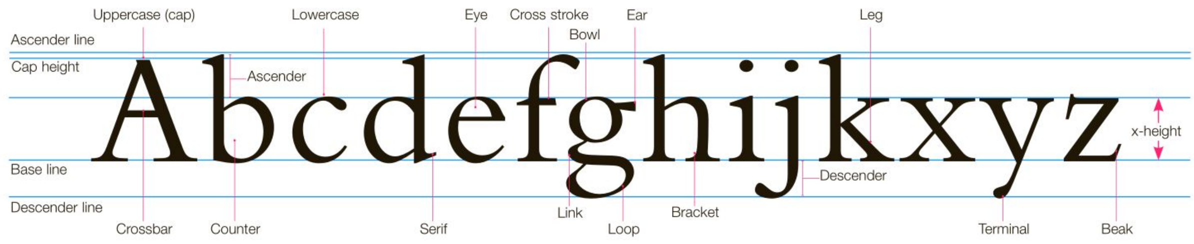
Mathematical rules for composition or for creating a grid are an indispensable tool. However, a comprehensive understanding of the content, knowledge of the real-world environment in which the design will be used, and the psychology behind human perception are necessary to create an effective composition.

1.4.4 Typography

Typography is arguably the part of graphic design with the longest historical tradition of standardization, rules, and best practices. It concerns itself with arranging type - written language, clearly and appealingly. From clerics in middle ages copying scriptures by hand to the invention of the press, typography followed guidelines to provide the reader with legible publications. For that reason exploring the whole system of typographical laws is outside the scope of this thesis, and only the terms and concepts essential for later discussion will be defined.

Typography has a close connection with language. The linguistic meaning of the content that is being presented is the overall defining element (Dabner & Swann, 2013). Typography can be defined as idealized writing. The imperfections of the handwritten type are unified and polished. On the other hand, the typographer's job is to convey the author's voice and the tone of the message of the content (Bringhurst, 2004).

Typeface is the basic building block of typography. It is a collection of letters, usually the whole alphabet plus special characters, designed to share visual attributes. Each typeface can be defined by 25 characteristics of its anatomy, which allows them to be measurable and categorizable. The font is a specific size, weight, and style of a typeface. Some of the



essential characteristics of a typeface are serifs and x-height (Image 1).

Image 1: Anatomy of type (source: Dabner & Swann, 2013)

Typefaces with serifs were used historically in carving and then print. Serifs are referring to the small extra strokes on the end of the defining lines of a letter. Sans-serif typefaces are more geometrical and offer a wider variety of weights and styles within the typeface. Generally, the sans-serif typefaces are used in more expressive use-cases, such as headlines and posters. On the other hand, the serif typefaces for a longer body of text, for example, in books. X-height defines the vertical height of the typeface, the height of a letter "x". Since the creation of new typefaces moved to the digital environment, its number has been growing exponentially. The ability to search and categorize them is indispensable. When selecting an appropriate typeface for design, the subject matter, and the author's style must be considered. Different languages and alphabets work better with different types of typefaces. The medium in which the design will be presented and the length of individual segments of the copy require different considerations (Dabner & Swann, 2013).

Letter spacing (kerning), word spacing, and line-height (leading) affect the text's legibility. Basic rules can be expressed mathematically, but optical adjustments are necessary. "There is no automated function on any computer that can replace the keen eye of an experienced designer" (Dabner & Swann, 2013, p. 72). The reader tends to perceive the shape of the words, a large body of text creates textures that evoke certain emotions in the viewer, and its effect needs to be considered. The psychology of this holistic tendency of human perception was discussed in the previous chapter. The columns of text can be justified to create visually pleasing elements or left with ragged ends. With justification, word break and hyphenation are usually necessary to prevent the optical rivers of excessive space between words. Widows and orphans are single words of a paragraph left at the end or beginning of a column of text and need to be avoided for legibility and continuation. The ideal number of characters per line has been standardized to 60-72, depending on the size of the typeface (Bringhurst, 2004; Dabner & Swann, 2013).

The proportions of a page or different intervals of size between levels of headlines can be derived from various mathematical systems. Musical intervals, intervals present in nature, such as the golden ratio and many others, but precise calculations are not the ultimate purpose (Bringhurst, 2004). Many typographic rules can be calculated and automatized, but the final optical corrections are always superior and made by hand.

1.4.5 Color

Color can evoke a particular emotion or mood, describe reality, or codify information. It creates relationships between elements, connecting or differentiating them, hiding or highlighting one in favor of the other, creating a hierarchy. Although graphic design was throughout one of its defining periods, only black and white, color plays a fundamental part of human psychology in visual perception (Lupton & Phillips, 2015). Associations that color can evoke are rooted in nature (green evokes nature, red blood, blue evokes the sky or large body of water). The cultural connotations of colors evolve historically and differ across the world (Dabner & Swann, 2013).

The physical nature of color and light was discovered by Isaac Newton with his invention of the prism, that deconstructs light into its spectral colors. The color wheel (Image 2), an essential tool of color theory, is based on this discovery. It depicts basic colors and the relationships between them. The primary colors are red, blue, and yellow. Secondary colors are created by mixing two of the primary colors, tertiary colors, by further mixing primary and secondary colors. Based on a color's position on the wheel, its analogous or contrasting (complementary) color can be easily picked (Lupton & Phillips, 2015; Dabner & Swann, 2013).

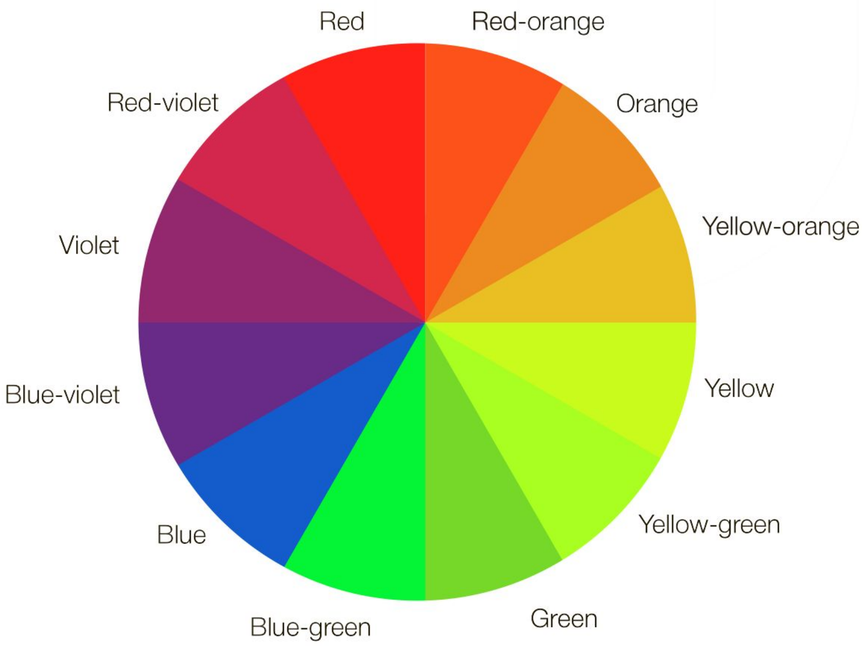


Image 2: Color wheel (source: Dabner & Swann, 2013)

Color can be defined by three characteristics: hue, tone, and saturation. Hue is the generic name of the color that differentiates it from others. The color wheel, for example, depicts different color hues. Tone describes the relative lightness or darkness of the color. Saturation defines the intensity and whether it seems bright or dull (Dabner & Swann, 2013). To be able to describe the colors, different models were created. The two most prominent are RGB and CMYK. RGB is an additive model used for graphics that are presented on the screen. The screen composes the resulting color using the combinations of red, green, and blue light of varying intensity. CMYK is a subtractive color model used in print. Printers use cyan, magenta, yellow, and black ink dots to create the image (Lupton & Phillips, 2015).

The effects of the color on the viewer differ based on the context. Lighting and viewing conditions, the texture and background of used material and also size and shape of the object affect the resulting perception. Relative to other design elements, color can create harmony or contrast, which should be carefully managed to reinforce the intended message and hierarchy (Dabner & Swann, 2013).

In contrast to a painter, the designer usually creates a color palette, a swatch of colors used across the entire project. These are carefully selected to work together in a visually pleasing way while being distinctive and following rules for accessibility (Lupton & Phillips, 2015). Using a defined group of colors is indispensable for the color-coding of information. Color is one of the first visual characteristics that the human brain perceives and guides the eye through elaborate systems of data, or physical spaces such as airports or hospitals (Dabner & Swann, 2013).

1.4.6 Conclusion

While defining the basic principles of graphic design, a duality of systematic mathematical rules on one side and psychology, emotions and perception on the other, was discovered. The golden ratio, rule of thirds, and grid guide composition of elements, but a deep understanding of the content, target group, and medium leads to an effective design composition. Rigorous rules of typography are polished by the final optical touches of a designer, and socio-cultural connotations expand the physical nature of lights wavelengths in different parts of the world.

2. Artificial intelligence

In this chapter, I will discuss the formation of the field of A.I., its current developments, and the underlying principles to provide a basis for the evaluation of potential tools for graphic designers.

2.1 Formation

The founders of the field of A.I. research in the 1950s-60s had a goal to teach a machine to perform a range of cognitive tasks, effectively simulating a single human mind. Besides solving mathematical tasks, they envisioned a machine that would understand images, written and spoken language, and react to them accordingly (Manovich, 2018).

2.1.1 Thinking machines

The term “artificial intelligence” was first used by John McCarthy, one of the pioneers in A.I. He defines it as a “science and engineering of making intelligent machines” (McCarthy, 2007, p. 1). Alan Turing, the founder of theoretical computer science, proposed a test to answer whether machines can think. The Imitation game is a theoretical scenario where a machine tries to convince a person that it is, in fact, a human. Without any physical evidence, solely based on communication, the person can ask questions, and the machine tries to simulate a human response (Turing, 1950). Simulating human intelligence was, in the beginning, the primary goal of A.I. researchers, achieving “automation of cognition” (Manovich, 2018, p. 2). McCarthy argues that since some of the mechanisms of human intelligence are yet to be described, achieving what is called an Artificial General Intelligence (AGI) is currently impossible. AGIs goal is to understand and learn any cognitive task that a human being can do. Currently, versions of Artificial Narrow Intelligence (ANI) are being implemented and used. ANIs are capable of performing only a specific, defined task. McCarthy suggests that implementing cognitive mechanisms in A.I. is not limited to simulating mechanisms present in humans or animals. Creating non-biological cognitive mechanisms is part of engineering an A.I. since studying problem-solving, not the human brain, is usually the starting point when developing an A.I. McCarthy argues that the limiting factor is not computational power, but the understanding and programming of cognitive mechanisms (McCarthy, 2007).

2.1.2 Computational power

Since Charles Babbage proposed a mechanical programmable machine plan, which he called the Analytical Engine, the idea of an all-purpose computational device is dominantly considered an ideal platform for achieving artificial intelligence. Alan Turing suggests that digital computers are capable of simulating any computational machine and, therefore, can act as universal machines, and the primary considerations left are their computational capacity and programming (Turing, 1950). Since the invention of first digital computers, the combined computational power of the world's digital devices has grown decisively. A study by Martin Hilbert and Priscila López suggests that besides the exponential increase of processing speed and storage space offered by electronic devices, digitizing information played a significant role. "While only 25% of the information flow of broadcast networks had been digitized in 2007, the digitization of storage and telecom is almost complete (94% and 99.9% digital in 2007, respectively)" (Hilbert & López, 2012, p. 958). Recently GPUs (Graphics processing unit), used initially as a specialized part of a personal computer to render graphics, thanks to their parallel structure, provide more effective computation for a range of complex algorithms (Hilbert & López, 2012). GPUs are presently being widely used for A.I. based computations to give an example: NVIDIA, a company specialized in the development and production of graphic cards, now provides the computational platform for the Tesla autopilot feature (Csongor, 2019).

The concept of quantum computing promises an even more radical jump in the computational capacity of digital computers. While not going to the complicated physics concepts of quantum mechanics, quantum computing can be explained in contrast to conventional computing by comparing bits and qubits. Bits are the primary logical unit of conventional transistors. They can have either a value of 0 or 1. Qubits, in contrast, can acquire a value of 0, 1, both, or any value in between simultaneously. This ability to work in parallel would make it millions of times faster (Woodford, 2019). As seen with the GPUs, parallel computation is a crucial prerequisite for A.I. Ray Kurzweil, in his book "Singularity is Near," explores to what ends could the exponential developments in computation lead. He proposes a time frame in which the non-biological intelligence will reach the level of human intelligence. He identifies this moment as the “Singularity” and further suggests that after reaching the same level, A.I. will necessarily continue outpacing the human ability of cognition (Kurzweil, 2005).

2.1.3 Programming

With the universal platform of a digital computer and promises of exponential growth in its computational power, the last part remaining to be solved is the programming of the A.I. Turing proposes a concept of a "child machine," a computer programmed only with an ability to learn from experience and edit its code accordingly. He identifies two distinct problems in this approach: the programming of the initial state and learning mechanisms, and the educational process. Turing argues that unlike a human child, the machine has limited input since it lacks a physical body. Furthermore, concepts of motivation and an ability to set goals independently would pose a severe challenge (Turing, 1950). More recently, a concept of recursive self-improvement expands on Turing's premise. It proposes a software that rewrites and improves its programming in repeating cycles. Self-written A.I. suggests a possibility of superintelligence, A.I., that would be able to develop its own intentions and consciousness, surpassing rapidly human cognition. Without humans understanding its inner workings (Spacey, 2016).

2.2 Current state

The original quest for an AGI, a machine that would be able to perform a range of tasks similar to humans, has not yet come to fruition. With the increased digitization of information and computational capabilities, A.I. instead became a simulation of many minds working on a specific task, what Manovich calls “super-cognition” (Manovich, 2018).

2.2.1 Big data

Big data is a term loosely defined. It is mainly used for the type of data that requires a supercomputer. However, what is considered a supercomputer is evolving every year.

Instead, the networked nature of the data, interconnections, and relationships is what makes them big. The ability to gather, store, and interpret large interconnected datasets leads to a new way of doing research generally. It provides a tool that might redefine the meaning of learning (Boyd & Crawford, 2011).

Approach to A.I. since its beginning as a field of research was to write large amounts of code that would serve as its guiding rules. This top-down perspective is also described as “symbolic A.I.” because it is based on symbolic logic. For example, a translation tool would be programmed with all the grammatical rules of a given language and its vocabulary and then provided with the logic to translate between languages (Lewis-Kraus, 2016).

Marcus Du Sautoy, Professor of Mathematics at Oxford, in his book “The Creativity Code,” describes how big data changed the course of A.I. development “the flood of data is the main catalyst for the new age of machine learning” (Du Sautoy, 2019, p. 67).

2.2.2 Machine learning

Principles of machine learning are inspired by the structure of the human brain and existed since the 1950s. The concept of the perceptron, an artificial neuron, takes various inputs, weights them, and if the calculation passes a given threshold, it fires a signal to another perceptron (Du Sautoy, 2019). Layers of interconnected perceptrons are what is referred to as a neural network.

While processing data, each time the network makes a mistake, it updates the weights on each connection between the artificial neurons (Spacey, 2016). Based on the number of layers of a neural network, it can detect more complex patterns. These more complex networks are referred to as deep neural networks (Lewis-Kraus, 2016). Machine learning is driven by a meta-algorithm that guides its learning process, builds up layers of questions and corrects thresholds of individual artificial neurons and the weights of connections between them based on the data it encounters. Big data provided the learning space for neural networks to become effective (Du Sautoy, 2019).

The notion of data being objective and representative of truth can be considered misleading. The reliability of its source needs to be considered, and the interpretation of data is subjected to biases and blind spots (Boyd & Crawford, 2011). Since the human brain is not well equipped to assign a probability, evaluating the effectivity of a machine-learned

A.I. that acts as a black box, without its reasoning being known to the human, is based mostly on belief. Ability to accurately assign probability is developed over many experiments. The A.I. has the advantage of a much higher interaction rate with the data (Du Sautoy, 2019). The training data consist of labeled content, prepared by a human, A.I. develops an ability to assign a probability that a particular content meets a condition, which is then compared to the assigned label. Throughout many trials and errors, slowly, the A.I. learns how to predict correct labels even for content that it has not seen before. This process is called supervised learning. It relies heavily on the complexity of the labeled training data provided by a human (Lewis-Kraus, 2016).

However, these datasets, provided to the A.I., can contain certain blind spots that lead the A.I. to develop a sense of causation when there is only correlation. To give an example: the U.S. military inquired an A.I. capable of detecting tanks in images. The development team created a large dataset of pictures with a tank in various situations and angles and then created another dataset of reference images without the tank in them. They failed to realize that the pictures with the tank were taken on a cloudy day and the reference images on a clear day. The resulting A.I. learned to differentiate the weather, not the presence of a tank (Du Sautoy, 2019). To overcome the possibility of biases and blind spots in the datasets provided to train the A.I. another approach was developed.

2.2.3 Deep learning

To avoid the necessity and possible dangers of human-labeled data when dealing with broader problems that cannot be easily defined, unsupervised learning can be implemented. Given significant enough dataset and processing power and time, the A.I. can learn to identify patterns and their associations on countless objects. An example of unsupervised learning is clustering when the input data is sorted into clusters with similar properties. Another approach is reinforcement learning, which involves feedback from the environment that serves as a teaching mechanism for the A.I. (Joshi, 2020).

Deep learning differs from traditional machine learning in its ability to learn directly from raw data without hand-coded labels or other human-provided knowledge (NVIDIA, n.d.). Multilayer architecture of a neural network is necessary for a multistep analysis of the input data. Identifying the factors of variation that can lead to a conclusion about the content is processed in multiple steps, starting with discovering simple concepts and building more complex ones from them. “Deep learning achieves great power and flexibility by representing the world as a nested hierarchy of concepts, with each concept defined in relation to simpler concepts, and more abstract representations computed in terms of less abstract ones” (Goodfellow, Bengio & Courville, 2016, p. 8). Other A.I. can provide the datasets used to train. Multiple A.I.s can serve as an input source or an evaluator. An elaborate architecture of specialized A.I.s can coordinate together. (Spacey, 2016).

2.2.4 Computer vision

Since graphic design is a predominantly visual field, computer vision, and a computer’s ability to process images will be discussed separately.

Simon Prince, professor at University College London dedicated to the research of machine vision and image processing, defines computer vision as an ability to “extract useful information from images” (Prince, 2012, p. 20). He recognizes the complexity of visual data in the fact that there are hundreds of distinct objects in real-world scenarios, but usually, none of them is in a “typical” situation and fully visible. Even recognizing the borders between objects is not an easy task for a computer (Prince, 2012).

Most of the research in computer vision is devoted to simulating human abilities. “Most deep learning for computer vision is used for object recognition or detection of some form, whether this means reporting which object is present in an image, annotating an image with bounding boxes around each object, transcribing a sequence of symbols from an image, or labeling each pixel in an image with the identity of the object it belongs to.” (Goodfellow, Bengio & Courville, 2016, p. 448). Even these relatively small advances in comparison to the expectation of the early AI researchers have an impact on real-world use such as “digital photography, visual effects, medical imaging, safety and surveillance, and Web-based search” (Szeliski, 2011, p. 733).

Understanding the visual content has seen its most significant advances for an average user in photography. Automatically retouching photos, categorizing them, or even synthesized artificial images is available to the general public. “Within ten years, you won’t need a camera to make an image, software will be able to synthesize a photo by working from a list of descriptive terms.” (Lyndersay, 2018) said in a 2018 interview Alex Savsunenko CEO of Skylum software, a company focused on creating AI-driven photo editing software. The first significant tool leveraging computer vision released publicly was Google Photos. This allowed users to automatically search and categorize their photos by recognizing objects and faces in images and using geolocation. (The Verge, 2019)

From passively gaining knowledge from visual data is still a long way to synthesize life-like photographs. The next big step was made with GANs (Generative Adversarial Networks), which use two competing neural networks, leveraging the advantages of deep learning, as described in the previous chapter. While one is trained to recognize for example cats in real images, the other is trying to create fake images of cats and then past them to the first neural network for evaluation (Beckett, 2017). NVIDIA released in March 2019 a new tool that can turn very simple doodles into photorealistic landscapes (Image 3). "It's like a coloring book picture that describes where a tree is, where the sun is, where the sky is. And then the neural network is able to fill in all of the detail and texture, and the reflections, shadows and colors, based on what it has learned about real images." as Bryan Catanzaro, vice president of applied deep learning research at NVIDIA, described their new application (Salian, 2019).

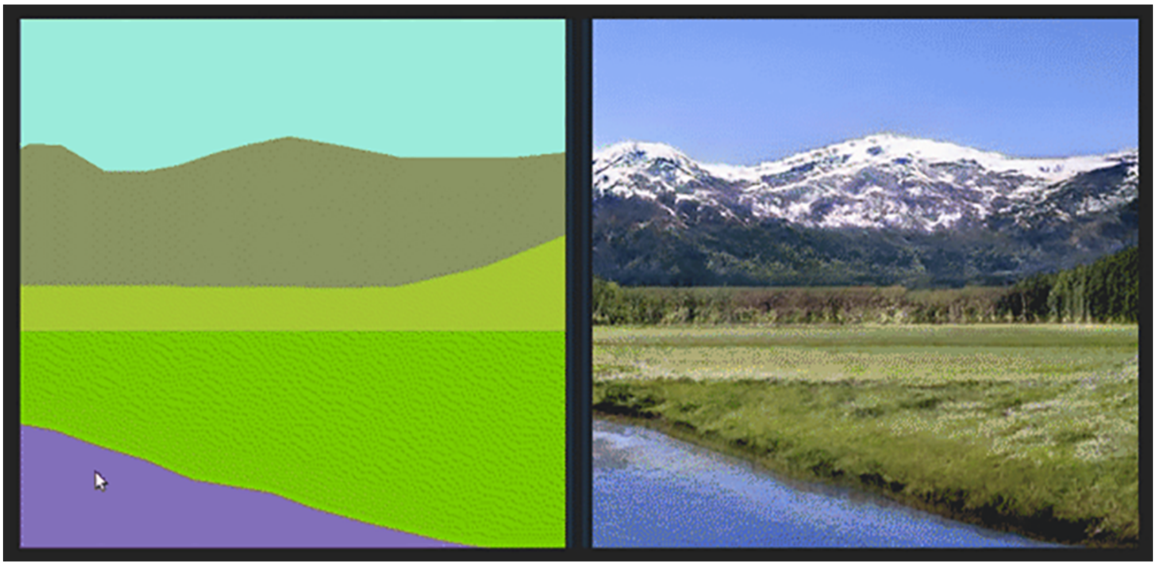


Image 3: NVIDIA GauGAN

(source: https://www.nvidia.com/en-us/research/ai-playground/)

2.2.5 Applications

Besides computer vision, A.I. already has many real-world applications, those that could be relevant for graphic design, based on the discussion in chapter 1.4, will be briefly summarized.

Natural language processing is another example of an ability that concerned A.I. researchers since the beginnings of the field and was made possible with the bottom-up approach, training the A.I. from large datasets. Machine translation and speech recognition are among the most prominent achievements in this field, now widely available for public use in devices such as mobile phones (Goodfellow, Bengio & Courville, 2016). The ability to understand and formulate natural language responses is the basis for chatbots and virtual assistants such as Alexa, Siri, Cortana, or Google Home. Providing a more natural way of interacting with the computer can increase effectiveness and customer satisfaction (Wilson & Daugherty, 2019).

Affective computing is the computer's ability to decode emotion and sentiment from language, tone of voice, or facial expressions. It is currently being used in market research or political polling. Concerns of privacy and misuse of such insights are a topic of discussion in its implementations. Besides further expanding the quality of human-computer interactions, affective computing is being used as a therapeutic tool, for example, for treating PTSD. Monitoring exhibitions of stress or anger can serve as a warning tool for the user, helping them avoid making decisions in affect, such as stock trading or while driving (Kleber, 2019).

Personalization and recommendation systems can provide users with tailored experiences, predicting associations between a user and an item. "Examples include selecting posts to display on social network news feeds, recommending movies to watch, recommending jokes, recommending advice from experts, matching players for video games, or matching people in dating services." (Goodfellow, Bengio & Courville, 2016, p. 473).

2.3 Aesthetics

Discussions on computer aesthetics and whether it is capable of being creative are, in its extent, and philosophical nature outside the scope and interest of this thesis. As was established in chapter 1.2 graphic design does not share these concerns with the art. However, the ability of computers to be creative will be explored, as the design process involves imagination and new ideas.

2.3.1 Creativity

Margaret Boden, a cognitive scientist in her book "The Creative Mind," defines creativity as "the ability to come up with ideas or artefacts that are new, surprising and valuable" (Boden, 2004, p. 1). She suggests that creativity influences all parts of our life, even those more mundane. Expanding the property of novelty, she defines two types of creativity in this aspect: P-creativity and H-creativity. P-creativity stands for personal, something that is a new idea personally, but albeit without the knowledge of the author, someone had already thought of it before. H-creativity is an idea or artifact that is objectively, historically unique, and new. The surprise attribute of creativity stands for something unexpected and not obvious. She defines three ways in which this surprising factor can occur.

The most basic one is trough combinational creativity, which, based on knowledge of existing ideas or artifacts, trough combinations of the familiar achieves something unfamiliar. Creativity, through the exploration of new ideas within a conceptual space, a structured style or manner of thought, is the successive level of combinational creativity. Conceptual space can include forms such as a specific culture, genre of music, and poetry style. Within these given boundaries, new ideas are created, which can further reveal the limits and potential of the given conceptual space. The highest form of creative surprise can be, according to Boden, defined as transformational creativity. It is creating something previously unthinkable, outside the conceptual space. Boden suggests, as well as the discussion in chapter 2.2, that all three levels of creativity can now be achieved by artificial intelligence. The third aspect, the value of creative ideas, is what Boden identifies as the part that can be unique to human creativity. It is hard to define, given the perceived value of an idea can change in time or be subjected to individual opinions (Boden, 2004).

The computer-generated creative ideas lack in comparison to human creative endeavors in three aspects: evaluation, elaboration, and communication. Humans evaluate A.I. output. Whether the idea is worth attention or not, is decided by the programmer. Elaboration and inspiration to further explore a new idea are not present in A.I., unlike humans, its creative process is definite, producing finite, separate works. Communication and argumentation, reacting to the feedback of the creative community or audience, is an inseparable part of the human creative process. “Artificial creators are weakest when it comes to the social dimensions of creativity” (Sawyer, 2012, p. 110). Many fields that involve visual creativity are highly collaborative. The ability to communicate ideas and defend them is necessary; for example, in the movie industry (Sawyer, 2012). As chapter 1.2 suggests, graphic design is also such a highly collaborative field.

2.3.2 Cultural A.I.

Lev Manovich suggests that the current implementations of A.I. tools are influencing our notions on what is aesthetic. Namely, suggestion and recommendation based platforms, described in chapter 2.2.5, such as Instagram or Spotify, can lead to a flattening of creative diversity. Photography is the most prominent example with software already widely used that enables users to perform automatic adjustments, filters, cropping, and selection. He proposes a taxonomy to describe cultural A.I. tools into four categories:

1. Selecting content from more extensive collections. Which involves recommendations, curation, searching, and filtering of content.
2. Targeting content. For example, tailored advertisements and market segmentation.
3. Assistance in the creation or editing of content.
4. Fully autonomous creation.

Manovich identifies several influences that can acquire opposing tendencies. The diversity of global aesthetics can be simultaneously enriched by the gradual expansion of internet users in developing countries and their cultures, while the influence of already established global trends can diminish their unique local aesthetics. Recommendation systems can either show the user the most popular content or enrich their experiences by selecting items he would most likely not find, based on his current behavior and taste. Manovich proposes that A.I. could, besides providing useful tools, also serve to appreciate and explore the global cultural diversity fully, which was for centuries inevitably simplified by forcing categorization and genres. In his view, cultural analytics could use unsupervised learning (see 2.2.3), avoid omitting information about cultural artifacts, map, and understand them in full global diversity. He sees the role of A.I. as a tool expanding human creative abilities “Human experts usually make the final decisions or do actual production based on ideas and media generated by A.I.” (Manovich, 2018, p.8).

3. Tools

By exploring the goals, best practices, and basic principles of graphic design in chapter 1, and the concepts and current abilities of artificial intelligence in chapter 2, I have defined the demands and the potential of AI-driven tools for graphic design. This chapter will explore such tools that are currently available to the general public as well as experiments and research. An attempt to evaluate their benefits for designers utilizing the previous theoretical findings will be made. The aim is to provide a representative and diverse sample, not to create an all-inclusive list.

3.1 History

Automatization was historically quickly adopted in print, which is arguably a predecessor of modern graphic design. The first revolution in book publishing came with letterpress, a famous invention of Johannes Gutenberg that allowed mass production of affordable publications. Driven by rising demand for books that became accessible to a broader audience, printers adopted and invented new technologies such as linotype, which provided an even quicker method for preparing printing templates. A move from a mechanical approach to chemical-based printing templates leads to an invention of offset printing, which allowed, for example, the mass adoption of newspapers. Each new technology, while being more productive, required fewer people to operate it. But a rising production of printed works balanced the perishing occupations, and people working in those positions often became operators of the new technology (Cope & Kalantzis, 2001).

The digital revolution affected the field of graphic design on a professional level but also created an entirely new amateur level of home production of graphic materials. With the introduction of Macintosh and graphical user interface to the general public also came new software for printers called Postscript. It allowed the creation of a new field - Desktop publishing (DTP). Preparing, editing and arranging all materials, which are used to create a publication, could be done by a single person using the DTP software (Lysakowski, 2017).

Arguably the most prominent software tool used by graphic designers is Adobe Photoshop. First released in 1990 for Macintosh, Photoshop gradually added new features and became available for more platforms, recently a full version of Photoshop was released for iPad tablets. The first versions of Photoshop included processes for replicating photographic effects on digital images. Ability to further enhance available tools trough plugins was present from early versions of Photoshop. Throughout its development, various new features were introduced. Support for vector graphics, layers, macros, editing history, export for web and color management was already present in the 2002 version 7.0 (Image 4) (WDD, 2010).

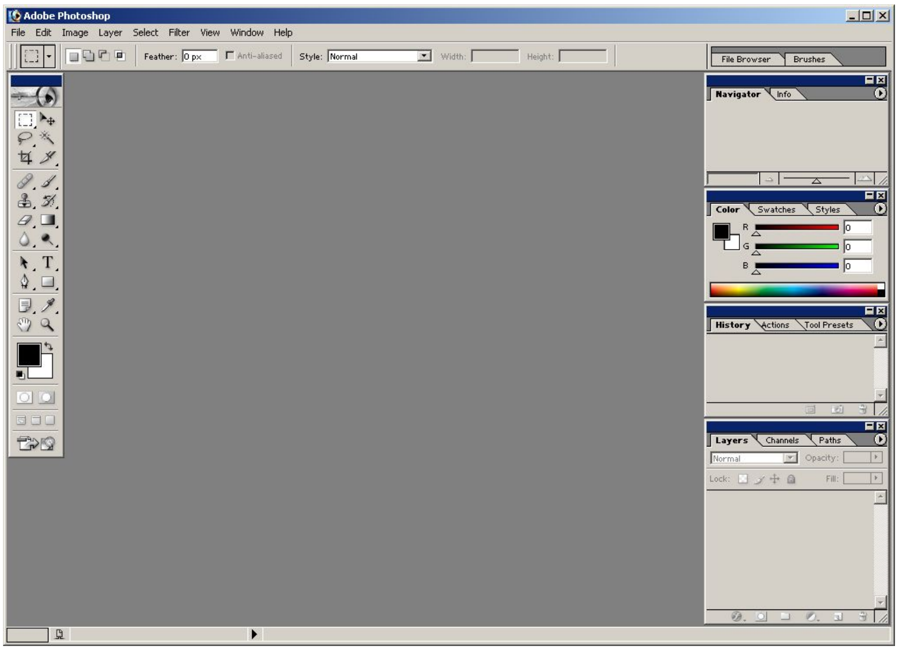


Image 4: Empty workspace in Adobe Photoshop 7.0
(source: https://guidebookgallery.org/apps/photoshop/empty)

Lev Manovich proposes a classification of the available tools in Photoshop, but in all media software in general. The first distinction is whether the tool can work with all data types (such as text, vector graphics, 3D model, and raster graphics) or only with one specific type. An example of a non-specific tool is the cut, copy, paste operation. The second classification is based on whether the tool simulates an analog predecessor (such as paintbrush or typing) or is a digital-only tool that does not have an equivalent in the physical world. The first type usually requires some manual control from the user. The second type provides a higher level of automation. According to Manovich, these are all of the procedural or generative techniques and tools. They do not manipulate the media content as such but operate on the digital data representations. Manovich suggests that all elements of digital media processing are influenced by "…media and cultural practices, on the one hand, and software development, on the other" (Manovich, 2011).

Although graphic editing software is not limited to Adobe Photoshop, notably, the first version of an open-source alternative GIMP was released in 1996 (Gimp.org), Adobe remains the dominant software for media authoring and editing. Adobe launched a new AI-driven platform Sensei that integrates into many of its products various automatization tools previously unachievable by standard algorithms. These and other AI-driven tools and research experiments will be explored and described in the next chapter to outline and evaluate the current AI tools for graphic design.

3.2 A.I. driven tools

3.2.1 Research

In chapter 1.4.1 I have differentiated between factual and visual research. The most relevant type of research to explore in the context of AI-driven tools for graphic design is the visual research and primarily the research of secondary sources. Arguably the three most used platforms for discovering such visual sources are Dribble, Behance, and Pinterest. Behance, as of 2018, had over 10 million (Zicari, 2018) active users, graphic designers, illustrators and other visual artists or people interested in their works.

Behance uses personalization and recommendations based on machine learning. "Your Daily Recommendations is populated using machine learning and is based on the projects you view and appreciate." (Behance Help, 2019). Dribble, which had in the first half of 2020 on average 13 million visits per month (SimilarWeb, 2020), is another platform for graphic designers and visual artists. For example, it uses algorithms that extract a color palette from uploaded images to allow searching by preferred colors (Dribble.com, 2020). Pinterest implements machine learning to provide users with more tailored search results and recommendations. The goal of these improvements is to increase user engagement by providing personalized feeds (Pinterest Engineering, 2015; 2017).

As Manovich suggests (see chapter 2.3.2), recommendation systems that adapt to user tastes can lead to a flattening of creative diversity, arguably not the desired effect for graphic designers. On the other hand, the implementation of computer vision to extract useful meta information from uploaded images, such as its color palette, identifying contained objects, and automatically tagging it accordingly, can improve the designer's research process. For example, Shutterstock, a platform providing stock images, created an AI-based tool that enables searching images not only by objects they contain but also by their composition in the photograph (Image 5).

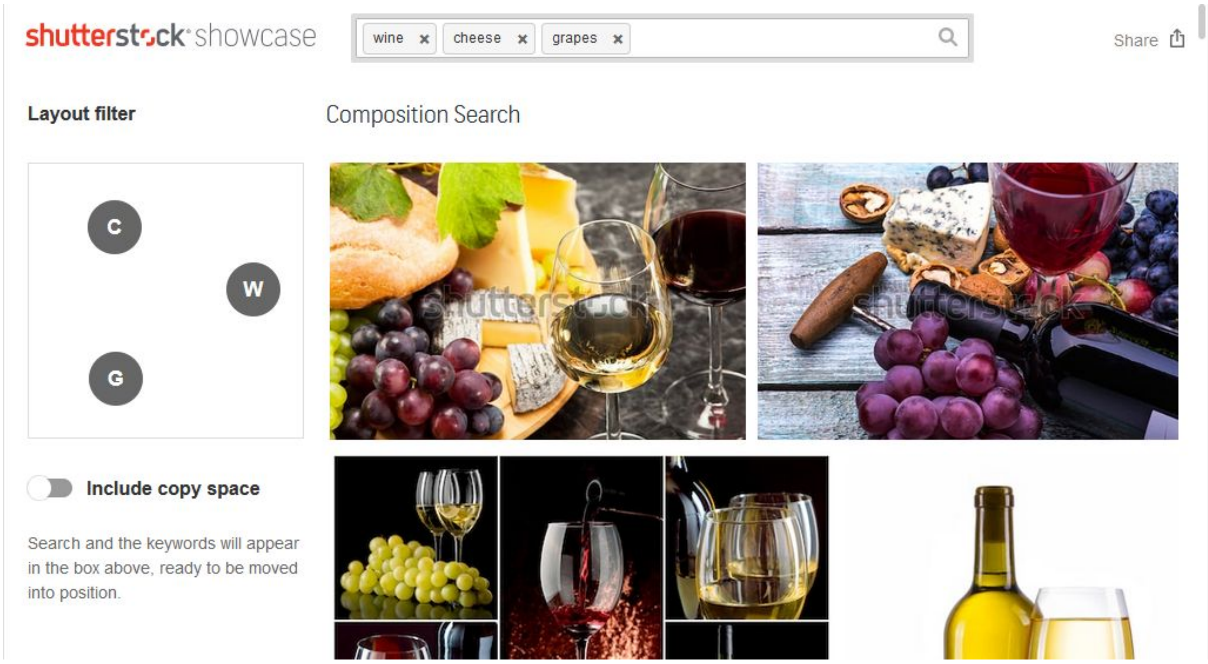


Image 5: Shutterstock Composition Search
(source: https://www.shutterstock.com/showcase/compositionsearch)

3.2.2 Typography

As was discussed in chapter 1.4.4 digitalization lead to an exponential growth in available typefaces. For example, the Google Fonts service, which provides free typefaces for web use, currently hosts almost a thousand different typefaces (Google Fonts, 2020). Some non-AI approaches like curated lists of font pairings and recommendations were created to help designers select from the wide variety of fonts available. These projects were created both by independent designers (e.g., Typewolf.com) and graphic software companies Canva [1] and Adobe[2].

[1] https://www.canva.com/learn/the-ultimate-guide-to-font-pairing/
[2] https://justmytype.co/typekit/

Canva also provides a web-based tool[3] that generates font pairings. How this type of tool can work will be explored on a similar open-source tool Fontjoy, which describes its inner workings. As was discussed in chapter 1.4.4, various characteristics can describe typefaces. Visually pleasing font pairing requires typefaces that share some of these characteristics, but they contrast in some specific way. A multidimensional graph representation of typefaces can be created with each axis representing one characteristic (such as weight, x-height, obliqueness, and letter-spacing). Creating such a map by hand would be very time consuming, but using AI techniques, it can be achieved "To automatically extract features, a common approach is to use a deep neural net. With this approach we don't actually need to specify which features we want, rather the deep learning model discovers the features for itself and we use the resulting data as our map." (Fontjoy, 2020).

Adobe Sensei platform provides tools for other Adobe Creative Suite applications that can recognize fonts from images and photographs (Converse, 2018). However, this feature could be considered a part of the research process, as it mainly helps designers collect inspiration (see 1.4.1).

Some more experimental tools aim at automating the process of balancing the size of various types of written content (such as headlines and paragraphs). While not being strictly AI-driven, as they use the top-down approach to algorithmization (see 2.2.1), these tools fulfill the demands of graphic design principles by automating calculations of mathematical ratios (see 1.4.4). Example of this type of tool is Modularscale.com, an adaptive modular scale by Florian Schultz (Image 6), who currently works on a more cohesive tool that bundles various design automation tools at useratio.com. Another example is René[4] by Jon Gold which is a declarative permutational tool, that creates and displays variations of design generated by parameters set by the user. Setting ideal white spaces between type is also a process that can be at least partly algorithmized, as Gridlover.net aims to achieve. HuulaTypesetter[5] is an AI-driven tool providing suggestions on how to improve text sizes on already existing websites. It was trained on a dataset of around four thousand webpages using machine learning.

[3] https://www.canva.com/font-combinations/
[4] rene.jon.gold
[5] https://huu.la/ai/typesetter

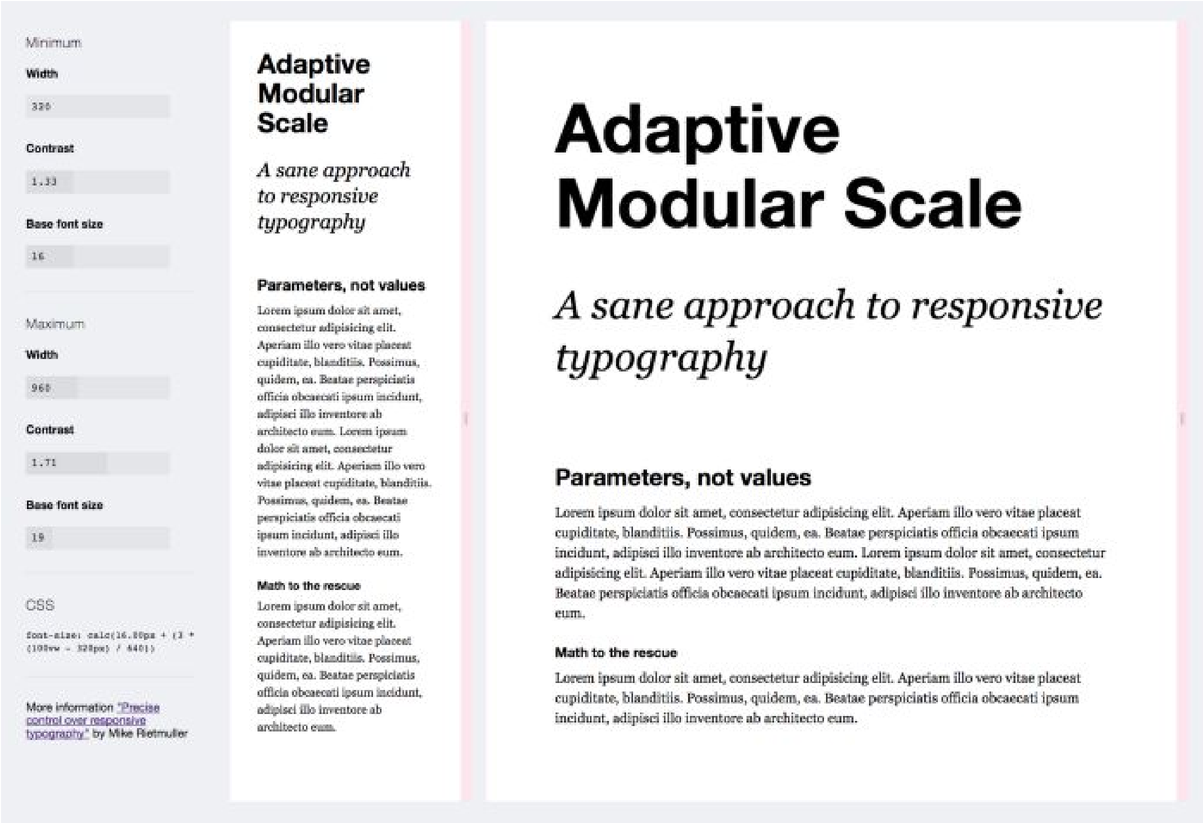


Image 6: Adaptive Modular Scale

(source: https://medium.com/@getflourish/designing-with-intent-be6664b10ac)

Selecting suitable typefaces in relation to other typeface, images or illustration used alongside, it can be automatized. A 2013 MIT research aimed at achieving this functionality by analyzing an image and properties of a typeface to suggest a suitable pairing (Morris, 2013). Pairing a typeface with an image or an icon is one of the challenges present in a logotype design process. Therefore in continuation, tools providing automation of branding and logo creation will be explored.

3.2.3 Branding

Having a unique logo is considered a basic necessity for businesses, trough logo and branding in general, a company becomes relatable, communicates necessary information about the nature of the company and makes it distinguishable from its competitors (Decker, 2017). Presently many online tools automate the creation of logos. Some of them are based on templates, others provide simplified and partly automatized graphic editors, and many of them are based on AI. A closer look at the process and advantages will be at two of these AI-driven tools Brandmark.io and Looka.com. More similar tools are currently available, but all generally share the same methods, and the creative process does not differ significantly. Combining symbols, fonts, colors, and a layout is guided by machine-learned AI that ensures that the final design follows basic design principles (The Looka Team, 2019). The process considers basic information about the business, such as the name of the company, the industry it operates in, and the aesthetic preferences of the user, such as preferred color palette and symbols he considers viable for the design. Brandmark suggests color palettes based on keywords the user enters to describe his business. While these tools provide usable logos and other branded materials such as business cards and social media kits, they do not aim at replacing graphic designers, but mainly at making logo design accessible for small businesses or individuals "Convolutional neural nets probably won't replace designers in the near future, but does open the door to new tools that can democratize the design process and make it a lot more accessible to everyone." (Brandmark, 2020).

Exploration of AI-driven branding tools leads us to an important finding about the target group of AI-driven graphic design tools in general. Automation and guided creation make some processes accessible for amateur non-designers while achieving designs that avoid making basic mistakes. A comparison can be made with the democratization of printing techniques made by DTP software (see 3.1).

3.2.4 Color

Following the exploration of design principles for color in chapter 1.4.5 a predicament can be made that designers can learn the principles for color palette creation by gaining extensive experience and intuition or making complex mathematical calculations. Testing whether the selected colors provide a contrast that is accessible to, for example, a color-blind user is a function that can be automated and is provided by, for example, Adobe Color or Coolors.co. Various stand-alone tools driven by AI exist that aim at solving the relationship problems between multiple different colors. Tools like Colormind.io, Coolors.co, or ColorSpace[6] provide automatizations for creating color swatches and groups of colors that relate to each other in different ways. ColorSpace, for example, offers 25 types of different color palettes generated based on one color preselected by the user.

[6] Mycolor.space

Creator of Colormind.io explains the process of training GAN (see 2.2.4) from Adobe Color[7] generated color palettes to extract viable color swatches from images that are either randomly selected from various art or photography styles or a user uploaded image (Colormind, 2020).

While beneficial for graphic designers, AI-driven color generators such as Colormind.io are an external tool. Integrating well into the typical workflow of a designer is an important predisposition for any widely adopted tool. For example, Coolors.co is a color palette generating service that also provides a plugin (see 3.1) for Adobe software.

3.2.5 Photography

In chapter 2.2.4 I have discussed how computer vision allowed for first AI-driven categorization tools for consumer photography. Recognizing objects in photographs can be utilized in the research phase of graphic design and while searching for stock photos (see 3.2.1). Tools that help the user capture the photograph and tools for editing and modification of photography, retouching or cropping, will be explored next.

Technological advancements in phone photography reached a point where the physical capabilities of upgrading the optics and sensors are limited. (O'Malley, 2018) Large phone manufacturers like Google, Apple, and Huawei use dedicated chips just for processing photos and even an NPU (neural processing unit). Notable features leveraging this new hardware include Google HDR+ that merges multiple frames with different exposure and settings to a single photo, compensating physical limits of phone-sized optics to create a DSLR level photography. (Byford, 2019) Multiple cameras in Huawei phones and AI-driven processing can recognize a scene and adjust settings for the best possible resulting shot. (Tchebotarev, 2019) Vilém Flusser wrote in 1983 even before the introduction of digital photography "…just as generally the hard side of apparatuses, the hardware, is getting cheaper all the time, the soft side of them, the software, is getting more expensive all the time." (Flusser, 2016, p. 30).

Similarly to branding AI-driven tools (see 3.2.3), photographic tools that are most prominent at the moment aim at a target audience that consists of amateur users, providing aid for casual photographers to avoid making basic mistakes. Artistic AI-driven

[7] https://color.adobe.com

filters are another example of tools aimed primarily for the casual user. Prisma[8] is a popular application that applies artistic styles to user photographs. Since it is not an open-source project, the inner workings are not publicly accessible, but another open-source project[9] that achieves similar functionality and a research paper titled "A Neural Algorithm of Artistic Style" published in 2015 describes methods that produce the same effect. By using machine learning methods, elements of a specific artistic style and its patterns are extracted from a group of preselected artworks. Then instead of merely overlaying the original photograph by a filter, the algorithm reproduces objects from the photograph provided by the user using the distilled artistic style (Gatys, Ecker & Bethge, 2015).

Synthetic photography (see 2.2.4) could arguably, in the foreseeable future, provide an alternative to stock photography. Thispersondoesnotexist.com is a website that generates photorealistic images of people who do not exist in the real world. "The algorithm behind it is trained on a huge dataset of real images, then uses a type of neural network known as a generative adversarial network (or GAN) to fabricate new examples." (Vincent, 2019). A simple plugin for Sketch[10], a popular graphic design software, integrates this tool into the design workflow (Image 7).

Image 7: Images of people generated by Thispersondoesnotexist.com (source: https://www.theverge.com/tldr/2019/2/15/18226005)

[8] https://prisma-ai.com/
[9] https://github.com/anishathalye/neural-style
[10] https://gumroad.com/l/thispersondoesnotexist

Adobe Sensei platform powers AI-driven tools in various applications of the Adobe Creative Suite ecosystem. In Photoshop, for example, using computer vision allows the designer to make intuitive selections of objects by simply drawing an imperfect shape around the desired object, which is then fine-tuned by the AI. Content-Aware Fill is another example of this type of tool "Seamlessly fill a selected portion of an image with content sampled from other parts of the image." (Adobe, 2020).

3.2.6 Layout, UI and Web Design

Designing a layout involves a sophisticated understanding of various types of content used (such as photography, text, and typefaces) and the relationship between them that impacts their composition (see 1.4.3). Tools that aim to achieve automatization of design at this level are still predominantly in an experimental phase. In 2010 group of Spanish researchers created "Gaudii," a system which they describe as "Intelligent Automated Graphic Design Generator, which utilizes principles and techniques known from the fields of Evolutionary Computation and Fuzzy Logic" (Morcillo, Vallejo, Castro-Schez & Albusac, 2010, p. 1). By programming a complex set of algorithms with the top-down approach (see 2.2.1), they achieved satisfactory results, but as they state utilizing machine learning and computer vision, such a system could be significantly improved (Morcillo, Vallejo, Castro-Schez & Albusac, 2010). Combining computer vision and natural language processing (see 2.2.5) into a content-aware layout generation tool can be already achieved, but still presents many challenges to be solved (Zheng, Qiao, Cao & Lau, 2019). "DesignScape" (Image 8) is another experimental tool that suggests corrections of layout and proposes different approaches to the composition. It was created by Adobe and the University of Toronto in 2015. However, as their research suggests, the user reception of such tools is not straightforwardly positive "However, we found that suggestions were not always desired. Some users preferred to have complete control over the design process, and found that automatic suggestions took away from their creativity" (O'Donovan, Agarwala & Hertzmann, 2015).

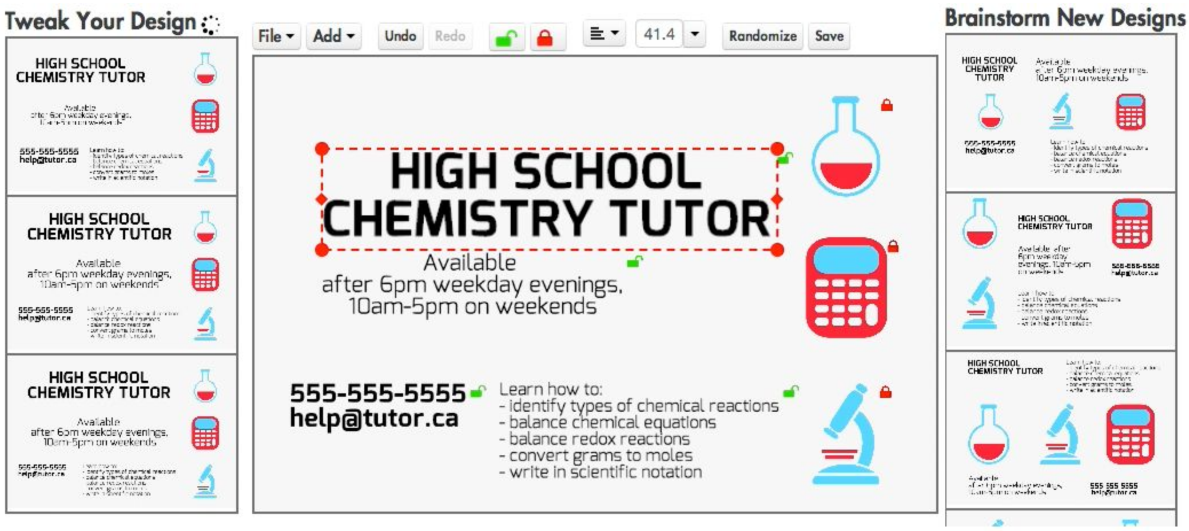


Image 8: DesignScape
(source: http://www.dgp.toronto.edu/~donovan/design/index.html)

In 2016 an A.I. driven website builder that promised its users to create unique websites based on their content and business needs was released to the public. theGrid.io, after a successful crowdfunding campaign, received mostly negative reviews, and in 2019 all of the created websites were taken down (Westfall, 2019). Presently various A.I. aided website builders are available. Tools such as Wix ADI or Bookmark.com promise automation of website building without the need for a graphic designer or programmer. “Wix ADI learns about you and applies this knowledge to create the perfect site for your needs. From billions of combinations including layouts, images, text, contact forms & more...” (Wix, 2020). Examples of other platforms providing guided creation of websites include Firedrop[11] or Adobe Spark[12]. They share many common aspects and mostly provide the same level of aid as the already discussed DesignScape: automatically adjusting the layout, sizes of images, and type to fit in the given space and avoid overlapping. Automatic website builders were being used even without A.I. driven features, mainly based on predefined templates, and the introduction of such features did not change their primary mission of enabling low-budget creation of online presence for individuals or small companies. Similar to the branding tools discussed in chapter 3.2.3. these tools do not primarily aim at replacing professional graphic designers.

As we have learned from the discussion of principles behind current A.I. (see 2.2), learning from large datasets and following patterns is its main strength. A.I. can produce personalized visual experiences by combining data about the user, such as his preferences

[11] https://firedrop.ai/
[12] https://spark.adobe.com/

and previous engagement with the product. Netflix is a global online on-demand media streaming service that offers a large number of titles. Netflix is beginning to use A.I. to automatically generate the poster thumbnail of movies or series for various languages and even personalize the thumbnails to appeal to the individual user by displaying a particular character or invoking a specific mood (Image 9). Creating such a large amount of images by hand would be arguably very time-consuming (Netflix Technology Blog, 2016; 2017; 2020). In 2016 Alibaba, a Chinese e-commerce company, used A.I. called LuBan to generate over 400 million banners for a promotional campaign. "If we assume it takes a human designer 20 minutes to design one single banner, then we will need 100 designers to work non-stop for 150 years to produce the same amount." (Xu, 2017). Following predefined patterns, the A.I. is capable of generating large amounts of design mutations in a fraction of the time that a human designer could.

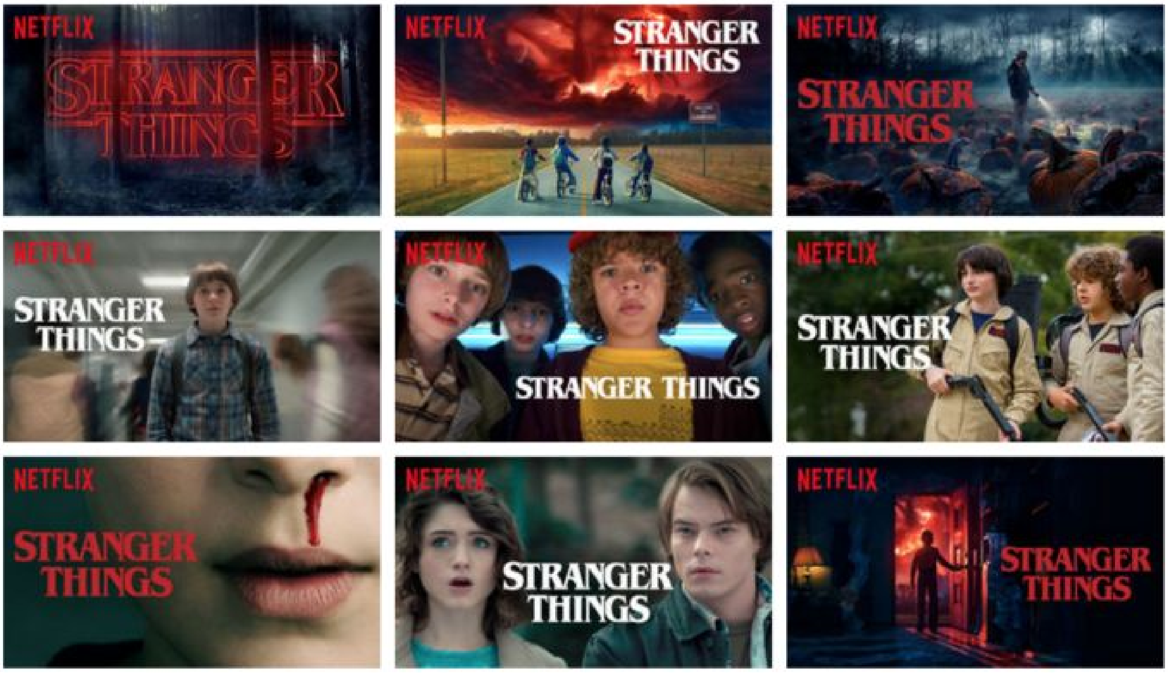


Image 9: Different artworks generated by A.I.

(source: https://netflixtechblog.com/artwork-personalization-c589f074ad76)

3.2.7 Conclusion

Trough exploration of A.I. driven tools presently available various topics for further discussion were discovered. Services providing guided or semi-automated creation of branding and websites are primarily aimed at small businesses, which arguably would not seek graphic designers' services, except junior freelance designers, because of budget restrictions. Generally, the overviewed tools were mostly experimental and not yet matured for production use. Automation of production of a large number of well-defined designs following strict patterns is arguably a factor that could, in the foreseeable future, influence the work of junior designers and will be explored further. Seamless integration of new tools to current workflow seems to be relevant to graphic designers since many of these tools are provided as plugins or extensions for popular graphic software. While graphic software such as Adobe Photoshop or Sketch enables the use of third-party plugins, Adobe Sensei is introducing A.I. based tools across many of their applications in the form of an A.I. assistant. As Adobe Creative Suite is currently used by over 90% (Adobe, 2019) of world creative professionals, the Adobe Sensei platform will be used as a base example in the research.

3.2.8 Reception

Graphic design connects to technology and art, with the concern for easing users' lives at its center. Theoretical discussions and experimentation are not uncommon for designers, and therefore the introduction of A.I-based tools gained much attention within the community. I will review the academic discussion first and then also the articles that appeared in magazines dedicated to design or technology.

A qualitative study between students of graphic design was conducted at Georgia Southern University in 2019. Respondents were asked what their opinion on the future of graphic design is and showed some samples of A.I. generated designs. “when interviewing 14 of the students 100% claimed they do not expect graphic designers to become obsolete in their lifetime. This outcome can be expected as those students are currently studying to pursue a career in graphic design, however interestingly enough, when informed of current trends in automated design 35% said they were discouraged.” (Doehling, 2019, p.16). The discouragement was mostly driven by disappointment by the quality of the results generated by automated design (Doehling, 2019).

Some academic papers review and summarize the advancements in A.I. tools for graphic design in a more speculative way, without conducting any quantitative or qualitative research. Nigel Cross, a design researcher, argues that through the attempt to replicate human design processes in a machine, we can expand our understanding of how designers think (Cross, 2001). In more recent papers, reflecting the new abilities of A.I. driven tools, a need for a more active role of designers in reevaluating graphic design education and practice is accentuated. “new technologies should be combined to cultivate innovative thinking and train “interdisciplinary” talents vigorously for the sustainable development of the graphic design industry” (Wu, 2020, p. 5). “Despite its proximity, graphic design education and practice are largely sidelined from participating in the highly scientized spheres of computational aesthetics and applied image processing.” (Cook & Kwon, 2019, p. 262). Refocusing the education and practice of graphic designers from the more routine tasks to a creative and multidisciplinary field with an ability to self-reflect and understand its processes is a way for designers to participate in the formation of the A.I. tools (Karaata, 2018).

Various articles and blog posts with titles such as “Automation Threatens to Make Graphic Designers Obsolete” (Peart, 2016), “Why Web Design is Dead” (Nouvel, 2015), “Yes, AI Will Replace Designers” (Oh, 2019) or “When Websites Design Themselves” (Tselentis, 2017) began to appear reacting to the release of platforms such as theGrid.io. Albeit their sensational headlines, they arrive at similar conclusions: graphic design will remain a relevant field, although transformed. Some authors argue that automation of various tasks will allow designers to spend more time utilizing the added value their human cognition can provide in originality, creativity, and insight (Tselentis, 2017; Teixeira, 2017). As the number of interfaces and ways of interacting with them grows, the designer’s role will involve more strategic thinking, to ensure consistent user experiences across devices (Peart, 2016; Nouvel, 2015). The ideal way of integration of A.I. into the designer’s workflow is suggested to be in a form of an assistant, automatizing routine tasks, suggesting improvements, and offering advice (Prevost, 2018; Annuziata 2019; Nečas 2018). The avant-garde notion of graphic design as a political instrument resurfaces in the light of recent discussions of the effect A.I. and automation will have on our lives (Shaughnessy, 2018; Laranjo, 2016). In the next chapter, I will describe the conducted study, which aims at confirming the previously discussed views in the practice of Czech graphic designers.

4. Research

The majority of reviewed academic works documented the technological development of A.I.-driven tools (see 3.2), and the other relevant studies have already been referenced in the related chapters. At the time of writing this thesis, academic research investigating artificial intelligence usage and perception within Czech or Slovak graphic designers do not, at the best of my knowledge, exist. Therefore the study will generate primary data. To formulate hypotheses, I have reviewed relevant literature concerning graphic design, namely its history, relation to art and technology, and basic principles. These findings clarified what the goal of graphic design is, what kind of problems concern designers, and how they approach them. In a 2019 survey created by Google and AIGA called "Design Census" 9429 designers described their work as a designer. The survey focused on job satisfaction, benefits, gender and equality, which is not the main aim of this thesis, however we will compare some of the data with our collected sample (Design Census, 2019).

Furthermore, the current state of artificial intelligence was reviewed and its potential development. Findings from these two chapters convened and helped us evaluate the currently available A.I.-driven tools for graphic design. I have identified the most relevant questions, areas of graphic design where current A.I. cannot yet substitute the human mind, and I will examine the practice of Czech graphic designers and their attitudes towards the type of A.I. that is possible in the future.

4.1 Hypotheses formulation

To formulate the hypotheses, I will be using the findings from the discussion in chapters 1, 2, and 3. To fulfill the research goal of this thesis, I have concluded that research questions are not necessarily needed, and I will formulate the hypotheses based on the literature. The reasoning behind every hypothesis will be discussed individually. Their concrete operationalization and relation to the collected data will be discussed in chapter 5 - analysis. Designers or graphic designers in the formulation of these hypotheses are meant explicitly as Czech or Slovak graphic designers. Proper formulation of null and alternate hypotheses, as well as articulation and evaluation of potential sub-hyphotheses, will be realized in chapter 5 - analysis.

H1: Junior graphic designers in the majority of their work carry out tasks related to the production part of the design process.

As we have seen from the investigation of design principles in 1.4., basic rules for graphic design can be expressed through algorithms. With the example of Netflix artwork generation and Alibaba promotional banners (see 3.2.6), we can assume that automatizing designs following a given pattern is already available. The experience and multidisciplinary knowledge (see 1.4.1) that a graphic designer can provide as an added value is so far irreplaceable. I assume that junior graphic designers are recently mainly tending to tasks that do not require insight or experience they do not yet have. Alternatively, if they work as freelancers, clients with a lower budget who would seek out their help, now have new A.I. driven tools at their disposal (see 3.2.3 and 3.2.6). If this hypothesis is confirmed, the call of some academics (see 3.2.8) for a reevaluation of the education process of graphic design could prove necessary.

H2: For the majority of graphic designers communication and presentation is part of their work.

As was discussed throughout chapters 1.1, and 1.3.1, designers see themselves as problem solvers, making products that other humans can benefit from, making technology accessible. On the other hand majority of design work is arguably conducted because a client inquired it. Thorough research and general knowledge help the designer understand the user, but understanding the client's needs, which are often not clearly defined even in the client's mind, requires an ability to communicate (see 1.2.2). Explaining design decisions to persuade the client about the quality and reasoning behind a project is arguably one of the advantages that A.I. does not possess. As discussed in chapter 2.2, A.I. cannot present its decision process in a human-readable way, as it works as a black box. A study conducted in 2015 explored the role of client communication in relation to the accessibility of graphic design. "A survey of 122 graphic designers and clients identified that these two groups may not be communicating with each other effectively with regard to visual accessibility" (Cornish, Goodman-Deane, Ruggeri & P. John Clarkson, 2015, p. 176). Whether designers perceive this advantage in their everyday practice will be studied.

H3: Majority of graphic designers utilize sketching in their design process.

Using analog tools for concept generation, sketching in short, besides providing a medium that can convey ideas in their initial and rough form (see 1.4.1), also expands creative ideas in multiple ways compared with the computer-based tools: evaluation, elaboration, and communication (see 2.3.1). The lateral thinking process and free associations are characteristic of a highly parallel structure of human cognition. A machine equivalent of this type of thinking achievable through quantum computing is still only in its theoretical phase (see 2.1.2). As discussed in chapter 1.2.2, a practice of reflection-in-action, constant evaluation, and elaboration of even unfinished concepts is a part of the creative process.

Although the benefits of sketching are widely accepted in theory, as the mentioned studies showed in practice (see 1.4.2), some designers tend to work with digital tools even where they constrain them. How strongly Czech graphic designers incorporate sketching in their practice will be therefore examined.

H4: Designers are opened to the implementation of new tools into their workflow.

H5: Majority of designers actively implement currently available A.I.-driven tools into their workflow.

Through exploration of tools for automatization of graphic design in chapter 3 and personal experience working with graphic designers, an assumption was made that the ease of implementation into their standard working process is an essential factor for adoption of new tools. Arguably currently available A.I. tools do not fulfill this predisposition.

H6: Designers would appreciate an A.I. assistant built-in graphic software.

A non-academic research inquired by Adobe and conducted by the Pfeiffer Consulting in 2018 used both quantitative and qualitative approaches interviewing 75 professional designers from the U.S., Germany, and the UK. Its goal was to evaluate creative processes in relationship with new technology (Pfeiffer, 2018). A part of this study exploring the position of graphic designers on the possible use of an A.I. assistant will be replicated in the study as it is relevant to the research goal. Adobe has a majority of the market of graphic design software. Therefore, their tools are most likely to be adopted by graphic designers. I will use questions from this part of the Adobe research as an inspiration in the study.

4.2 Methodology

To evaluate the hypotheses I have chosen to conduct quantitative research. I have created an original questionnaire that consists of 25 questions. All of which serves to answer the hypotheses or to describe the sample. The questionnaire was created in an electronic form using Google Forms, a free online tool by Google. Using an online questionnaire appears to be the most suitable form for data collection in this case. It allows us to reach a large population of potential respondents. An online form ensures anonymity and convenience. We can reasonably assume that graphic designers have an internet connection at their disposal and a high level of proficiency in computer skills. Therefore, they would not have any technical problems in completing the questionnaire. The chosen platform provides reliable data collection. All responses are automatically saved in a consistent form; the potential risk of their loss or unwanted modification is negligible.

On the other hand, a disadvantage of the online form lies in the potential misunderstanding of the question by the respondent, and I cannot with certainty verify that respondents will answer all questions truthfully. For that reason, I have planned and conducted a pilot with four respondents from the target group. They were selected from the author's acquaintances who work as graphic designers with various specializations and different experience levels. The results of this pilot were incorporated into the questionnaire by changing the wording of certain questions or by providing additional information and examples. Such as examples of products that each of the categories used to describe different specializations of graphic design can produce “Marketing materials (banners, posters, printed or online advertisements, social media...)”.

Another disadvantage of online questionnaires is their low return. I had to, therefore, address a larger group of potential respondents. The questionnaire was mainly distributed via social networks. I have selected several Facebook groups that Czech graphic designers use to discuss related topics, share their work, seek consultations, or post job offers. Another distribution channel was through the author's business acquaintances as he, in his career as a freelance web developer, worked with a large number of graphic designers and digital agencies. To encourage sharing the questionnaire with colleagues, following the snowball sampling method (Miovsky, 2003), I have also provided a short list of interesting A.I. driven tools and articles at the end of the questionnaire for respondents who would find this topic interesting. The questionnaire received a solid response, and the activity on social networks suggests that this topic is indeed interesting for graphic designers. Throughout the 8 days of data collection, from 13th of July to 20th of July 2020, 223 designers filled the questionnaire. Defining the population of Czech graphic designers is largely speculative, one indicator could be the number of Linkedin profiles that include the keyword “Graphic designer” in Czech in their description. That number was at the time of writing this thesis 8859 (Linkedin, 2020).

Since the target population of the research consists of Czech or Czech speaking graphic designers, the questionnaire was written in Czech, and its full version is available in the attachments section (see Attachment 1). I will further refer to these questions by their unique number and translation in English. In formulating the questions, I have followed recommendations for questionnaires, as stated by Czech academic literature, such as using clear and concise formulations and avoiding suggestive wording as defined by Miroslav Disman (Disman, 2014). The questionnaire was divided into four sections, while the last section, which was optional, contained an open question to provide space for any further comments and a contact email for the respondent if he was interested to learn about the findings.

Questions in the first section (1.1 - 1.4) were categorical questions that allowed us to define respondents by their seniority, type of business, and specialization. The categories used to define parts of the design process, based on the discussion in chapter 1.4, were: research, concept generation, production, and communication. I have used these categories consistently in multiple questions. Business types were divided as: freelance, boutique (small team, under 10 people), agency (larger team, 10 and more people), and an internal team. The internal team category was introduced as working continuously on a single, or a handful of projects has different characteristics than working on various projects for different clients. The specializations of graphic design were defined based on a compilation of articles from various design magazines (Cann, 2018; Matijević, 2019; Spacey, 2017; Goorevich, 2019) arguably they are more closely reflecting the reality of graphic design, than theoretical works. The second section (2.1 - 2.7) was dedicated to questions about their work process, using categorical questions and standardized four point Likert scale. Furthermore, the third section (3.1 - 3.12) concerned the implementation of A.I. tools in the respondent's design workflow and their opinion on the possible developments in this field. For questions that involved some speculations on the respondent's part, I have used a 5 point Likert scale, including a neutral middle level.

To evaluate the formulated hypotheses, I have analyzed the collected data, as will be discussed in the following chapter, as well as defining the relation of individual questions to the hyphotheses.

5. Analysis

In this chapter, I will first describe the collected sample, and then for each hypothesis, describe decision rules, questions that were used for its evaluation, and the statistical tests that were used to calculate its significance. For all of the calculations, I have used the table processor Microsoft Excel, the specific functions that were used will be described when necessary. All of the referenced calculations and tables are available in the attachments section (Attachment 2) and the collected data set in Attachement 3.

5.1 Sample description

I have acquired data from 223 respondents unless stated otherwise the *n* variable in any statistical operations that follow is considered equal to all of the respondents n = 223 since except for the last open-ended question of the questionnaire all were required. As was already discussed in the methodology section, defining the total population of Czech graphic designers cannot be based on current statistics, only very speculative indicators. One could be the number of Czech Linkedin users, that state graphic design as their profession, which was in July 2020, slightly under nine thousand (Linkedin, 2020).

5.1.1 Seniority

The first two questions 1.1 "How long have you professionally worked as a graphic designer?" and 1.2 "You would describe your current position as?" were used in combination to learn about the respondent's seniority and experience. Both questions were categorical. Question 1.1 offered four time-spans: less than 2 years, 2-5 years, 5-10 years, and more than 10 years. The second question asked the respondent to self assign himself in a category of seniority: junior, medior, or senior. To correct any possible problems with the self-assessment and increase the validity, I have reassigned any respondents based on the following key. Designers who answered they had less than 2 years of experience and assigned themselves as mediors were moved to the junior category. This concerned a total of six respondents. Furthermore, similarily any respondent that selected option 2-5 years in the first question and assigned himself as a senior, was moved to the medior category. Five respondent's seniority was adjusted in this way. None of the respondents selected their experience as less than 2 years and self-assigned himself as a senior. This operation created a more symmetrical overlap of the three levels of seniority. The correlations between juniors and mediors, as well as between mediors and seniors, became almost equal after this correction (Table 2).

CORRELATIONS BEFORE CORRECTIONS

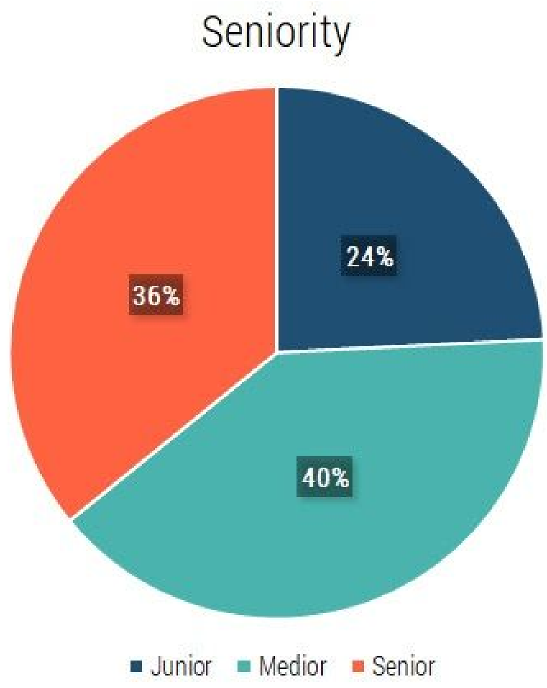
	Junior	Medior	Senior
Junior	1		
Medior	-0,115	1	
Senior	-0,882	-0,274	1

CORRELATIONS AFTER CORRECTIONS

	Junior	Medior	Senior
Junior	1		
Medior	-0,262	1	
Senior	-0,838	-0,264	1

Table 2: Correlations between seniority levels

For the calculation of correlations, I have used the Analysis ToolPak - an extension of Microsoft Excel, providing functions for statistical data analysis. The negative correlations suggest that one variable's small values tend to be associated with larger values in the second variable. The correlation is expressed between values 1 and -1. A positive correlation suggests that the two variables are similar in their values. Negative correlation suggests the opposite and correlation close to zero suggest that they are unrelated (Office Support, n.d.). As shown in Table 2, between juniors and seniors, the negative correlation is quite strong, which is not surprising. For any following analysis involving seniority levels of graphic designers in the sample, I will use these modified values. A diverse sample in terms of seniority was acquired, trending towards the more experienced: 24% juniors, 40% mediors, and 36% seniors (Graph 1).

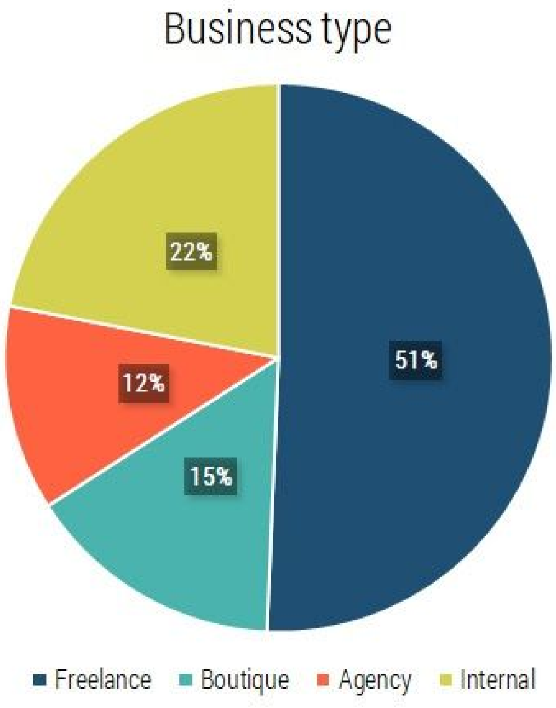


Graph 1: Seniority levels

To compare with the Design Census 2019 data, which surveyed their respondents only in terms of years of experience, we will aggregate some of the offered time-span options. Categories "10-14 years", "15-20 years", and "20+ years", which would translate to our senior category, reached 40%. A percentage that is very similar to our collected sample (36%). Categories "5-9 years" and "1-4 years", can be compared with our medior category and had in total 56%. However, a slight overlap with our junior category and their time-spans "less than 1 year" (4%) and "1-4 years" could explain the more junior trend in our sample. (Design Census, 2019). In short, our collected data sample is very similar in seniority distribution to the Design Census survey, although could suggest a slightly larger percentage of the junior category.

5.1.2 Business type

Question 1.3 asked the respondents, "The type of your employement is best described by?" which allows us to define the collected sample into four categories: freelance, boutique (small agency), agency, and an internal team. Different types of employment can suggest differences in the responsibilities of graphic designers and the respondent's team structure. The majority of respondents identified themselves as freelancers (51%), followed by an internal team (22%), boutique (15%), and agency (12%) (Graph 2).

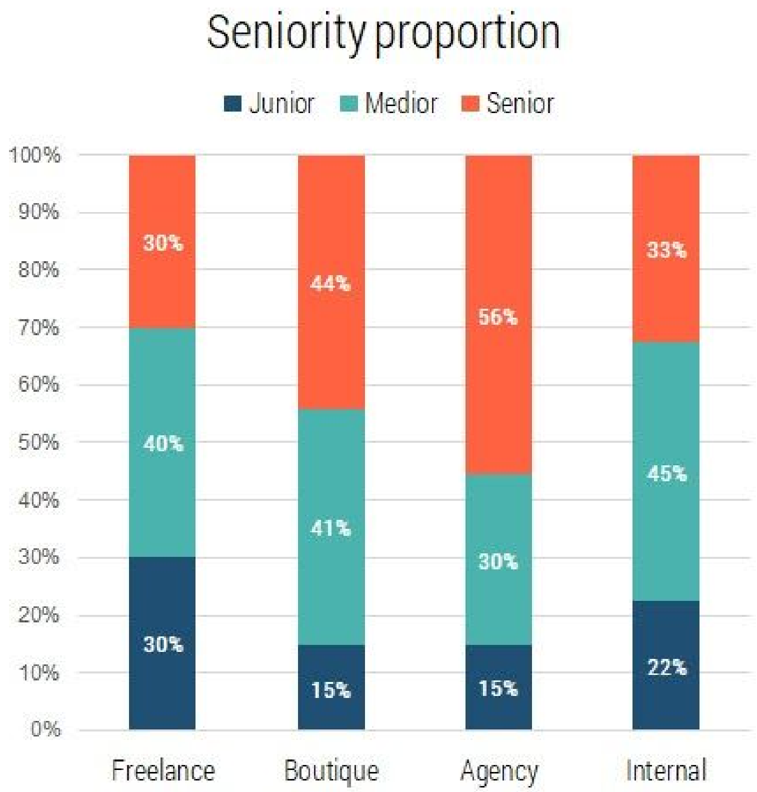


Graph 2: Business type

The prevalence of freelance designers in the collected sample can be explained by the necessity of freelancers to maintain a more extensive network of connections within the community and by their proactivity, therefore, they were more likely to come across the questionnaire. Also, given they have less rigid time schedules, they would be more open to finding time to respond. Finally, the selected method of distribution of the questionnaire trough social networks further amplifies the previously stated reasons. This type of distribution could provide, in fact, a higher diversity of opinions, since freelancers can maintain many different workflows between them.

The comparison with the Design Census data in the sense of employment type is mostly only illustrative since their survey does not explicitly target graphic designers and offered different categorization types in the questions. However, the prevalent categories were "Full-time employee (in-house)" with 42% and "Full-time employee (agency/consultancy)" with 28%. "Freelance" and "Self-employed" categories totaled at 18%. A tendency toward more freelancers can be identified within Czech graphic designers, or rather in our data sample. On the other hand, only 6% of the Design Census respondents answered that they do not do any work outside of their regular employment.

I have analyzed the relation between the seniority and selected business type of respondents. The proportions of seniority within each business type (Graph 3) show that most junior designers fall into the freelance category (30%), and on the other hand, the most significant portion of senior designers was in the larger agencies (56%).



Graph 3: Seniority proportion

Using the same Analysis ToolPak function as in previous chapter 5.1.1, I have calculated the correlations between the four types of business regarding the seniority of the respondents (Table 3). A slight negative correlation was found using the correlation test in Analysis ToolPak between freelancers and designers working in larger agencies (-0,156). A strong positive correlation was discovered between internal teams and freelancers (0,891), which both have a more significant percentage of junior graphic designers and a smaller percentage of seniors. Smaller boutique agencies have a positive correlation with larger agencies, both having higher levels of seniority.

CORRELATIONS

	Freelance	Boutique	Agency	Internal
Freelance	1			
Boutique	0,419	1		
Agency	-0,156	0,832	1	
Internal	0,891	0,786	0,310	1

Table 3: Correlations between business types

To test the independence of these two variables - the type of business and seniority, I have calculated the Chi-squared test for independence. I have formulated the null hypothesis H_0 as "The business type and seniority are independent," and an alternate hypothesis H_A as "The business type is not independent of seniority" at the 5% level of significance. I have calculated the expected frequencies and used an Excel function CHISQ.TEST that simplifies the process of calculating the test (Table 4).

ACTUAL VALUES

	Junior	Medior	Senior	total
Freelance	34	45	34	113
Boutique	5	14	15	34
Agency	4	8	15	27
Internal	11	22	16	49
total	54	89	80	223

EXPECTED VALUES

	Junior	Medior	Senior
Freelance	27,363	45,099	40,538
Boutique	8,233	13,570	12,197
Agency	6,538	10,776	9,686
Internal	11,865	19,556	17,578

CHI SQUARED TEST SIGNIFICANCE

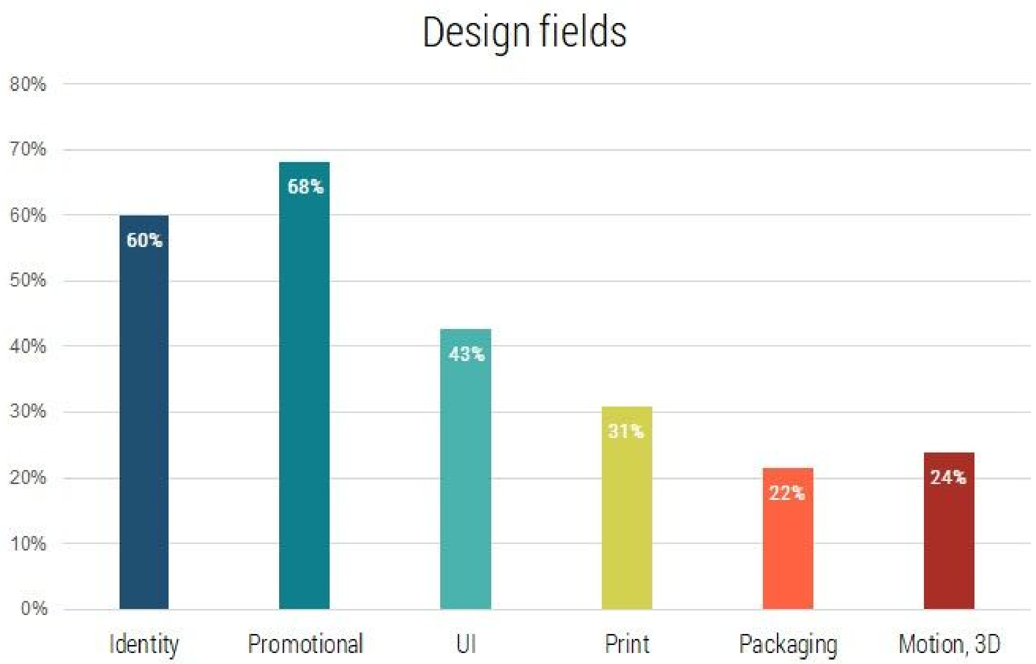
0,137

Table 4: Chi squared test for independence - Business type and seniority

Since the Chi-squared test significance is larger than the set level of significance (0,137 > 0,05) we can conclude, that there is not enough evidence at the 5% level of significance to reject the null hypothesis H_0 , and therefore the research suggests that the business type and seniority of the designers are independent. The collected sample is arguably, in this sense, diverse.

5.1.3 Field

As was discussed in chapter 4.2 I have defined six specializations or fields of graphic design for question 1.4 of the questionnaire "To which types of graphic designs do you dedicated most of your worktime?”. This question allowed multiple selections and a possibility to enter a new user-specified specialization if none of the six predefined categories would apply for the respondent. The six categories and the percentages of graphic designers dedicated to these fields can be seen in the following graph (Graph 4).



Graph 4: Fields of graphic design

I will briefly specify each of the categories more closely, using the examples and descriptions utilized in the questionnaire.

- Visual identity (such as branding, logotypes)
- Marketing and promotional materials (such as banners, posters, printed or online advertisements, social media)
- UI - user interface (such as web design, mobile applications)
- Printed publications (such as book design, magazines, catalogs)
- Packaging
- Motion (animations)
- Other

Respondents mostly used the predefined categories; some of the answers included their specializations. These were assigned to the closest related categories already present. Such as “typography” was coded as printed publications, “merchandise” was assigned as packaging since they both deal with the design of spacial objects, “3D” and “visualizations” were assigned as motion design. The fields with most responses were marketing and promotional design (68%), and visual identity (60%). I have calculated the correlations between these fields (Table 4).

FIELDS CORRELATIONS	Identity	Promotional	UI	Print	Packaging	Motion
Identity	1					
Promotional	0,210	1				
UI	0,054	-0,170	1			
Print	0,070	0,187	-0,165	1		
Packaging	0,137	0,147	-0,032	0,169	1	
Motion	0,068	-0,003	0,009	-0,055	0,066	1
average	0,108	0,074	-0,061	0,041	0,098	0,017

Table 5: Correlations between graphic design fields

These calculations suggest that the field of UI - user interface design is the most exclusive, since it has the lowest average correlation (-0,061) with the other fields (calculated using the correlation function in Analysis ToolPak), primarily with the design of marketing materials and printed publications.

On average, a designer engages in 2,43 fields. This average number decreases with the size of the business, but the median and modus values suggest that it is not statistically significant (Table 5).

NUMBER OF FIELDS BASED ON BUSINESS TYPE	Freelance	Botique	Agency	Internal
avg	2,58	2,50	2,37	2,27
mod	2	1	3	1
stdev	1,21	1,33	1,18	1,30
med	2	2	2	2

Table 6: Number of fields based on business type

I have analyzed the relation between the number of fields and the seniority of designers (Table 6). An increasing tendency can be observed with the experience. Juniors, on average, dedicate themselves to 2,1 fields and seniors to 2,8 fields.

NUMBER OF FIELDS BASED ON SENIORITY	Junior	Medior	Senior
avg	2,06	2,43	2,80
mod	1	3	1
stdev	0,9984264	1,1568731	1,3998192
med	2	2	3

Table 7: Number of fields based on seniority

Since the tendency is more distinctive than in the previous analysis, I have also conducted a chi-squared test for independence (Table 7). However, because some of the expected frequencies are lower than five, which is a prerequisite for the chi-squared test for independence (Office support, n.d. b), although the significance (0,027) would suggest that these two variables are not independent, I will not draw any conclusions. A possible solution would be to create a joint category "3 or more fields", to achieve the minimal numbers in expected values, but since this calculation would not help us with any of the formulated hypotheses, I will not investigate further.

ACTUAL VALUES

	Junior	Medior	Senior	total
1	19	22	19	60
2	19	26	16	61
3	10	28	18	56
4	6	8	19	33
5	0	4	5	9
6	0	1	3	4
total	54	89	80	223

EXPECTED VALUES

	Junior	Medior	Senior
1	14,529	23,946	21,525
2	14,771	24,345	21,883
3	13,561	22,350	20,090
4	7,991	13,170	11,839
5	2,179	3,592	3,229
6	0,969	1,596	1,435

CHI SQUARED TEST SIGNIFICANCE
0,027

Table 8: Chi squared test for independence – number of fields and seniority

5.2 Hypotheses testing

H1: Junior graphic designers in the majority of their work carry out tasks related to the production part of the design process.

To test this hypothesis, I will use the already discussed data that helped us define the seniority of the respondents (see 5.1.1), and question 2.1 of the questionnaire "With which part of the design process do you usually spend the most time?". The four parts of the design process, as described in the questionnaire, are:

- Research (about the company, the product, target group, competition)
- Concept generation (brainstorming, prototyping)
- Production and finalization (including implementation of feedback)
- Communication and presentation (within the team, to the client)

I will test the following hypotheses, the alternate hypotheses for all of those are that the two variables are not independent:

- $H1_0$ "The worktime division is independent on seniority."
- $H1B_0$ "The percieved importance of different parts of the design process are independent on seniority."
- $H1C_0$ "The percieved importance of different parts of the design process are independent on business type."
- $H1D_0$ "The percieved repetitivness of different parts of the design process is independent on the field of graphic design."
- $H1E_0$ "The percieved repetitivness of different parts of the design process is independent on seniority."
- $H1F_0$ "The percieved repetitivness of different parts of the design process is independent on business type."

The results are visualized in the following graph (Graph 5). From the simple visual comparison, we can see that junior graphic designers dedicate most of their worktime to concept generation (57%). We can also see an increasing tendency of the time spent with communication and research based on experience.

Graph 5: Worktime division based on seniority

To test the first hypothesis, I will use the chi-squared test for independence, which, for this test, will be described in more detail. In other tests of the same type throughout the analysis, I will be using the already mentioned Excel function CHISQ.TEST.

Firstly I have defined the null hypothesis $H1_0$ as "The worktime division is independent on seniority" and the alternate hypothesis $H1_A$ as "The worktime division is not independent on seniority." Then I have calculated the actual and expected values (Table 8).

TIME SPENT - ACTUAL	Junior	Medior	Senior	total
Research	4	8	10	22
Concepts	31	39	35	105
Production	18	37	28	83
Comm.	1	5	7	13
total	54	89	80	223

TIME SPENT - EXPECTED	Junior	Medior	Senior
Research	5,327	8,780	7,892
Concepts	25,426	41,906	37,668
Production	20,099	33,126	29,776
Comm.	3,148	5,188	4,664

Table 9: Worktime division – actual and expected values

For the calculation of χ^2 I have used the following equation.

$$\chi^2 = \sum_{i=1}^{k} \frac{(X_i - Np_i)^2}{Np_i}$$

Afterwards, I have defined the levels of freedom *df* by multiplying the number of rows and columns in the following way *(r-1)*(c-1)* and defined the decision rule using the Excel function CHISQ.INV. Since the $\chi 2$ value is less than the decision rule (5,996 < 12,592) and also the significance of chi-squared test is higher than the 5% level of significance (0,424 > 0,05) we do not have enough evidence to reject the null hypothesis that the division of worktime is independent on seniority (Table 9).

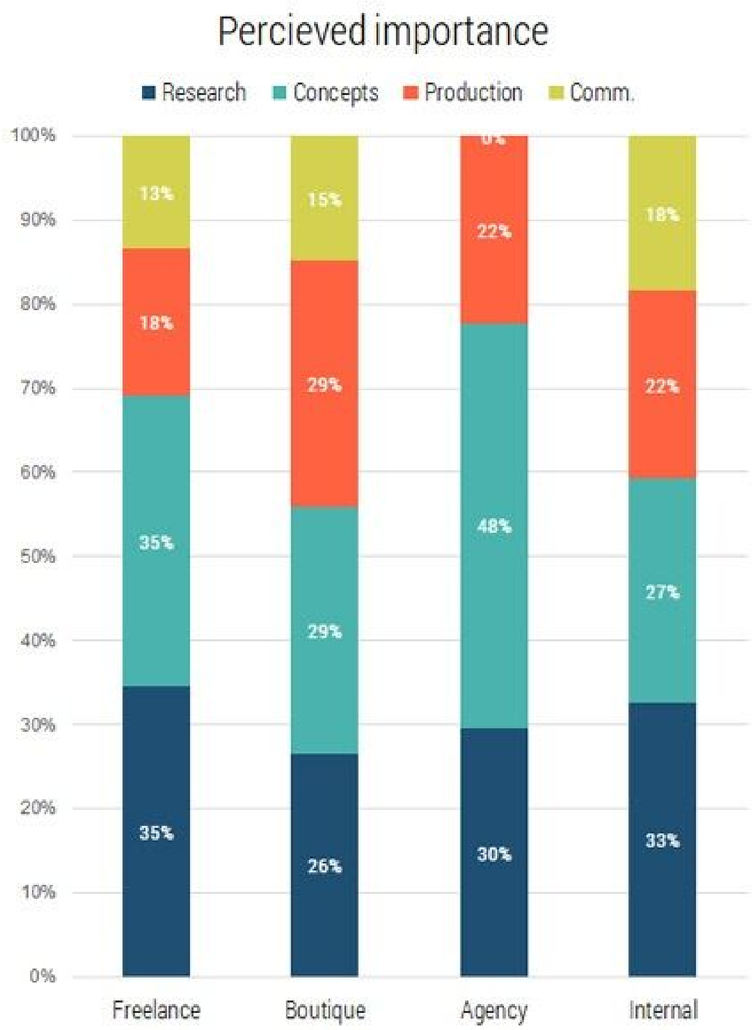
TIME SPENT - CHI TEST	
df	6
chi square	5,996
decision rule	12,592
probability	0,424

Table 10: Worktime division – Chi squared test

From the conducted test for independence and visualization (Graph 5), we can conclude the research suggests that junior designers spend most of their work time on concept generation as well as mediors and seniors (both equally 44%). I will use the results from question 2.2, “Which part of the design process do you percieve as the most important?” to investigate further.

Graph 6: Percieved importance based on seniority

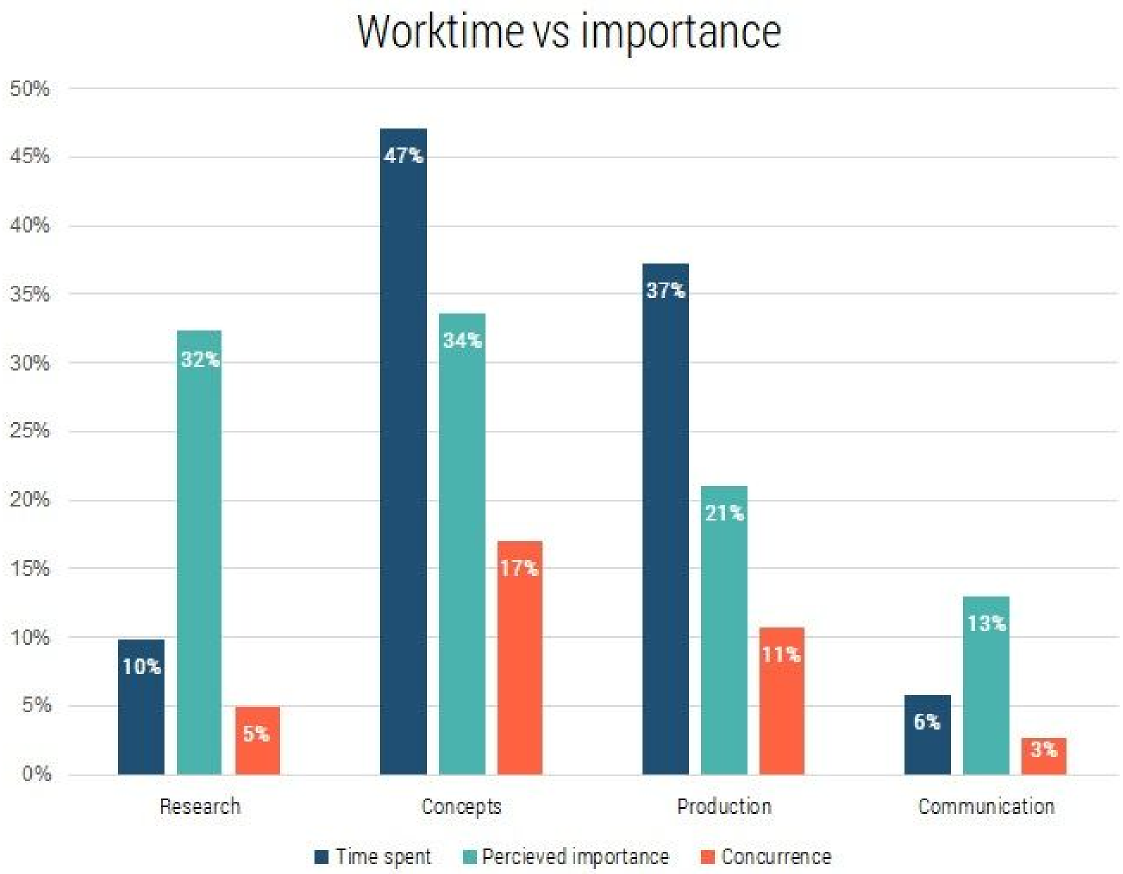
As we can see from the results of this question (Graph 6), a decreasing tendency to the percieved importance of research can be suggested with seniority. One explanation might be in the increasing confidence that comes with experience. Senior graphic designers might not feel the need to confirm their intuitive assumptions by research since they can base their instinct on previous projects. Communication is the part of the design process that is perceived as the least important across all three categories. I have conducted the chi-squared test, which with the resulting probability (0,615), suggests that perceived importance is independent of seniority. Therefore I will not reject the $H1B_0$ hypothesis. This could be given by the composition of the team designers work in and what their responsibilities are.



Graph 7: Percieved importance based on business type

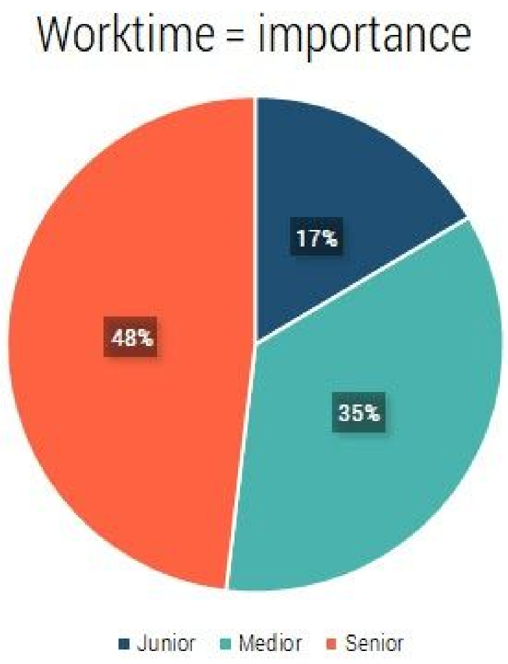
What most stands out in the visualization of perceived importance based on business type the designer works in (Graph 7), is that respondents from larger agencies do not perceive communication as necessary. This suggests that the constitution of teams is an essential influence on the designer's process. However, similarly to the relationship between perceived importance and seniority, the chi test for independence (0,376) suggests that there is no statistically significant reason that would allow us to accept the alternate hypothesis. Therefore I will not reject the $H1C_0$ hypothesis.

Furthermore, I have investigated the relationship between the part of the process that designers spend most of their time and what they perceive as the most important. The most significant difference can be seen in research and communication. The responses suggest for both of them that designers feel they do not spend enough time on them. In contrast, an inverse tendency is in concept generation and production, where designers spend more time on these parts of the process, while not perceiving them as necessary (Graph 8).



Graph 8: Percieved importance vs time spent (n = 223)

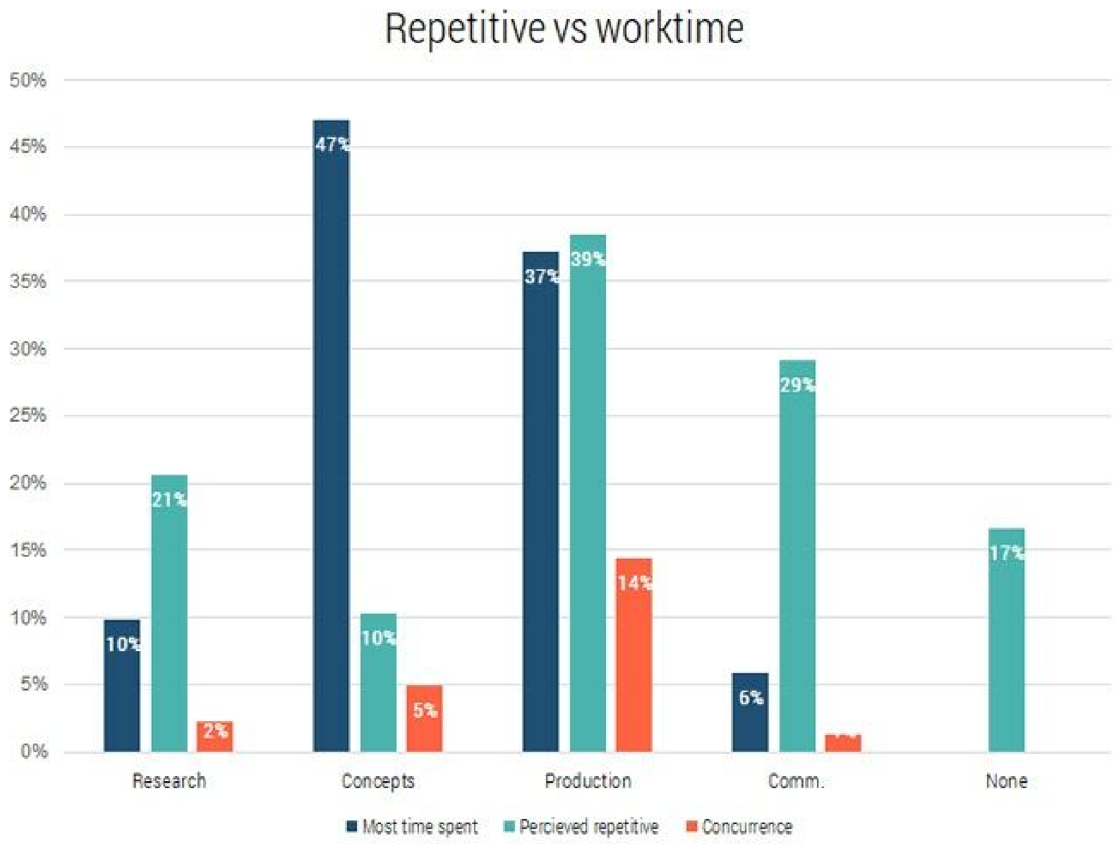
In continuation, I have explored the answers where the most time spent and perceived importance corresponded. In total, 35% (n = 79) of respondents selected the same part of the design process in both questions. Based on seniority, the chance to spend the most time working on the part of the process perceived as the essential increase with experience (Graph 9).



Graph 9: Concurrence of percieved importance and spent worktime based on seniority (n = 79)

From that 35% (n = 79) of answers where both importance and spent time concurred, 48% were seniors, and 47% selected concept generation as the most critical part of the design process.

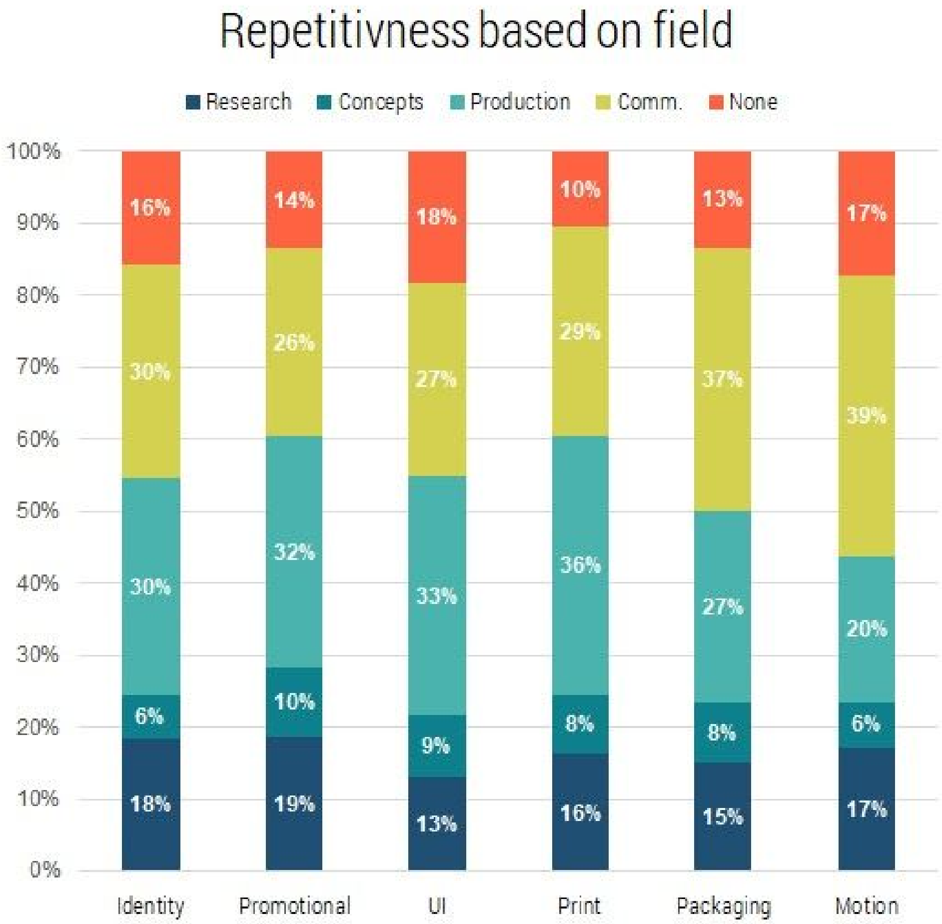
I have used another question 2.7 "Do you percieve some part of your process as mundane and repetitive?" to further concretize the parts of the design process that would trough their automatization alleviate the work of designers. This question used the same four previously defined parts of the design process but allowed to select multiple answers or enter another option. The average number of selected options was 1,15, and the most often selected number - modus 1. Respondents used the possibility to enter other options mainly with variations that were coded as a new category "none" (17%) and "export," which was added to the production category.



Graph 10: Concurrence of percieved repetitivnes and most time spent

Analysis of data collected in response to this question in comparison with results from question 2.1 shows us that the production part is both perceived as the most repetitive (39%) and also concurs with the most time spent (14%) (Graph 10). I have conducted the independence test, which did not, with statistical significance, indicate that these variables are not independent.

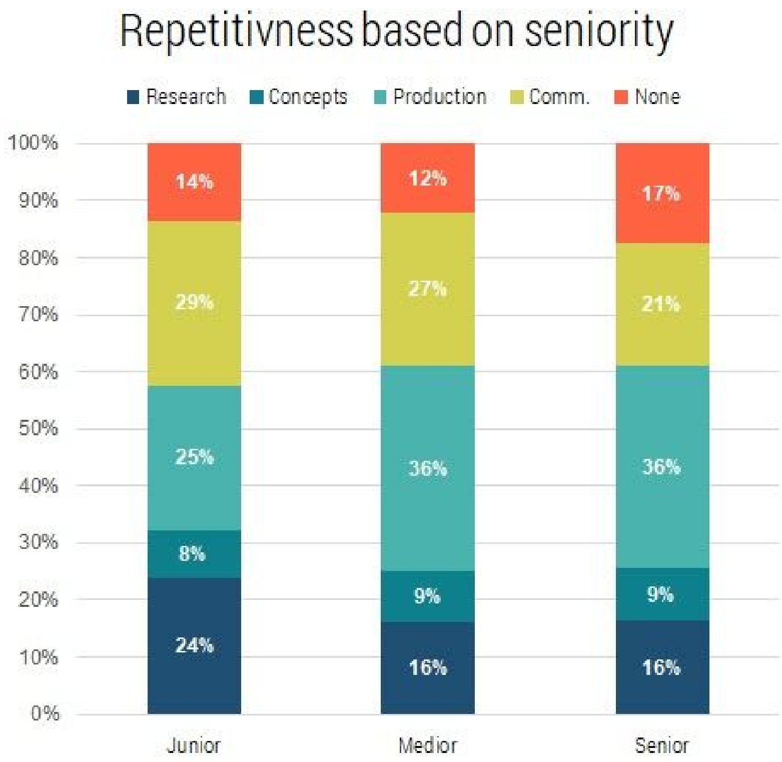
I have investigated the perceived repetitiveness in relation with the design specialization of respondents. Across all specializations, the most selected option was production (highest for print: 36%), except for packaging and motion graphic design. In their case, respondents selected communication as the most repetitive part of their process (37% and 39%, respectively).



Graph 11: Percieved repetitivness based on field

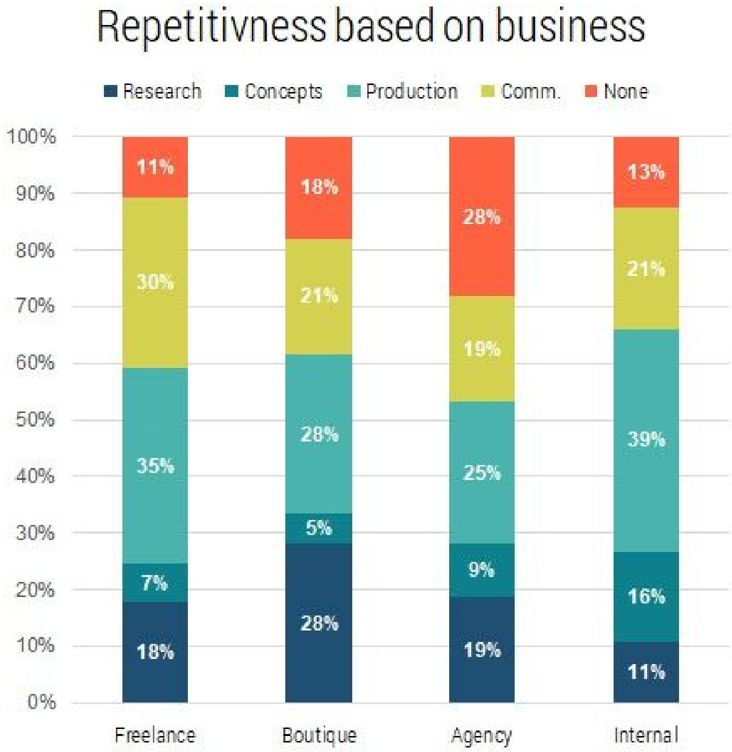
Since the independence test did not with statistical significance indicate that these variables are not independent, we can only speculate about the possible correlations and not reject the $H1D_0$ hypothesis. In print, the perceived repetitiveness of production might stem from the DTP practice of preparing and adjusting of print materials.

Based on seniority, the data suggests, that juniors perceive as most repetitive communication (29%), while mediors and seniors identically production (36%). Seniors selected “none” the most (17%), which coincides with the previous findings (Graph 9). I did not find enough evidence at 5% level of significance to reject the $H1E_0$ hypothesis again by conducting the chi-squared test for independence.



Graph 12: Percieved repetitivness based on seniority

Concerning the type of business, I have found that larger agencies have the highest percentage of respondents who selected “none” (28%). Possible explanations lie in the already discussed constitution of teams and the division of responsibilities. The internal team has the highest percentage of responses that selected production as the most repetitive part of the process (39%). This could stem from possible reoccurring assignments.



Graph 13: Percieved repetitivness based on business type

I have concluded that the chi-squared test for independence (0,048) at 5% level of significance suggests we can reject null hypothesis $H1F_0$ and accept the alternate hypothesis $H1F_A$. What designers perceive as repetitive is dependent on the type of business they work in (Table 10).

REPETITIVE vs BUSINESS - ACTUAL

	Freelance	Boutique	Agency	Internal	total
Research	23	11	6	6	40
Concepts	9	2	3	9	14
Production	45	11	8	22	64
Comm.	39	8	6	12	53
None	14	7	9	7	30
total	130	39	32	56	201

REPETITIVE vs BUSINESS - EXPECTED

	Freelance	Boutique	Agency	Internal
Research	25,871	7,761	6,368	11,144
Concepts	9,055	2,716	2,229	3,900
Production	41,393	12,418	10,189	17,831
Comm.	34,279	10,284	8,438	14,766
None	19,403	5,821	4,776	8,358

CHI SQUARED SIGNIFICANCE
0,048

Table 11: Chi squared test for independence – percieved repetitivness based on business type

I will shortly recapitulate the previous findings. Junior designers spend most of their time with concept generation (57%). The time spent on a particular part of the design process and seniority of the designer are independent variables. The concurrence of perceived importance and time spent for 35% of the respondents is specified by high seniority (48% seniors) and mainly occurs in concept generation (47%). The perceived repetitiveness is highest for production (39%), where also the highest concurrence with the most time spent appears (14%). The part of the design process that is perceived as repetitive is not independent of the business type.

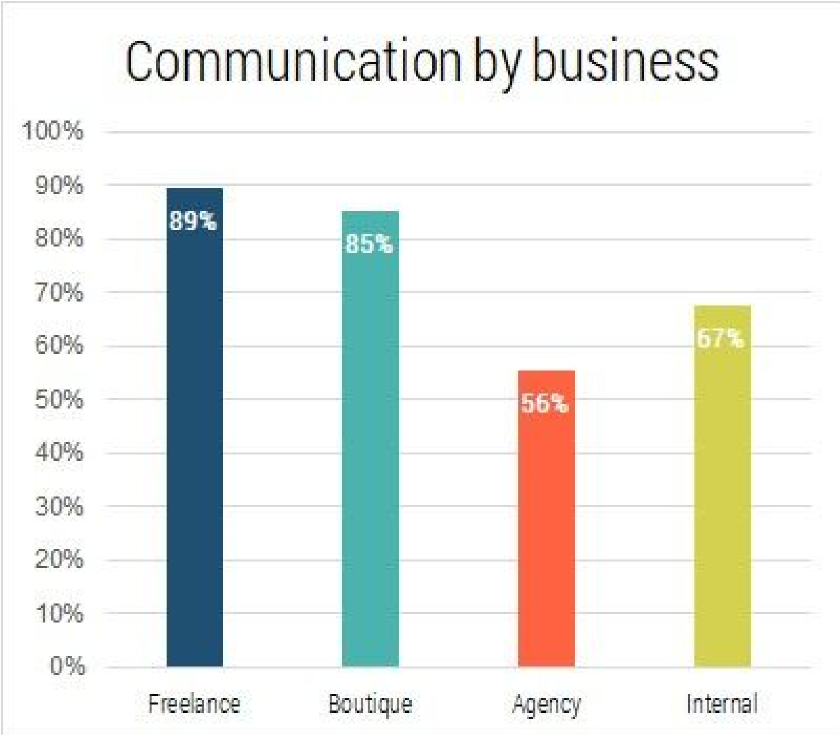
H2: For the majority of graphic designers communication and presentation is part of their work.

To test this hypothesis, I have used data from questions 2.3 “Are presentation or other types of communication a part of your work?” and 2.4 “Do you percieve the ability of the graphic designer to persuade and communicate as important for the success of the project?”. Both implemented the standardized Likert scale. For further calculations, I have combined the positive and negative answers into binary values. Question 2.4 received an overwhelmingly positive response. I will not use it for further investigations since it indicates that the wording of the question might have been too suggestive. The pilot research did not reveal this problem.

I will test the following hypotheses, the alternate hypotheses for all of those are that the two variables are not independent.

- $H2_0$ “Less than 50% of designers need to communicate with the client or prepare presentations of their work”. In other words p = 0,5 and for the alternate hypothesis $H2_A$ p > 0,5.
- $H2B_0$ “Whether designers communicate with the client or do presentations in their work is independent on the type of business they work in.”
- $H2C_0$ “Whether designers communicate with the client or do presentations in their work is independent on their seniority.”

In total, 80% of respondents answered positively. Based on business type, the most significant amount of positive answers can be observed in the freelance category (89%) and boutique agencies (85%), the least amount of positive responses are in the agency category (56%).



Graph 14: Communication based on business type

To test the $H2_0$ hypothesis, I will perform the population proportion test (Table 11). Using the following equation and Excel function NORM.S.INV to set critical values.

$$z = \frac{\hat{\pi} - \pi_0}{\sqrt{\frac{\pi_0 (1 - \pi_0)}{n}}}$$

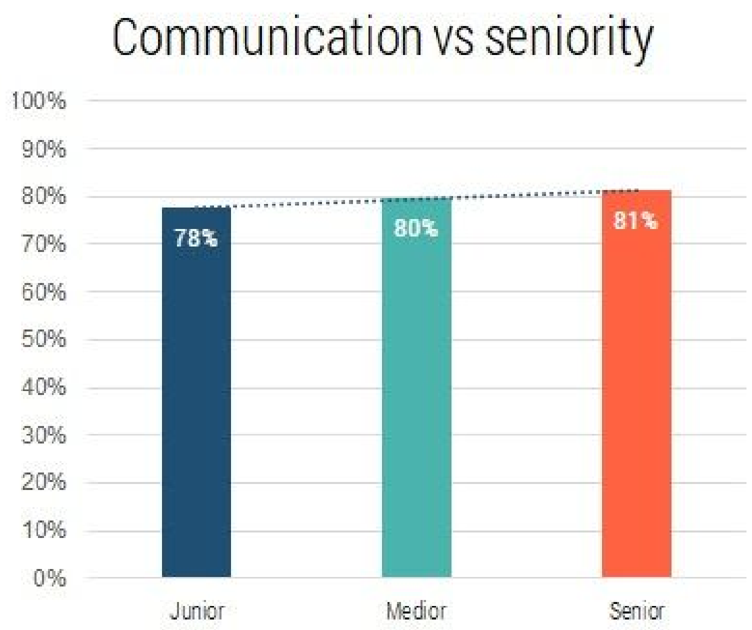
Since the measured proportion was 80%, it is not surprising that we were able to accept the alternate hypothesis $H2_A$ at 5% and also 1% level of significance. More than 50% of designers communicate or do presentations of their work.

POPULATION PROPORTION	
$\hat{p}$	0,8
p	0,5
n	223
n*p > 5	111,5
n*(1-p) > 5	111,5
z	8,9599107
z-crit 5%	-1,6448536
z-crit 1%	-2,3263479
p-value	1

Table 12: Population proportion test - communication

I will test the independence of whether designers do presentations or communicate with the client in their work based on business type (Graph 14). The chi-squared test suggests that we can accept the alternate hypothesis $H2B_A$ at 5% and also 1% level of significance. The differences can stem again from the constitution of teams within different business types and the designer's responsibilities.

Based on seniority, we can detect a slightly increasing tendency from junior to senior level (Graph 15) without statistical significance. We were unable to reject the null hypothesis $H2C_0$ using the chi-squared test for independence.



Graph 15: Communication based on seniority

H3: Majority of graphic designers utilize sketching in their design process.

I have utilized data from questions 2.5 “Do you use analog tools (paper, pencil) for concept generation?” and 2.6 “Do you percieve usage of analog tools as beneficial in design process?”. The Likert scale was again transformed into binary yes or no answers for further evaluations.

I will test the following hypotheses, the alternate hypotheses for all of those are that the two variables are not independent.

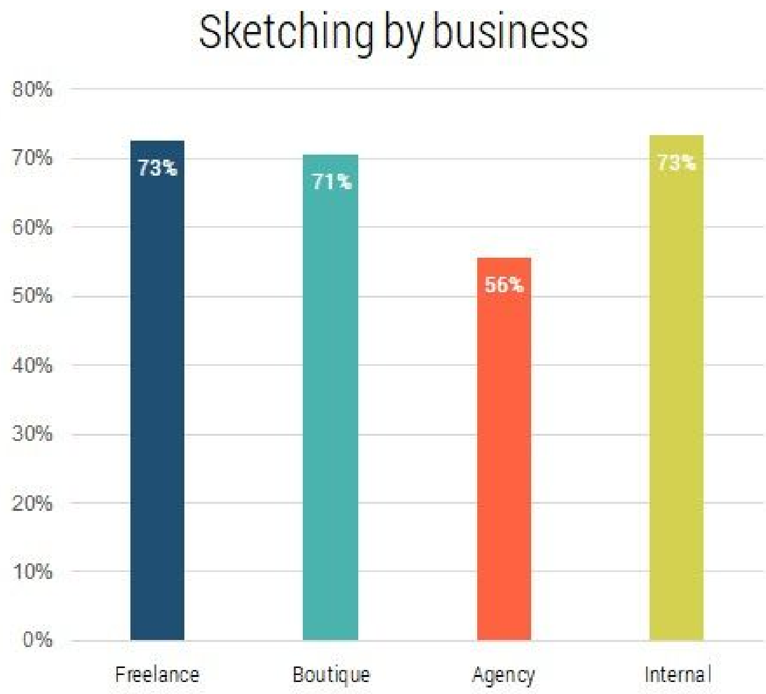
- $H3_0$ “Less than 50% of designers use and apreciate analog tool in their process”. In other words p = 0,5 and for the alternate hypothesis H3A p > 0,5.
- $H3B_0$ “Whether designers implement analog tools in their work is independent on the type of business they work in.”
- $H3C_0$ “Whether implement analog tools in their work is independent on their seniority.”

I have related the data from questions 2.5 and 2.6, to define the portion of respondents that both implement analog tools and appreciate them, which was 68%. To test the statistical significance, I have performed a one-tailed population proportion test (Table 12).

POPULATION PROPORTION	
$\hat{p}$	0,68
p	0,5
n	223
n*p > 5	111,5
n*(1-p) > 5	111,5
z	5,3759464
z-crit 5%	-1,6448536
z-crit 1%	-2,3263479
p-value	1

Table 13: Population proportion test - sketching

Based on the results, we can reject the null hypothesis $H3_0$ at both 5% and 1% level of significance. Furthermore, I have examined the relationship between the usage of analog tools and seniority. I have discovered only a slightly decreasing tendency in the implementation of analog tools between levels of seniority (from 72% to 69%). Chi-squared test did not provide enough evidence to reject the null hypothesis $H3C_0$.



Graph 16: Sketchingbased on business type

Based on business type (Graph 16), we can see that the lowest amount of analog tools usage is between designers working in larger agencies (56%). The chi-squared independence test did not provide enough evidence to reject the null hypothesis $H3B_0$.

H4: Designers are opened to the implementation of new tools into their workflow.

I have used data from questions 3.1 "Do you actively follow developement of new tools for graphic design?" and 3.2 "Have you implemented a new tool into your design process during the last year?" to answer the following hypotheses:

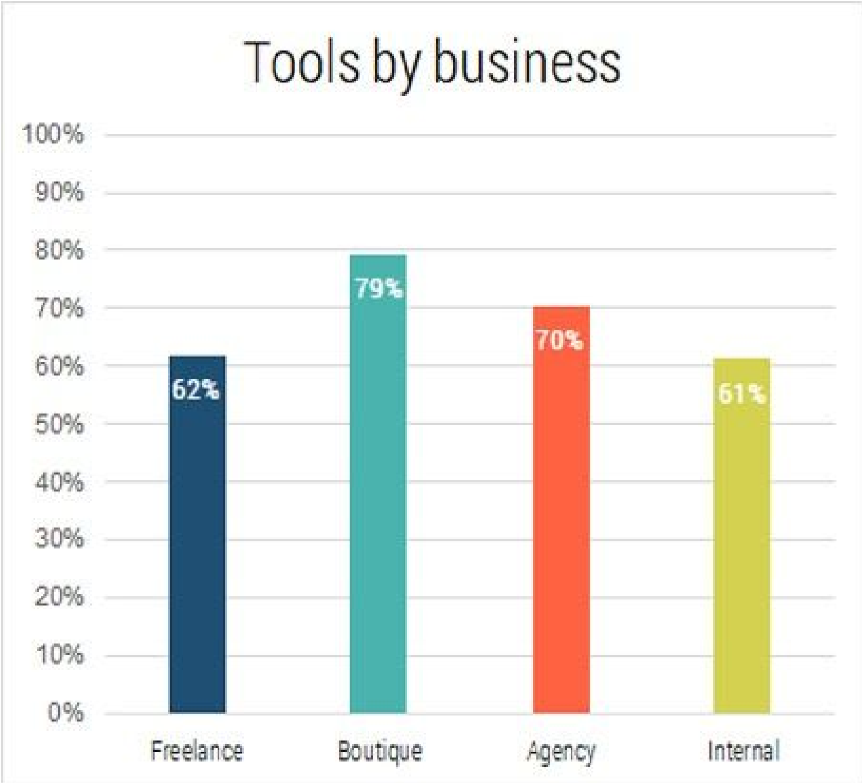
- $H4_0$ "Less than 50% of designers seek and implement new tools into their process". In other words p = 0,5 and for the alternate hypothesis $H3_A$ p > 0,5.
- $H4B_0$ "Whether designers implement new tools into their process is independent on the type of business they work in."
- $H4C_0$ "Whether designers implement new tools into their process is independent on their seniority."

65% both follow and have implemented some new tools into their design process. I will use the population proportion test to test hypothesis $H4_0$ (Table 13). We can accept the alternate hypothesis, that more than 50% of designers seek and implement new tools into their workflow.

POPULATION PROPORTION	
$\hat{p}$	0,65
p	0,5
n	223
n*p > 5	111,5
n*(1-p) > 5	111,5
z	4,4799554
z-crit 5%	-1,6448536
z-crit 1%	-2,3263479
p-value	0,9999963

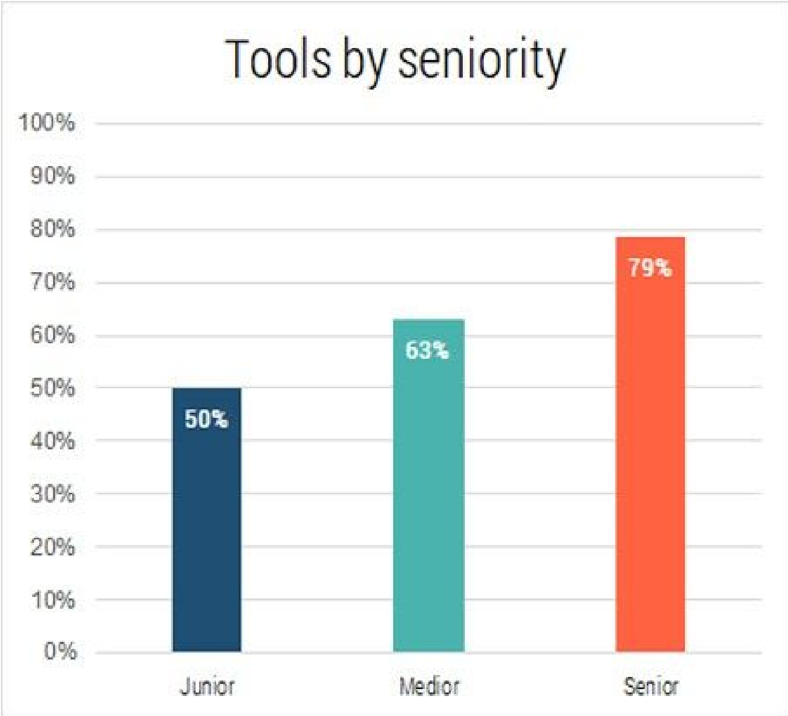
Table 14: Population proportion test - new tools

Out of the 65% (n = 146) that actively pursue new tools, I have analyzed the proportion of different business types. The highest percentage has the boutique agency category (79%) and the lowest is internal team (68%). The difference is not statistically significant. Based on the chi-squared test significance (0,239), we cannot reject the null hypothesis $H4B_0$.



Graph 17: Tools implementation by business type (n = 146)

On the other hand, we have found enough evidence at the 5% level of significance, that the implementation of new tools is not independent on seniority, chi-squared significance (0,002). Therefore we can accept the alternate hypothesis $H4C_A$. The inclination to actively seek out and implement new tools increases with seniority from 50% of juniors to 79% of senior graphic designers. The reason for this can lie in the more control seniors have over their workflow.



Graph 18: New tools implementation by seniority (n = 146)

H5: Majority of designers actively implement currently available A.I.-driven tools into their workflow.

Questions 3.3, 3.4, and 3.5 were included in the questionnaire to gain data about the actual implementation of A.I. tools, as described in chapter 3. I have asked designers whether they used any tool for automatizing photography, working with color or layout in the last six months. I will test the following hypotheses:

- $H5_0$ "More than 50% of designers implement A.I. tools into their process". In other words p < 0,5 and for the alternate hypothesis H5A p = 0,5.
- $H5B_0$ "Whether designers implement A.I. tools into their process is independent on the type of business they work in."
- $H5C_0$ "Whether designers implement A.I. tools into their process is independent on their seniority."

AI TOOLS	Photo	Color	Layout
1	65	54	23
2	46	52	30
3	69	72	61
4	43	45	109
avg	2,404	2,484	3,148
mod	3	3	4
stdev	1,102	1,069	1,009
med	3	3	3

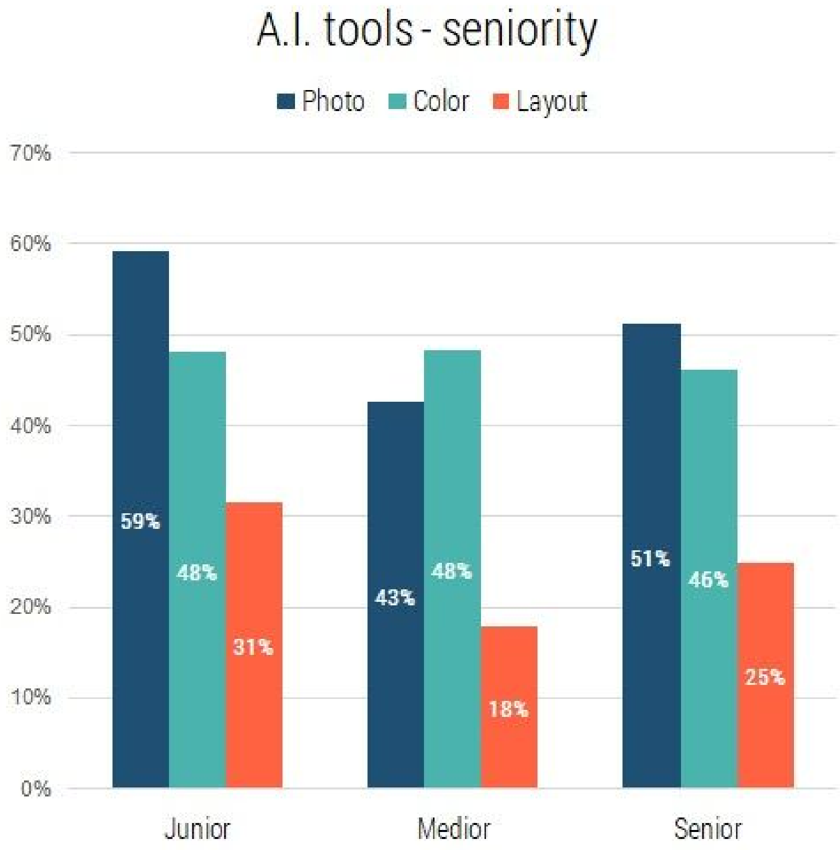
Table 15: A.I. tools

The results indicate an overall inclination towards the negative side of the Likert scale. In total average positive answers for all three questions were 40%. I will perform a population proportion test to evaluate the first hypothesis.

POPULATION PROPORTION	
$\hat{p}$	0,4
p	0,5
n	223
n*p > 5	111,5
n*(1-p) > 5	111,5
z	-2,9866369
z-crit 5%	-1,6448536
z-crit 1%	-2,3263479
p-value	0,0014103

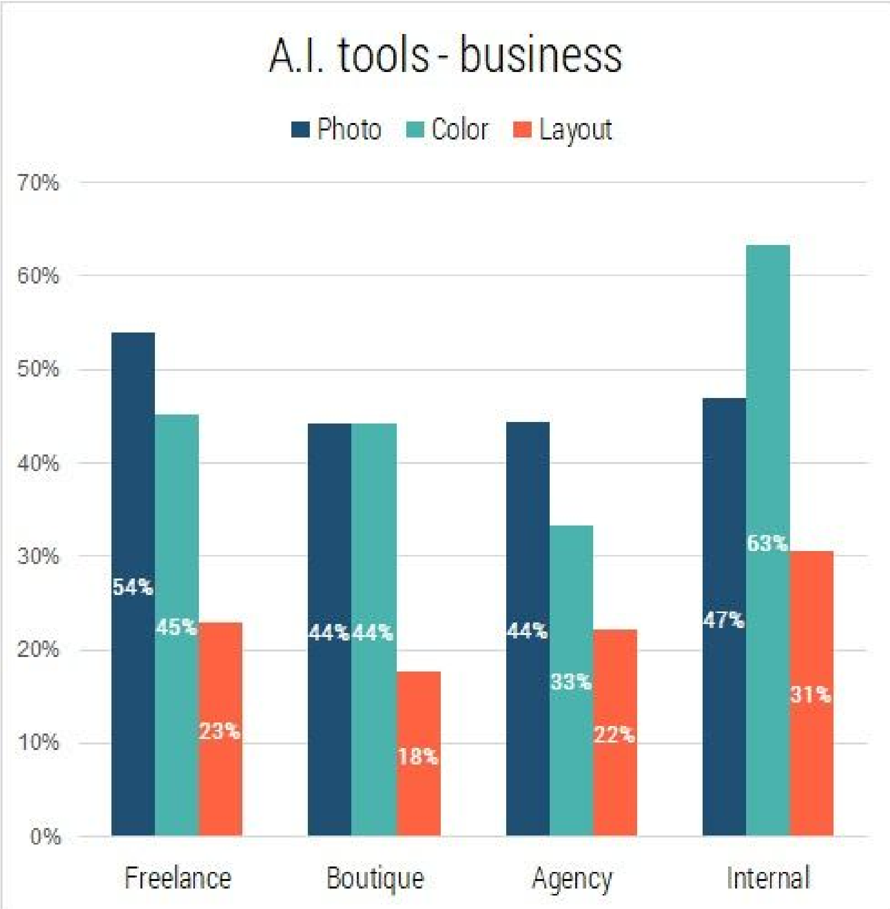
Table 16: Population proportion test - A.I. tools

Since both z-value < z critical value and p-value < 0,05 we can at the 5% and 1% level of significance reject the null hypothesis and conclude that it is less than the majority (50%) of graphic designers who actively implement A.I. tools.



Graph 19: A.I. tools usage by seniority

Based on seniority, junior designers have the most positive relationship with A.I. tools (59% photo, 48% color, 31% layout). This inclination of juniors does not correspond with the general implementation of new tools discussed previously (Graph 18). Since they do not yet have extensive experience, they might resort to A.I. tools to compare their results and check for basic mistakes. The independence test did not provide enough evidence to reject the null hypothesis $H5C_0$.



Graph 20: A.I. tools usage by business type

Differentiated by the business type, usage of A.I. tools reveals a higher percentage in internal teams, specifically the use of automatization for color (63%). Since the chi-squared test for independence did not provide enough evidence to reject the null hypothesis $H5B_0$, we cannot assign any statistical significance to the higher percentage in internal teams.

H6: Designers would appreciate an A.I. assistant built-in graphic software.

I have included a battery of questions in the questionnaire to investigate the designer's attitudes towards a possible A.I. assistant. As was discussed in chapter 4.1. I have replicated some of the questions from Adobe research in the following way:

- 3.6 “Can you imagine collabarating with an A.I. based assistant in graphic design?”
- 3.7 “Would you appreciate an A.I. based assistant that could reduce repetitive tasks in graphic software?”
- 3.8 “Would you appreciate an A.I. based assistant that could create different design variants based on defined parameters?”
- 3.9 “Would you appreciate an A.I. based assistant that could suggest relevant assets (such as photography, icons, fonts)?”
- 3.10 “Would you appreciate an A.I. based assistant that could predict audience reactions?”
- 3.11 “Would you appreciate an A.I. based assistant that could teach you new features?”

I have used a five-point Likert scale, providing a neutral middle level, since the questions require some speculation on the part of the respondent. First, I have compared the results of question 3.6, with an average of all the following questions that dealt with more specified situations.

A.I. ASSISTANT

	Generally	Automatiz.	Variants	Assets	Target gr.	Teach	Concrete Qs
1	59	81	45	56	77	97	71
2	56	68	65	75	73	79	72
3	72	52	55	47	32	25	42
4	28	18	45	36	20	18	27
5	8	4	13	9	21	4	10
avg	2,417	2,085	2,623	2,404	2,260	1,892	2,253
mod	3	1	2	2	1	1	1,4
stdev	1,115	1,038	1,182	1,146	1,279	1,012	1,132
med	2	2	3	2	2	2	2,2

Table 17: A.I. assistant

Question 3.6 that have asked in a more general sense about the respondent’s attitude received results that averaged 2,417. Since modus was 3, it can suggest that the attitude of designers, in general, is mostly neutral. In contrast, the average of the specified questions resulted in more positive answers, on average, 2,253 and modus, on average, 1,4. The most inconsistent answers were for the assistant that could predict reactions of the target group (standard deviation 1.279) and the automated creation of variants. These responses can be given by skepticism towards the ability of the A.I. to understand human nature and to be genuinely creative. As will be discussed further, many designers share this hesitancy, arguing that A.I. based creativity would lead to monotonous results. Much like as Manovich posed in chapter 2.3.2. In general, the assistant that could provide design variants received the most negative answers (average 2,623 and median 3).

Based on this data, and the results of the Adobe research, I will test the following hypotheses:

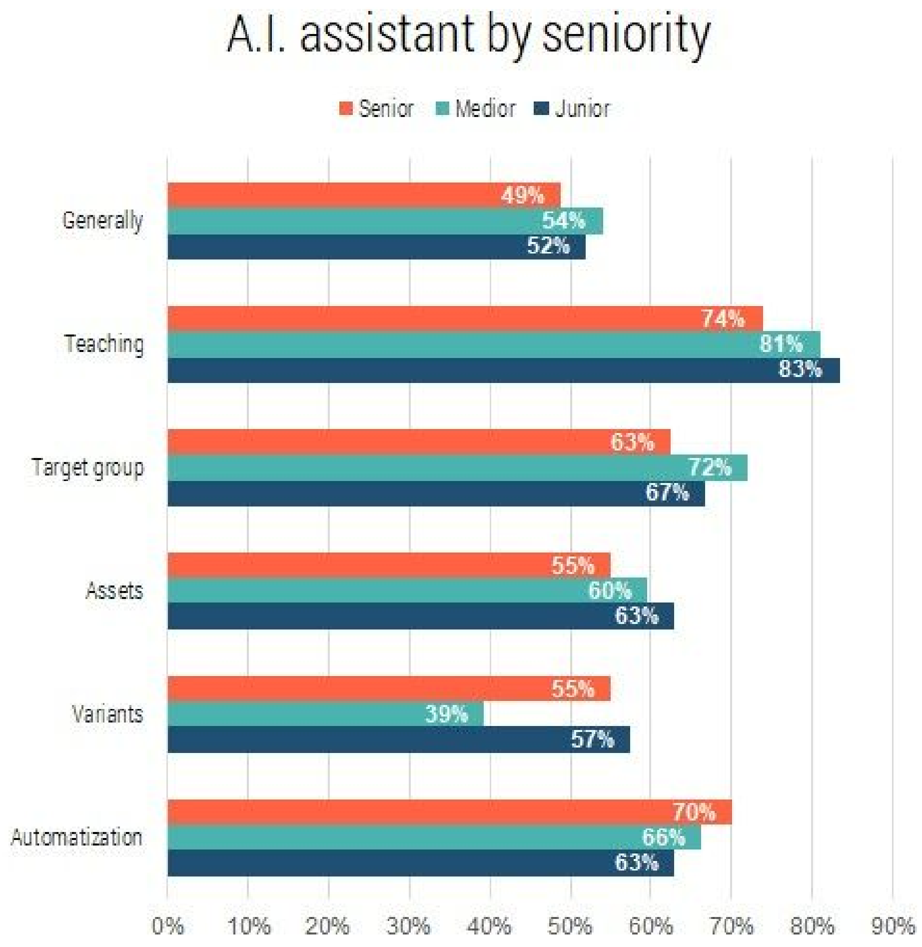
- $H6_0$ "Less than 50% of designers would appreciate A.I. assistant in their process". In other words p = 0,5 and for the alternate hypothesis $H6_A$ p > 0,5.
- $H6B_0$ "Whether designers would appreciate A.I. assistant in their process is independent on the type of business they work in."
- $H6C_0$ "Whether designers would appreciate A.I. assistant in their process is independent on their seniority."
- $H6D_0$ "Results from the conducted research and Adobe research have the same means of variance."

To test the first hypothesis, I have calculated the positive answers (1 and 2 on the Likert scale) for each of the questions, and the resulting percentages were averaged to 62%. Next, I have conducted the population proportion test (Table 16) and concluded that we could reject the null hypothesis $H6_0$ and accept the alternate, that in fact, more than 50% of graphic designers would appreciate an A.I. assistant.

POPULATION PROPORTION	
$\hat{p}$	0,62
p	0,5
n	223
n*p > 5	111,5
n*(1-p) > 5	111,5
z	3,5839643
z-crit 5%	-1,6448536
z-crit 1%	-2,3263479
p-value	0,9998308

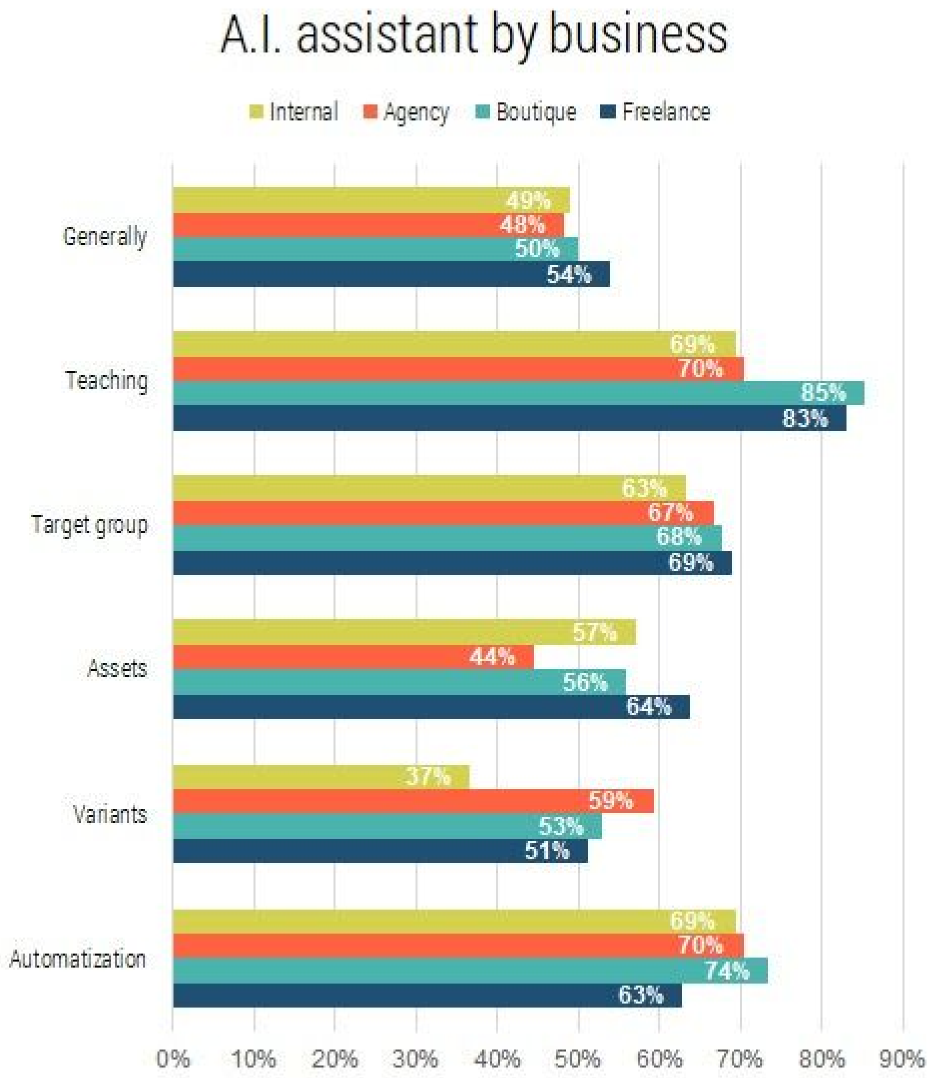
Table 18: Population proportion test – reception of A.I. assistant

Based on seniority, the overall reception is slightly decreasing with the higher level of experience, but the chi-squared test did not provide enough evidence to reject the null hypothesis $H6C_0$.



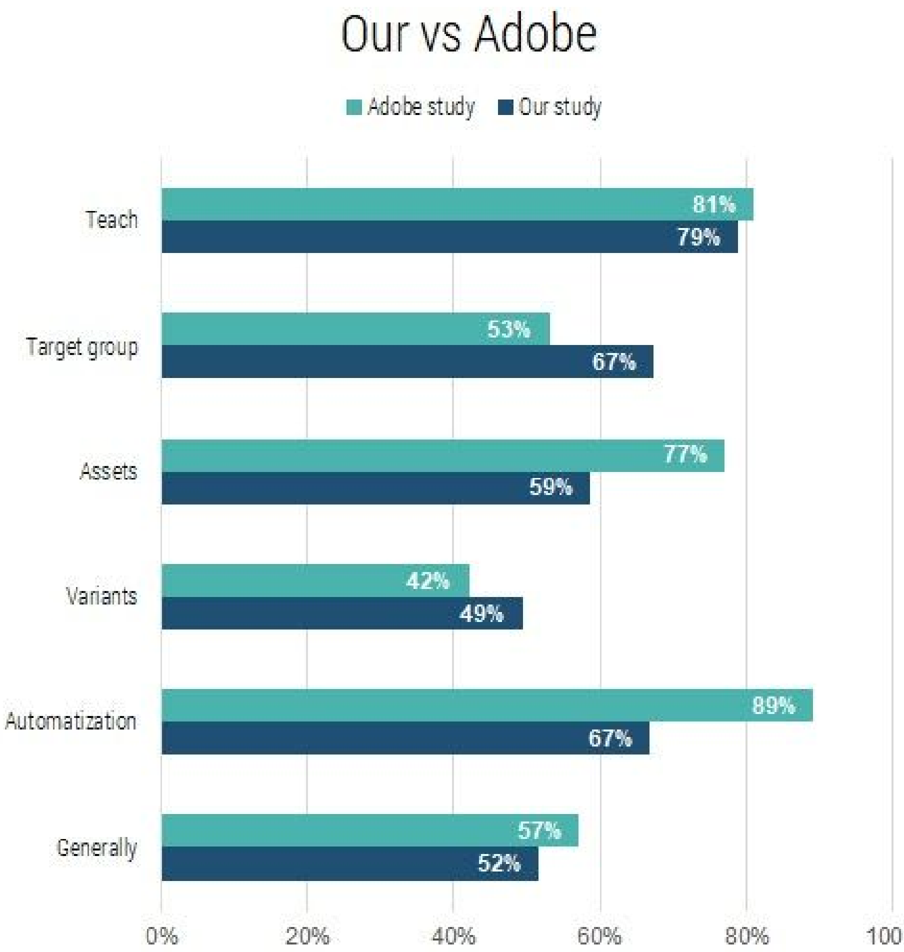
Graph 21: A.I. assistant reception by seniority

Similarily when investigating the possible correlations between the reception of a possible A.I. assistant and the type of business designers work in, we have not been able to reject the null hypothesis $H6B_0$ using the chi-squared test. Internal teams had the highest overall positive attitude, boutique agency the lowest.



Graph 22: A.I. assistant reception by business type

To test the last hypothesis, I have summarized and compared the two sets of results (Graph 23). The most protruded differences can be seen in higher levels of positive reception for automatization in software and assets suggestion in the Adobe study.



Graph 23: Comparison of results of my research and the study inquired by Adobe

To test $H6D_0$, I have used the two-sample t-test, utilizing the Excel functions F.TEST and T.TEST. Both the f-test (0,145 > 0,05) and t-test (0,241 > 0,05) on the 5% level of significance suggest, that we cannot reject the null hypothesis. Results of the research in terms of the attitudes towards an A.I. assistant do not differ from the Adobe research results in a statistically significant way.

All of the mentioned calculations and contingency tables are available in the attachments (Attachment 2).

5.3 Summary

Based on the conducted study, the formulated hypotheses could be tested and evaluated. I will summarize those findings that were statistically significant and provide context and discussion.

The answers from open questions 3.12 “In what way, do you think, could an A.I. assistant change the work of graphic designers?” and 4.1 “Anything else you would like to add that concerns the topic and was not explicitly mentioned in the questionnaire?” from the questionnaire were explored, reoccurring topics identified and each answer was tagged and categorized by the appropriate topic. I have used some of the relevant answers from question 4.1 since many respondents used this opportunity to elaborate on their answer from 3.12.

5.3.1 Design process

Through investigation of the designer’s practice, I have found, that most time is spent on concept generation (48%), while also being perceived as the most crucial part of the design process (34%). I have not found enough evidence that would suggest these opinions are not independent of seniority or business type. The diversity of designer’s practice, different responsibilities, workflows, compositions of the team vary for all levels of seniority and business types. The part perceived as the most repetitive was production (39%). The highest concurrence of selecting the most repetitive part and spending the most time doing it happened in production (14%). The perceived repetitiveness is not independent of the type of business the designer works for. The most significant percentage of selecting “none” as the part perceived as repetitive occurs in larger agencies. With seniority, the concurrence in spending the most time on the part that is also perceived as the most important grows, as well as the highest percentage of selecting “none” as the part perceived as repetitive. Job satisfaction in graphic design currently mostly comes with seniority and well-defined responsibilities inside the team. As 4% of respondents noted, the introduction of A.I. tools or an A.I. assistant could transform their process, freeing time for higher-level tasks that involve more insight and creativity. Most of the respondents (30%) said that such an assistant could lead to a higher effectivity and allow for faster completion of specific tasks. The positive effect of reducing necessary but uninspiring tasks, leaving more space for designers to be creative, was also cited by 4% of the respondents.

5.3.2 Communication and sketching

The two parts of the design process identified as currently not replaceable by A.I. are communication and sketching. Communication and presentation of ideas involve the ability to argue and persuade the client to pick a solution he could be skeptical of in favor of the user, as discussed in chapter 1.2.2. and elsewhere, the goal of good graphic design is to ease the life of the user while supporting the client's business. As the study has shown, majority of designers engage in the presentation or other communication within the team or with the client (80%), but not many of them perceive communication as an important part of their work (13%) or spent most of their work time with it (6%). Many respondents feel that the communication process is repetitive (29%), which is the second most significant percentage after production. We can observe a statistically significant dependence on the business type, but not on the designer's seniority in terms of the amount of communication in his work. Freelance designers, who from the nature of their work, have to communicate with the clients, selected communication as the second most repetitive part of their work (30%), and only 13% of them as the most important. However, some of the respondents are aware of the discussed A.I. tools that mostly target smaller businesses or individuals who do not necessarily want to hire a professional designer. Paraphrasing one of the respondents: "In the moment when design becomes democratized, and dissolution of elites (graphic designers) takes place, the responsibility of cultivating aesthetic values will fall upon all of us, without regard for education, experiences or a sense for what is artistic. On the other hand, the client will be able to produce everything he needs to his satisfaction. The role of designers will be transformed into a visual consultant." Another respondent argued that the perceived value of the designer's work would decrease, as the client will not appreciate or acknowledge the added value designers can provide. The devaluation of the designer's work could increase the price gap between services. In this sense, 5% of respondents expressed their concern about the loss of jobs in graphic design. The ability to "sell" their abilities and persuade clients that a well-researched design, with human insight, will help the client's business will be arguably increasingly important. On the other hand, the overall quality of professional graphic design could be alleviated, as designers would be able to work increasingly on projects with adequate budgets.

In chapter 1.4.2 sketching was described as a tool that stimulates parts of creativity that are exclusive to humans. As the study showed, designers involve analog tools into their process (68%) and acknowledge their value. The implementation of analog tools is independent of seniority and business type. Arguably, sketching is being used intuitively. The respondents also noted that computer creativity could lead to monotonous results, loss of creative diversity (5%). Posing arguments similar to those Manovich articulated in his discussion about cultural A.I. (see 2.3.2).

5.3.3 A.I. tools

The results imply that designers introduce new tools into their process (65%) and increasingly so with their seniority. On the other hand, less than 50% of respondents have implemented the currently available A.I. tools. As was discussed, the ease of implementation into current workflows and used software is an essential predisposition for their adoption. 4% of respondents discussed the possibility of enhancing the current interfaces used in graphical software. Automatic adaption of the interface to the designer's typical usage or alternative types of interaction with the computer through voice commands were mentioned. The role of the Adobe monopol on graphic software was stressed by one of the respondents. "Adobe has not brought anything new in terms of software interface in the last 15 years, albeit there is a lot of what could be more effective." I have discussed the role of third party plug-ins and other extensions. The long history and large user base of Adobe software lead to a slower process of innovation. Introducing a radical change in their interface could potentially discourage designers that have grown accustomed to the standard interface and processes. General skepticism towards the proposition of A.I. tools was mentioned by 8% of the respondents. Among others (see 3.2.8) Jon Gold argues that designers should be more involved in developing new software tools for graphic design (Gold, 2016).

As was discussed, Adobe seems to pursue the path of an A.I. assistant. This could solve the previously discussed problem of keeping the interface familiar while harvesting the power of A.I. Using the assistant as a new non-interfering layer in their software, the designer can choose whether he will use its services or stick to his traditional workflow. The study's results show that Czech graphic designers view the prospect of an assistant similarily as those interviewed for the research inquired by Adobe. The ability of an assistant to teach designers new features and automatization of repetitive tasks were among those propositions evaluated most positively. The respondents also contemplated that the suggestions for assets such as stock photographs would be helpful (7%) and the automatic generation of different variants to provide a quick way to explore certain ideas that is not time-consuming (9%). Another feature respondents repeatedly mentioned was the automatic preparation of materials for print, resizing, and exporting for different social media and similar platforms (6%). Checking the consistency of elements across multiple screens or pages of a design project was also cited numerous times (5%).

5.3.4 Limitations

Some limitations to this research exist and need to be discussed. As no previous research of this topic was conducted, I had to create an original questionnaire, based solely on the inquiry of theoretical texts and commercial research. Each of the hypotheses I have tested could be very well used as a basis for entire research focused only on that particular problem. On the other hand, the study has provided primary data that future researchers can take inspiration from or compare with. The collected data sample, albeit sufficient for this study's purposes, was limited in terms of size and diversity. Using a more targeted distribution of the questionnaire by contacting, for example, digital agencies directly could be achieved with more resources in terms of available time and personnel that would approach and communicate with the agencies.

6. Conclusion

This thesis aimed to describe the current state of A.I. driven tools in graphic design and then based on the conducted research between Czech graphic designers to evaluate their opinions and experiences, providing a possible outlook for the future of the field.

I have formulated the hypotheses trough an investigation of the relevant literature and research in the fields of graphic design, artificial intelligence, and their concurrence in the currently available A.I. driven tools for designers. An original questionnaire was created and distributed in an electronic form, to test the hypotheses. The reactions to the research indicate that it’s topic is of interest to the designers and is being perceived as important. Comments on social media and the fact that over 30% of the respondents asked to be informed about the study’s results, some of them expressing willingness to participate in future research, further confirm this notion.

By statistical analysis of the data and their contextualization utilizing the theoretical investigation, an identification of the crucial problems for an A.I. driven graphic design was discussed. The results of hypotheses testing and comments from the respondents allowed to fulfill the aim of this thesis and to identify and describe the possible effects and problems for the future of graphic design. The research is limited by a number of factors, which were discussed and should be considered in the interpretation of the results. The following summary of the main findings is merely a suggestion, albeit based on academic research, as it tries to predict the future developments.

The multidisciplinary approach and specificities of human creativity, manifested trough the method of sketching in concept generation, emphasizes the design education and conscious self-development of designers in this type of thinking. As the study has shown, the use of analog tools is still strong but possibly stems mostly from its intuitiveness.

The democratization of graphic design through automatization and A.I. driven tools that are currently available could shift the market, providing an alternative for smaller businesses and individuals. The designer’s ability to persuade and communicate effectively with the client, base their design decisions on arguments and research, could prove essential, especially for freelancers. As have the results shown, the value of communication is not entirely appreciated among Czech designers. The added value of a good designer lies in the ability to think in broad social and cultural contexts. Involving users, seeking their opinions and reactions, is part of the human-centered design method, and will be arguably stressed even more in the future.

The interface of graphic software was both by exploring the reactions to A.I. tools among the professional public and trough the conducted study identified as a critical element for the adoption of A.I. driven tools into designer's workflow. The notion of an A.I. assistant that would not completely disrupt the traditional interfaces seems to be the path which major graphic software companies might take and is also perceived as the desired approach by the respondents. Active participation of graphic designers in the development of the new generation of graphic software is what seems to be crucial, instead of passively providing learning materials for the A.I. in forms of online portfolios and project presentations.

Several different ways to further expand research of this topic emerges. One possibility could be to conduct a qualitative study of the differences in design processes between subfields of graphic design and in different types of business. Identifying the range of responsibilities graphic designer can bear in different types of teams. Furthermore, an inquiry into the designer-client modes of communication could lead to findings further clarifying the position and future role of graphic design as a field.

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