



Determinants of Digital Competence in the German Creative Industries

MASTER THESIS

Cultural Economics &
Entrepreneurship

Jan Huber (482381)

Supervisor: Dr. Anna Mignosa

Second Reader: Dr. Ellen Loots

ESHCC Erasmus University

Rotterdam

Erasmus Universiteit Rotterdam
Erasmus School of History, Culture and Communication
Cultural Economics and Entrepreneurship

Master Thesis - Cultural Economics and Entrepreneurship

Determinants of Digital Competence in the German Creative Industries

Student: Jan Huber
Van Reynstraat 146
3034 JV Rotterdam
Student No: 482381
Phone: +49 162 – 463 566 5
Email: janmhuber@web.de

Thesis Advisor: Dr. Anna Mignosa
Second Reader: Dr. Ellen Loots

Cover Image: Arnaldo Pomodoro 'Sfera con Sfera', Dublin
(own image)

Date: June 11, 2019

Table of Contents

Abstract	1
Acknowledgements	2
1. Introduction	3
2. Theoretical Framework	5
2.1. Definition of Creative Industries.....	5
2.2. Output Perspective	6
2.3. Input Perspective.....	8
2.3.1.Humdrum Inputs	8
2.3.2.Creative Inputs	9
2.4. Influence of Reproducibility	11
2.5. Summary	14
3. Methodology	16
3.1. Assumptions.....	16
3.1.1.Organization Types	16
3.1.2.Function Types.....	16
3.2. Data Collection	18
3.2.1.Limitations and Strategies.....	18
3.2.2.Sample.....	19
3.3. Analysis Framework	21
3.3.1.Operationalization	21
3.3.2.Statistical Analysis Methods	24
4. Findings	26
4.1. Distribution of Digital Competence	26
4.2. Function Types.....	28
4.2.1.Prevalence of Skills	28
4.2.2.Competence Levels	31
4.3. Organization Types	33
4.3.1.Prevalence of Skills	33
4.3.2.Competence Levels	35
4.4. Reproducibility.....	36
4.4.1.Prevalence of Skills	36
4.4.2.Competence Levels	38

5. Discussion	41
5.1. Test of Assumptions.....	41
5.1.1.Organization Types	41
5.1.2.Function Types.....	42
5.1.3.Summary of Main Findings.....	42
5.2. Theoretical Perspective	43
5.3. Review of Individual Functions	42
5.4. External Factors	47
5.4.1.ICT Infrastructure.....	47
5.4.2.Policy.....	48
6. Conclusions	49
7. References	50
Statement of Originality	53

Abstract

This study examines the demand for digital competence articulated by cultural organizations in their job advertisements. In order to do so, job advertisements have been extracted from an online platform that focuses on the cultural and creative industries in Germany (Kulturmanagement Network). The advertisements have been analyzed with regard to how frequently skills and experience that pertain to digital ICT applications are mentioned, which level of skill is required and which factors may influence these frequencies.

The results show that advertisements most often do not make any mention of digital skills. When skills are required, they are most likely to fall into the most basic competence level. Examining certain organization types demonstrates that competence levels are distributed unevenly but no individual type can be certainly associated with a preference for digital skills or a certain level of skill. However, the study indicates that there is evidence for a dependent relationship between digital skills and certain functions. An analysis of a test case reveals that advertisements which fall into the function category of Marketing/PR are 28.4% more likely to require any digital skills and 31.2% more likely to specify advanced digital skills. In addition to this, the study confirms the assumption that digital skills are more likely to be mentioned in the context of reproducible outputs. The findings show that Marketing/PR positions that relate to reproducible outputs are the most likely to require advanced digital skills.

Key Words

creative industries, digitization, digital competence, (non-)reproducible outputs

Acknowledgements

This thesis could not have been completed without the help of a few people to whom I hereby want to express my gratitude. Firstly, I would like to thank my supervisor, Anna Mignosa, for deconstructing complicated thoughts when they were unnecessary and adding them when they were necessary. (In my case, the text could not have been written on a typewriter.)

Furthermore, I want to thank my parents for their support during an eventful writing period that involved a lot of uncertainty. My friends and family had a great deal of influence on this thesis and helped me in many different ways with their thoughtful criticism, engaging ideas and words of encouragement.

1 Introduction

The general context that underlies this research project is the growing importance of digital technologies for organizations that are not particularly specialized in technological goods and services. The adaption processes of these institutions can be said to be part of the larger phenomenon of digitization, a global force of change with increasingly significant economic and societal implications. Scholars within the study of Cultural Economics have begun to address the relationship between organizations that produce cultural, artistic or entertainment value and the increasing prevalence of digital ICT applications in all sectors of society. The academic literature concerning issues such as copyright and reproducibility, innovation and new business models in these industries emerges out of this discussion (Handke, 2010; Towse, 2016).

Not much attention has been paid to the adaption processes of cultural and creative organizations when it comes to the question of human capital. The motivation behind this research is therefore to collect information about how the creative industries respond to the challenges and promises that arise out of the trend of digitization by prioritizing digital competence in their search for employees.

Job descriptions that are published by an online platform that focuses on organizations within these sectors to advertise vacant positions have been chosen as the main research object for the project. Job advertisements comprise a large amount of information that can be operationalized according to a theoretical framework and analyzed with the use of quantitative statistical methods. Their texts yield information about the prevalence of digital skills, the specific level of digital competence that is required as well as additional information about the advertising organization itself. The central research question asks:

RQ: To what extent is digital competence required in the creative industries?

In order to answer this question in a systematic way, two additional sub-questions were formulated that focus on the specific determinants of this hiring demand. They ask:

SQ1: To what extent is the requirement of digital competence dependent on the characteristics of organizations?

SQ2: To what extent is the requirement of digital competence dependent on the characteristics of functions?

The questions will be answered by interpreting the results of a content analysis. Within this analysis, dependent variables will represent the prevalence and distribution of digital skills while independent variables will reflect potential influencing factors.

In order to determine what the influencing factors could be, the analysis will be preceded by a literature review of the relevant theoretical perspectives. The theoretical framework defines more closely what is meant by the research context of the creative industries. It will first discuss which unique characteristics are shared among the organizations and functions that fall into this category before analyzing what distinguishes specific organizations and functions. These distinguishing elements serve as the basis for assumptions about which factors may influence the creative industries in their search for digital competence.

After the introduction of the theoretical framework, the research methodology will be established. The methodology chapter describes the data collection process, the resulting sample and the components of the statistical analysis itself. Several limitations that have to be accounted for in this type of investigation will also be addressed.

The most substantial chapter then presents the findings of the content analysis in a descriptive way before specific results are discussed with regard to how they relate to the research question and its assumptions. The final chapters of the thesis summarize the most relevant conclusions and give an outlook over potential areas of future research.

2 Theoretical Framework

The framework that will be described in the following sections serves to provide a theoretical basis for the empirical investigation of the RQ: to what extent is digital competence required in the creative industries? Various relevant sources will first be reviewed in order to explore the connection between a need for digital skills and the context of the creative industries. The theory will then be used to investigate if some organizations or functions can be expected to require more digital competence than others or whether other factors can be expected to play a role.

2.1 Definition of Creative Industries

Throughout this paper, the term ‘creative industries’ will refer to the original definition of economic sectors established by the British Department of Culture, Media & Sports that is commonly utilized in academic literature (DCMS, 1998; Rozentale & Lavanga, 2014, p.2). This delineation is also reflected in several scholarly definitions (Caves, 2000; Throsby, 2008; UNCTAD, 2008). A useful analytical definition that follows this line and differentiates between process and product is provided by Caves’ description of a “set of industries producing goods and services that we broadly associate with cultural, artistic, or simply entertainment value” (2000, p.1). The distinction between process and product is important since both aspects are connected to different theoretical perspectives that are relevant to the research question as we will see in the following sections.

The following literature review represents an attempt to derive factors that influence the requirement of digital competence in these industries by analyzing the characteristics of the set of organizations that can be described as the creative industries. In order to find out where and when digital skills may be in demand, it is necessary to analyze the unique products that are created and the processes that occur in creative organizations¹.

The primary input and output characteristics of the creative industries can be deduced from the original definition provided by the DCMS. The primary input based on the characterization “creativity, skill and talent” is intellectual capital (DCMS, 1989; Throsby,

¹ Any attempt to distill theories into a process- or skill-based description is complicated by the fact that many of the generally agreed-on properties have not been independently proven or lack empirical justification (Rozentale & Lavanga, 2014). In addition to this, it is often noted that distinctions between process and product always remain somewhat artificial, which is especially true for sectors that tend to produce highly differentiated products (Handke, 2010).

2010; Rozentale & Lavanga, 2014). The primary output, even though it is not directly mentioned in the definition, can be inferred from the identification of intellectual property as a basic source of income (DCMS, 1989). Intellectual property, as described by the WIPO relates to “creations of the human mind” (WIPO, 2004, p.5). In order to arrive at a more specific definition of the main output, the value inherent in these creations can be divided into three different domains according to the aforementioned definition: “cultural”, “artistic” and “entertainment” (Caves, 2000, p.1).

It can now be said that: the creative industries rely on a combination of creative and non-creative inputs in order to generate outputs with cultural, artistic or entertainment value. This distinction allows for an organized review of different theoretical perspectives. Organization types can be distinguished by the different types of value they produce. Analyzing different product types therefore promises to reveal why some organizations require more digital competence than others. In the same way, function types can be distinguished according to the separation between creative and non-creative inputs. A discussion of processes reveals which individual functions may require digital competence within organizational types.

2.2 Output Perspective

All organizations within the creative economy generate goods and services that share some level of cultural, artistic or entertainment value. Several characteristics that are specific to this output indicate that creative organizations require a certain level of digital competence in order to deal with challenges or exploit competitive advantages.

Firstly, scholars have argued that the creative industries rely on innovative uses of technology to deal with risk and uncertainty. This characteristic arises out of the challenge of generating wealth based on intangible value and the unique role that human subjectivity plays in its assessment. In the creative industries, success ultimately depends on human tastes which results in high levels of demand uncertainty for producers (Rozentale & Lavanga, 2014). An “infinite variety” of highly differentiated products adds to this phenomenon and creates oversupply and quality uncertainty (Caves, 2000, p.6; Kretschmer, Klimis, Choi, 1999). “Nobody knows” how exactly subjective value corresponds to specific needs which is reflected in the fact that buyers can make decisions based on “traits, moods, styles” that supersede even their own judgement of quality (Caves, 2010; 2000, p.6). What is more, consumer tastes are also highly volatile and subjected to sociological phenomena such as herd

behavior which is compounded by the fact that outputs can have search and experience good characteristics (Townley and Beech, 2010; Handke, 2010).

Shiller explains that herd behavior is especially common in contexts where information is both highly relevant and limited (1995, p.181). The creative industries represent such a context since (1) consumers are dependent on quality signals while producers depend on demand signals and (2) there is generally not enough information being signaled. Caves describes the extraordinary lack of information as a state of “symmetrical ignorance” rather than asymmetrical information (Caves, 2000, p.14). Cooke & Lazzaretti argue that organizations typically react to this risk by producing high levels of novelty (2008). According to Rozentale and Lavanga (2014), high levels of technological advancement can therefore be expected to be prevalent within the creative economy (Power and Scott, 2004).

However, digital technology can not only be used to reduce risk but also affords special opportunities for the creative industries that other sectors may not have. ‘Digital Culture’ expert Kevin Kelly² (2019) points out that in today’s digital economy, organizations that produce goods with intangible qualities possess a competitive advantage based on the general decline of material production costs throughout all economic sectors (2018). Intangible qualities such as authenticity, personalization and interpretation cannot easily be replicated or automated and therefore possess inherent value according to Kelly (1999). The outputs of all creative industries therefore share a unique advantage based on their ability to provide these intangibles.

The prospect of exploiting competitive advantages can be expected to compel organizations to invest in digital competence and position themselves in the digital market. This includes creative sectors that focus on singular non-reproducible goods as well as sectors that specialize in mass reproduction and distribution since both can be described as “producers and carriers of symbolic content and meaning” based on the outputs they produce (KEA, 2006; Throsby, 2001; Rozentale & Lavanga, 2014, p.2). The unstable nature of a live performance, for example, guarantees a sense of authenticity and perceived importance that is enhanced by the presence of other people. Feelings of interaction and personal interpretation, however, can also be experienced by individual consumers of reproducible symbolic content.

² Kelly was the executive editor of Wired magazine and the author of several publications related to the connection between culture and the digital economy (<https://kk.org/biography>).

Different opportunities of marketing these intangible qualities will be further discussed in the following section.

2.3 **Input Perspective**

All organizations within the creative economy rely on a combination of non-creative and creative inputs in order to produce cultural, artistic and entertainment value. The following section will describe that the characteristics of these inputs indicate that digital competence is especially relevant for certain processes and less important for others. This represents the basis for assumptions about which types of organizations can be expected to demand higher or lower levels of digital competence.

On an abstract level, skills can be understood as inputs in a production function (Caves, 2000). A relevant common property of the production function of all creative industries sectors is its multiplicative nature: inputs have to perform with a certain degree of proficiency – which means that both creative and non-creative functions cannot easily be substituted – and a certain degree of conformance – which means that they have to interact with each other (Caves, 2001). Value chains of creative industries organizations therefore tend to be complex, fragmented and characterized by high levels of required coordination (Handke, 2010).

On a general level, all functions can be expected to require a minimum of digital competence based on the fact that the proliferation of ICT is a significant social phenomenon with far-reaching consequences. This is underlined by the argument made by Bekar and Haswell (2013) who state that digital ICT can be understood as a “General Purpose Technology”, a universal system of applications and externalities that essentially forces transformative adaption processes throughout all economic and societal sectors (p.10). Individual inputs along the value chain can be said to rely on digital competence when a specific application of digital ICT comes to use. Creative inputs have to be distinguished from non-creative inputs in order to draw more detailed conclusions.

2.3.1 **Humdrum Inputs**

Humdrum inputs are simply all functions that pertain indirectly to the primary process of exploiting creativity-based human capital for the sake of generating cultural, artistic or entertainment value. In other words, while creative inputs mark the first component of the

value chain, humdrum inputs characterize every subsequent step of the wealth creation for creative organizations (Handke, 2010).

Humdrum inputs occur within stable organizational structures more often than in temporary organizations and can influence or be influenced by the creative inputs (Handke, 2010). The influence of creative inputs can be analyzed by differentiating between ‘core’ humdrum functions and ‘intermediary’ functions. Functions that support, supplement or mediate creative outputs by directly adding to them can be regarded as intermediary functions whereas core humdrum functions concern operational activities that are several procedural steps removed from the creative inputs. Humdrum inputs can be expected to require a certain amount of digital competence based on the preceding discussion of the output of the creative industries.

Firstly, the process of mitigating risk and uncertainty requires core humdrum functions that harness the large variety of applications afforded by the “General Purpose Technology” of Digital ICT (Bekar & Haswell, 2013, p.10). This technology can, for example, be used to gather information by analyzing market structures, monitoring audience feedback or conducting computer-based research. Digital ICT systems can also improve the internal structures of organizations by facilitating communication and cooperation or automating elaborate tasks. In a context of perpetual uncertainty, proficiency with digital applications of this type can be expected to be especially valuable.

Secondly, digital competence is also required in humdrum functions that serve to exploit the aforementioned competitive advantages based on the intangible value of creative outputs. However, the specific output characteristics of certain organizations result in the fact that not all of them are able to pursue these advantages to the same degree. Section 2.4 will provide a basis for the argument that certain humdrum functions can be expected to require more digital competence based on this separation.

2.3.2 Creative Inputs

Creativity-based intellectual capital inputs can be described as chaotic or idiosyncratic in that they often contradict standard economic assumptions. Towse (2010) describes, for example, the relevance of the theory of intrinsic motivation in the analysis of artists’ labor markets which contradicts the neoclassical conception of motivation based purely on monetary rewards (Frey & Jegen, 2001). Imbalances between supply and earning also confirm the so-

called ‘starving artist syndrome’ which holds that “a taste for creative work increases the amount of effort supplied by diverting it from humdrum tasks” (Caves, 2000, p.4).

Artists nevertheless have entrepreneurial interests in that they seek to convert symbolic, social or cultural capital into economic capital (Scott, 2012). This connection forms the core of the cooperative effort that is characteristic of all organizations that generate value based on creative inputs. The merging of this autonomous artistic logic and the heteronomous financial logic that influences all forms of industrial organization generally demands that creative inputs are provided from outside of the organizational structure or within closed departments that diverge from the rest of the organizational hierarchy (Scott, 2012).

When it comes to the question of digital competence, traditional views of creative intellectual capital suggest that it would be resistant to technological innovation. The famous cost disease problem described by Baumol rests on the assumption that the arts are especially labor-intensive and the productivity of this labor is stagnant (Towse, 2010). The fact that technological progress reduces costs in other sectors by enhancing labor productivity therefore results in unequal wages and an eventual imbalance between labor cost and productivity in the creative sectors (Towse, 2010).

Not all creative inputs, however, are so-called artisanal creative inputs. This has been effectively pointed out by Blaug who argues that “the ‘arts’ that are costing more as time goes by are not the same ‘arts’ at all” (2001, p.131). Certain production techniques such as the writing of a literary work have been found to be relatively resistant to the transforming effects of digital ICT (Bekar & Haswell, 2013, p.12). Other forms of creative input, by contrast, such as the production of music have been rendered much less labor-intensive. According to Bekar and Haswell (2013), this difference can be attributed to the relatively stable “artisanal” nature of the production.

The domain of “artisanal” value usually refers to traditional craft goods such as, for example, artisanal textile, ceramics or metal products (ITC, 1997). In contrast to this, Bekar and Haswell employ this term by using it to describe non-automatable qualities such as, for instance, the competence of an opera singer (2013). Both understandings of “craft” imply that the creative input is dependent on the skills of a person and cannot be digitally replicated without loss of value. According to the official glossary definition of UNESCO and the International Trade Centre (ITC), a crucial characteristic of artisanal value is that “the direct

manual contribution of the artisan remains the most substantial component of the finished product” (1997). In Bekar and Haswell’s (2013) liberal interpretation, artisanal production techniques are present when the most substantial contribution remains dependent on human skills without the aid of technology – even if the nature of this contribution is purely performative. In order to avoid confusions with craft, the following sections will not refer to this characteristic as artisanal. Creative inputs of this sort will instead be described as technology-resistant.

In summary, the core process of creation can be expected to be either highly irrelevant or highly relevant for the demand for digital skills. This is because technology-resistant creative inputs do not require digital competence per definition. In contrast, if a creative practice has been digitally transformed, it is likely that the required digital competence can be understood to be a natural part of the necessary skillset. The specific artistry of a film editor, for example, represents such a case since it is largely based on software proficiency³.

2.4 Influence of Reproducibility

After discussing the input and output characteristics of the creative industries with regard to potential indicators for digital competence, the following section discusses how specific features at the level of inputs translate into factors that influence the level of digital competence at the level of outputs. Understanding which outputs can be linked to digital skills allows for assumptions about which functions and organizations may require digital competence.

Bekar and Haswell (2013) argue that so-called “core-creative” activities such as the production of an oil painting are “largely untouched by Digital ICT’s” while the commercial film industry relies heavily on digital technologies, and the development of a videogame would even be unthinkable without it (2013, p.12). This illustrates that the presence of technology-resistant inputs is reflected in a distinction between different types of outputs.

Reproducible outputs are often related to entertainment value rather than cultural or artistic value. They typically do not derive their value from a technology-resistant style of production and therefore do not lose value in the process of reproduction. In fact, reproducible

³ An exception to this can be found in the use of digital ICT as a creative technology itself that serves the production of “born digital works” that do not have analogue equivalents. (NESTA, 2018, p.38). Digital exhibits of this kind are currently still relatively rare, however, and can be summarized as contributions to “experimental culture” (ibid.).

outputs are often themselves based on information content and overcome spatial and temporal limits through the use of digital ICT (Handke, 2010). Reproducible cultural products are durable and produce durable rents since they do not “lose their entire value with the first instance of consumption” (Caves, 2000; Handke, 2010).

In contrast to this, non-reproducible outputs are generally associated with so-called “high culture” rather than “low culture” (Caves, 2000). They are generally focused on cultural or artistic value rather than entertainment value. The outputs of these organizations are “constrained by spatial and temporal limits” in their consumption and distribution (Handke, 2010). Non-reproducible outputs are therefore not information goods⁴ and their value is diminished in the reproduction process.

The fact that all outputs that rely on technology-resistant inputs lose value in the digital reproduction process represents a potential explanation for the separation between reproducible and non-reproducible outputs. The proportional amount of value that is lost – and therefore the degree of reproducibility – varies from case to case. For example, in the case of outputs that are the product of truly artisanal handicraft, the value that can be captured in the form of informational copies such as images or films is close to non-existent. In the case of an opera production, however, a digital recording arguably captures some relative value and can therefore be used to generate wealth even if the sale occurs at a fraction of the ticket price. Creative organizations of the performing arts such as theaters can be called suppliers of non-reproducible outputs even if they are generating revenue in this way since their main output is not fully reproducible.

Some scholars have argued that the process of monetizing goods that possess cultural or artistic value does not only require analogue participation but cannot even be described as a ‘consumption’ process. According to Klammer, becoming the owner of a certain cultural experience actually entails a “contribution” on the part of the audience (2015, p.19). He describes the notion of experience goods and the concept of ownership as problematic when it comes to artistic organizations which supports the assumption that reproducibility is a product of technology-resistant inputs⁵.

In contrast, if outputs are originally fixated as information goods, they do not lose value in the reproduction process and can therefore be mass-produced at minimal marginal

⁴ “anything that can be captured in bits” (Handke, 2010; cf. Hill, 1999; Varian and Shapiro, 1999)

⁵ Klammer argues, for example, that the transaction of buying a ticket to an art exhibition does not guarantee the owner of the ticket to become the owner of a certain experience unless they choose to engage with the exhibited art (2015, p.19).

cost (Handke, 2010). Organizations that focus on this group of products are therefore able to fully exploit the opportunities that the proliferation of digital ICT offers for suppliers of goods with intangible value according to Kelly (2018). In addition to this, Davenport and Beck argue that the current economy is characterized by a prevalence of information which means that attention – the ability to consume information – becomes a scarce resource. In this “attention economy”, producers of entertainment value possess an additional competitive advantage since they are able to attract attention to their outputs (Davenport and Beck, 2001, p.7). Finally, suppliers of reproducible creative goods are also less bound by the constrain of artistic integrity than artistic or cultural organizations which allows them to pursue commercial opportunities in secondary markets.

The combination of these advantages represents a potential explanation for the recent success of digital business models for non-reproducible creative industries. Audience development tactics are of special importance for these organizations since they provide advertisers with access to viewer engagement⁶. This multi-sided dynamic allows organizations to reduce the characteristic demand uncertainties of creativity-based outputs while exploiting the intangible value described by Kelly (2018) with an explicit focus on the attention economy. Internet platforms with large user bases that represent some of the most financially successful examples of creative organizations have incentivized artists to fulfill the prescriptions of marketers and seized large proportions of the resulting profit⁷. These suppliers of reproducible creative goods separate creative and humdrum inputs more effectively as they scale up and seize market power. The claim of a monopolistic position can therefore be regarded as a solution to the contract and organization problems identified by Caves (2000).

In summary, digital competence can be expected to be a prevalent requirement in organizations that focus on reproducible outputs since the transformation of one or many organizational channels entails countless digital applications. Various software-based applications become necessary in the design of a web-based platform; sales and advertising functions require a knowledge of the digital product itself and therefore also the opportunities

⁶ Viewer engagement can be measured in different ways from the number of clicks on audio or video elements to the number of pageviews on any website on the internet.

⁷ An example is the partnership program of the video content platform Youtube where creators can only start to earn money after demonstrating 4000 watch hours of engagement throughout the year. The platform then matches the videos up with appropriate advertisers and receives a share of the resulting revenue (typically 45%) (Mohan & Kyncl, 2018).

and restrictions of the underlying software; and finally, many technical problems such as the hosting and storage of large amounts of data have to be solved (NESTA, 2017).

Suppliers of non-reproducible outputs can be expected to rely on digital skills to a more limited extent that is focused on intermediary humdrum functions. Paintings allow for different forms of mediation such as digital archiving or supplementation in the form of additional educational content; performances of all kinds can be livestreamed or recorded; museums and galleries can offer interactive online tours of their collections or provide virtual and augmented reality experiences; and antiques sellers can foster discussion in online blogs and forums. However, the fact that outputs cannot be reproduced without loss of value means that the main product cannot be made available in digital form which inhibits the transformation effect.

2.5 Summary

The review of different theoretical concepts and perspectives provides a basis to answer the RQ: to what extent is digital competence required in the creative industries? Referring to the definition of the research context firstly allows for a basic distinction between input and output which provides the basis for answering SQ1 and SQ2: to what extent is digital competence dependent on the characteristics functions/organizations? The properties of functions and organizations can then be derived from a theoretical discussion of input and output in the creative industries.

The outputs of the creative industries share the characteristic of possessing cultural, artistic or entertainment value. This suggests two potential reasons for the requirement of digital competence: Firstly, the subjective quality of this value results in uncertainty – a lack of information and a need for signals – which can be remedied by technology (Kretschmer, Klimis, Choi, 1999; Caves, 2000; Cooke & Lazzaretti, 2008). Secondly, the symbolic aspect of this value results in unique qualities – intangibles such as, for example, authenticity – that are especially useful in the digital economy and require mediation with the use of technology (Caves, 2000; Davenport & Beck, 2001; Kelly 2017). The fact that all creative industries share these output characteristics indicates that the requirement of digital competence is indeed dependent on outputs and therefore also on organizational characteristics.

The shared input characteristics of the creative industries firstly reveal that functions can be expected to share a base-level of digital competence not only because of the above-

mentioned output characteristics but also because of the designation of Digital ICT as a General Purpose Technology (Bekar & Haswell, 2013). The fact that different kinds of inputs – namely, creative and non-creative or humdrum inputs – are present and are likely to influence each other does not in itself suggest that digital competence is dependent on functions (Caves, 2000; Blaug 2001). However, an investigation of specific inputs also shows that the characteristics of organizations and functions are connected by a factor that is likely to influence the level of demand for digital competence. The technology-resistant (artisanal) property of certain inputs strongly suggests that some functions require more digital competence than others (Bekar & Haswell, 2013). Inputs that are resistant to technological processing can explain the distinction of reproducible and non-reproducible outputs on the level of outputs (Handke, 2010).

In summary, the literature review suggests that the creative industries do rely on digital skills to a significant extent that is influenced by characteristics on the level of functions and organizations. A production process that is resistant to technology restricts the possibility of digital reproduction which, in turn, restricts further transformation processes. This reasoning can be tested by forming assumptions about the level of required digital competence among different functions and organizations within the creative industries. These assumptions and the chosen method of analysis will be outlined in the following chapter.

3 Methodology

In order to test whether the conclusions of the literature review are valid and relevant to the research question, a set of theoretical assumptions will be derived from it. The assumptions will then be systematically tested by analyzing job vacancy data. Within the analysis, the potential influencing factors are operationalized as independent variables while the required digital competence represents the dependent variable. The following sections will describe the formulated assumptions in more detail before discussing the data collection process and the framework of the analysis itself.

3.1 Assumptions

3.1.1 Organization Types

Assumptions about organization types are based on the output characteristics of the creative industries. All secondary output characteristics ultimately are a product of the primary output outlined in the main definition which states that creative industries provide goods and services with cultural, artistic or entertainment value. The assumptions state:

1a) A base-level of digital competence exists in all organizations. The subjective nature inherent in all outputs is likely to compel organizations into investing in novelty and technological advancement to mitigate risk and uncertainty. In addition to this, the symbolic quality of creative outputs provides an incentive to exploit competitive advantages based on the ability to provide intangible qualities with unique value in the digital creative economy.

1b) Organizations that focus on reproducible outputs require a higher degree of digital competence than suppliers of non-reproducible outputs. Their outputs are not only infused with intangible value but are themselves information goods that can be distributed and consumed online. The reproduction process requires digital competence and enables the transformation of other organizational channels based on the prospect of solving organizational problems and capitalizing on competitive advantages.

3.1.2 Function Types

Assumptions about function types are based on the input characteristics of the creative industries. All inputs characteristics ultimately arise out of the main definition of input which states that creative industries rely on a combination of creative and non-creative inputs. The assumptions state:

2a) Humdrum inputs for all organization types require a base-level of digital competence since Digital ICT represents a General Purpose Technology. In addition to this, humdrum functions serve to supplement or mediate creative outputs whether they are reproducible or not.

2b) Humdrum inputs can be expected to require more digital competence when the organization is focused on reproducible outputs. This is because this output type allows organizations to gain competitive advantages in the digital information economy by transforming one or many organizational channels with the use of Digital ICT. These advantages include mass-production of content at low cost, monitoring audience development in the form of viewer engagement and selling successful products to advertisers in secondary markets.

Table 3.0: Summary of Assumptions

Relevant Characteristic	Literature	Theory	Assumption	Organization	Function	Digital Competence
Output: Cultural, Artistic, Entertainment Value	Kretschmer, Klimis, Choi, 1999; Caves, 2000; Cooke & Lazzaretti, 2008; Throsby 2001; Rozentale & Lavanga, 2014	Demand Uncertainty, Product Differentiation, Volatile Tastes, “Symmetrical ignorance”, Intangible Value	(1a)	all	-	> 0
	Caves, 2000; Davenport & Beck, 2001; Handke, 2010; Kelly 2017	Information Goods, Durability, Attention Economy, Intangible Value	(1b)	reproducible	-	$> (1a)$
Input: Creative and Non-Creative Intellectual Capital	Bekar & Haswell, 2013	General Purpose Technology	(2a)	-	humdrum	> 0
	Caves 2000; Blaug, 2001; Scott 2012; Bekar & Haswell, 2013	Technology-Resistant Creative Inputs	(2b)	reproducible	humdrum	$> (2a)$

3.2 Data Collection

Job descriptions that have been published by organizations within the creative economy to advertise vacant positions have been chosen as the research object and the main source of data. Advertisements of this sort represent an “organic and naturalistic” data source that is easily accessible (Harper, 2012, p.30). However, the choice of collecting data based on job advertisements entails a number of implications that have to be taken into account in the process of constructing an effective methodology.

3.2.1 Limitations and Strategies

Harper identifies various drawbacks that are associated with the naturalistic quality of the collected data (2012). The process of mining job advertisements for data entails the extraction of text-based entries from a pre-existing database such as, in this case, an online job platform. The consistency and quality of individual entries can therefore vary depending on factors that are outside of the researchers’ control. Some inconsistencies can be addressed in the conceptual design of the study while others have to be accepted. The distorting effect of ambiguous texts, for example, can be mitigated by employing a strict method of operationalizing that relies on external reference points. In extreme cases, some observations may have to be discarded altogether. Xu points out that those cases can nevertheless be utilized as qualitative data which reflects projected values (1996).

Larger problems may arise out of the fact that “the population of job advertisements and its structure is practically unknown” (Kurekova et al., 2013, p.14). Data can be unavailable because of the restrictions of the chosen platform or because of the specific nature of the advertised position itself (Croneis & Henderson, 2000). This results in various uncontrolled or even uncontrollable variables (Xu, 1996).

According to a large-scale study of research projects based on job vacancy data (Kurekova et al., 2013), this issue can be addressed by focusing on representativeness and reliability in the data collection process. The two main recommendations given by the study underline that 1) the quality of the data source ought to be evaluated on the level of countries since “(d)ominant market share of a given job portal (...) can lead to reliable and transferable research results” and 2) the assessment of representativeness and reliability is contingent on the given research focus which means that “(t)he usage of data segments or sub-samples which can be considered (more) representative can address aspects of coverage and sampling

errors.” (Kurekova et al., 2013). Harper (2012) also states that the unknown size of the population calls for large samples (Mean: 575, Median: 236).

The collection of job vacancy data hence requires a “rigorous data management process” that takes the above-mentioned considerations into account (Harper, 2012, p.39). This process is further complicated by the fact the data collection has to be conducted over a relatively short span of time in order to produce a current representation of the population.

3.2.2 Sample

The platform that serves as a database in this case is the job portal “Kultur Management Network”, a service provided by the German company KULTURPERSONAL GmbH (KULTUREXPerten GmbH) specialized in HR and recruitment applications for creative organizations. All organizations that advertise vacant positions on the website are encouraged to provide relevant information about their entry by categorizing it according to a framework developed by the company. The framework can be regarded as the structural architecture of the database that assigns a maximum of six nominal variables to each job advertisement (since most entries do not hold information for all six categories).

The Kultur Management Network portal is the largest provider of job advertisements for the creative industries in the German-speaking countries⁸. Nevertheless, several uncontrolled variables exist since not all relevant organizations use this service and not all aspects of the job advertisement can be included in the analysis. In order to produce a reliable but also representative sample for this research, entries have therefore been collected with special regard to the variables that are significant to test some characteristics derived from the theory: “Area of Organizational Activity” represents the type of organization and “Area of Activity” represents the function type. Entries that contain ambiguous information about these properties (or no information at all) have been left out of the data collection process. The resulting sample reflects an attempt to construct a cross-section of the population of all relevant job advertisements which is unknown in size. The final sample comprises 250 observations that have been extracted between March 14, 2019 and May 5, 2019.

The sample comprises 14 different types of organizations and 22 different types of functions based on the original database structure. Due to the random sampling process, observations are distributed unevenly within these categories. The advertisements appear on

⁸ The platform (not the sample) also includes a small number advertisements from Switzerland and Austria.

the website based on the order of their original publication when no other categorical filter is present. The sample therefore indicates that, within the time frame of the data collection, some categories were more prevalently advertised than others. In the analysis, organizations and functions are grouped into sub-samples and categories with insignificant amounts of entries are left out in order to overcome this limitation⁹.

Table 3.1.2-1: “Areas of Organizational Activity”

“Areas of Organizational Activity”	Frequency	Percent
Library & Archive	6	2.4
Education & Society	9	3.6
Visual Arts	37	14.8
University & Research	7	2.8
Commercial “Creative Economy”	27	10.8
Cultural Policy & Public Administration	15	6.0
Cultural Tourism	2	0.8
Art Market & Exhibition Space	16	6.4
Media & Literature	15	6.0
Museum & Cultural Heritage	37	14.8
Music	48	19.2
Social Culture (“Soziokultur”)	3	1.2
Interdisciplinary	14	5.6
Foundation	14	5.6

Source: own elaboration

Table 3.1.2-2: “Areas of Activity”

“Areas of Activity”	Frequency	Percent
Consulting	2	0.8
Dramaturgy	4	1.6
Ensemble & Orchestra Management	8	3.2
Event Management	10	4.0
Finance/Controlling	13	5.2
Fundraising/Sponsoring	5	2.0
Artistic Director (“Intendanz”)	6	2.4
Curation	7	2.8
Artistic Production	4	1.6
Artist Management	7	2.8
Teaching/Research	5	2.0
Marketing/PR	49	19.6
HR	2	0.8
Project Management	32	12.8
Editorial Department	5	2.0
Film Director	2	0.8
Ticketing	3	1.2
Sales/Customer Service	1	0.4
Pedagogy	14	5.6
Administration	35	14.0
Research Assistant	14	5.6
Other	22	8.8

Source: own elaboration

⁹ The full dataset is available upon request to the author.

3.3 Analysis Framework

In the final analysis, certain properties of individual job advertisements will be measured with regard to their ability to predict other properties. Specifically, the analysis investigates whether information about the organization type and/or function type indicates whether an advertisement demands more or less digital skills. The information contained in each entry therefore has to be operationalized so that variables could be constructed in order to reflect the properties which are relevant to the research question.

3.3.1 Operationalization

Harper (2012, p. 38) describes the method of content analysis as a “systematic technique of segmenting data into describable linguistic units” that is frequently used in studies that rely on job vacancy data. Quantitative coding can be done manually by identifying certain words and counting their occurrence or by relying on prior sources with a certain degree of external validity (Harper, 2012). Operationalizing a theory represents a significant challenge based on the fact that concepts in the social sciences cannot be perfectly translated into discrete numerical values. Every choice in the construction of an operationalization framework therefore represents a somewhat flawed extrapolation based on human subjectivity that has to be regarded as a potential limitation.

Independent Variables: Determinants of Digital Competence

The first analysis model is designed to test whether general trends or correlations that are relevant to the research question can be found by investigating the database without altering the pre-existing structure. This approach will be used to test assumptions (1a) and (2a). The database contains two relevant variables that present a number of possible values. Both variables assign numeric values to their nominal contents: The category “Areas of Activity” is represented by the variable “*function type*” (*fcttype_kmn*) that includes 22 possible values such as, for example: “Administration” or “Marketing/PR”. The category “Areas of Organizational Activity” is represented by the variable “*organization type*” (*orgtype_kmn*) that contains 14 possible values such as, for example: “Music” or “Cultural Tourism”.

The second model tests assumptions (1b) and (2b). The “*reproducibility*” dummy variable (*reproduce*) registers whether the text of the advertisement indicates the presence of reproducible outputs. Based on the prior discussion of the theory, this means that two types of job advertisements can be captured: in the first case, the job advertisement indicates that the

advertising organization is predominantly focused on reproducible products as a main source of revenue. In the second case, the advertisements concerns a function that mainly relates to reproducible outputs within an organization that is normally focused on non-reproducible outputs (such as the sale of recordings in a performing arts organization).

In reality, however, the latter case only appears in a very small number of observations whereas the first case dominates the “*reproducibility*” category. When reproducible outputs are the main product, the relevant information can often be derived from the title or description of the organization. Exemplary organizations in the sample are: an audio book publisher, a broadcasting studio and a developer of tourism products based on virtual reality technology. In the ambiguous case where functions relate to reproducible outputs in non-reproducible contexts, the job description itself becomes especially relevant. In one such case, for example, a public education center advertises a position that mainly involves processing texts, fotos and videos for the organization’s media portal.

Dependent Variables: Digital Competence Demand

The degree of digital competence will be measured by referring to the Digital Competence Framework (DigiComp 2.0), a strategic initiative introduced by the EU Commission’s Directorate-General for Education and Culture (DG EAC) in 2011. The framework has been created to serve as a conceptual reference model that can be utilized to identify and measure the individual components of digital competence (Vuorikari et al., 2016). Even though the aim of this concept is to help all European citizens to evaluate their qualifications, the EU acknowledges that it is specifically useful as a tool for measuring professional skills. The framework provides the basic methods of measurement that are employed in the analysis of digital skills in the EU labor market (Kiss, 2017) and it has been integrated into the “Europass” website as an interactive tool¹⁰.

The framework contains two dimensions that provide the conceptual basis for this analysis of digital competence. The first dimension describes five categories that are designated as ‘competence areas’ while the second dimension describes various skills that are regarded to be exemplary ‘competence indicators’ for each of the five categories. Skills have

¹⁰ A project launched by Directorate General for Education and Culture to provide standards for employers and applicants when it comes to communicating professional skills (<https://europass.cedefop.europa.eu>)

been designated based on the EUROSTAT survey of internet usage in households and by individuals (EUROSTAT, 2017). The following table lists some examples:

Table 3.2-1: Digital Competence Areas & Indicators

Competence Area	Competence Indicator (example)
1. Information	“finding information about goods and services”
2. Communication	“participating in social networks”
3. Content Creation	“creating websites or blogs”
4. Safety	“using a security software or tool”
5. Problem Solving	“selling online”

Source: DigComp Framework, 2016

Not all competence indicators pertain to a demand for skills that is likely to be advertised in professional contexts. Some competences such as “sending/receiving emails” or “copying or moving a file or folder” have already become ubiquitous requirements that usually do not need to be mentioned while others simply have no professional application (Kiss, 2017, p.6). The two dimensions are therefore incorporated into the analysis as a guiding framework that is mainly employed to differentiate between individual competence indicators and competence areas.

DigiComp 2.1 adds a third dimensions of ‘proficiency levels’ to the framework. Four levels are differentiated by separating between various degrees of complexity and autonomy as well as different cognitive domains. In this analysis, however, tasks without a basic level of complexity and autonomy have to be left out of the equation since they have no professional application. A more simple and relevant differentiation can be constructed by referring to the first two dimensions of the framework: competence areas and competence indicators. A low number of competence indicators translates into a lower level of digital competence and vice versa. The following table represents a categorization based on this reasoning:

Table 3.2-2: Digital Skills Levels

Proficiency Level	DigiComp Framework Components
1. Foundation	One competence indicator in one competence area
2. Intermediate	Several competence indicators in one competence area
3. Advanced	Several competence indicators in several competence areas
4. Specialized	Several competence indicators in all competence areas

Source: own elaboration

The values of the dependent variables “*skills*” and “*skills lvl*” are based on this interval. It represents a measure that captures the degree of digital competence by registering the existence of digital skills mentioned in the job description (skills) and grouping

observations according to an ordinal hierarchy that represents the four proficiency levels (skills_lvl).

3.3.2 Statistical Analysis Methods

The variables will first be analyzed descriptively in order to test whether certain categories promise to be useful for further analysis. The sample is not normally distributed which is why not all measures of central tendency are applicable. This limitation can be overcome by referring to measures that are not very responsive to outliers. The tendency of skewed samples can, for example, be analyzed by utilizing the median value instead of the mean. As a measure of variability, the statistic of interquartile range represents an alternative to the range from highest to lowest score.

When it comes to bivariate methods, several analytical possibilities can be derived from the involved variable types. This is especially challenging since qualitative data which has been coded into numerical values cannot actually be treated as quantitative data. In the case of the independent variables “*organization type*” and “*function type*”, discrete numerical values have been assigned to a nominal measure. The alternative independent variable “*reproducibility*” is a dummy variable with discrete dichotomous values (yes/no).

Discrete variables can nevertheless be treated as continuous predictors (covariates) or categorical predictors (factors). In the first part of the analysis, they will be analyzed as factors which means that a response value that reflects digital competence is matched with each level of the predictor variable independent from the order of the predictor levels. The results of such a frequency analysis can be organized in a crosstabulation that showcases the existence of descriptive patterns. A Chi-Square Analysis will be used to reveal whether a significant relationship can be expected.

If the frequency analysis indicates that there may be a functional relationship between a response and a predictor, the variable outcome will be recoded and treated as a continuous covariate. A linear regression analysis is nevertheless impossible in this case since the response variables themselves are also not continuous. The variable “*skills*” (skills_lvl) represents the quantification of an ordinal hierarchy which means that digital competence levels are ranked but the distance between each jump in the scale cannot be regarded as equal. The step from “advanced” to “specialized”, for example, is arguably larger than the step from “none” to “intermediate” based on the preceding discussion of the framework.

In the case of an ordinal response variable, a logistic model can be used instead of a linear regression. This ordered logistic regression estimates the probability of an outcome that reflects one category of the response variable ($\text{logit}(p) = \ln(p/(1-p))$). In this case, the sample size is not large enough to yield significant results for all categories which means that a multinomial model cannot be constructed¹¹. Instead, the analysis will rely on a binary logistic regression that identifies probabilities of group membership for dichotomous variables. The variable “*skills lvl*” will be recoded into dummy variables that reflect each level of skills while the variable “*skills*” reflects the presence of any digital competence indicators. Both dependent variables are likely to yield significant results when outcomes of predictor variables with high frequencies are recoded into dummy variables and used as covariates.

¹¹ Harper points out that inferential statistics can only be applied to job vacancy data if samples are very large (2012).

4 Findings

In this chapter, the findings of the empirical analysis will be presented. Firstly, variables that represent the main research object of digital competence will be discussed. Categorical variables that reflect the context of function types and organization types will then be presented and analyzed in their bivariate relationship to the response variables. In cases where frequencies reveal a potential dependence, individual outcomes will be analyzed more closely. When the relationship has been proven to be potentially significant, the variable will be used as a predictor for certain levels of the response variable or individual outcomes will be recoded to be used as predictor variables. Finally, variables that concern the potential influence factor of reproducibility will be specifically analyzed with regard to their relationship to the response variable.

4.1 General Distribution of Digital Competence

The dichotomous variable *skills* registers any mentioning of digital skills in the observations, independent from the level of digital competence that is required. A univariate analysis of the measure demonstrates that, out of 250 advertisements, 157 mention a requirement of digital skills. A majority of the observations (62.8%) can therefore be said to fall into this category which leaves slightly more than one third requiring no level of competence (37.2%).

Table 4.1-1: Digital Skills

Skills		
	Frequency	Percent
yes	157	62.8
no	93	37.2

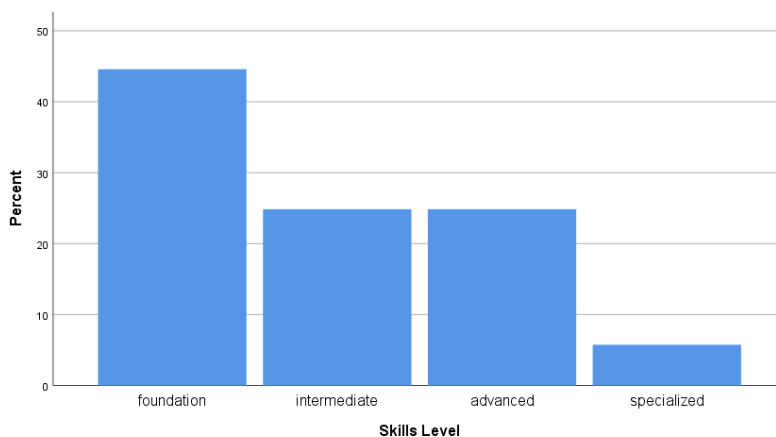
The full sample is positively skewed (0.655; z-value: 4.25) which corresponds to the mean of all observations shifting to the right. This can be explained by analyzing the second response variable *skills_lvl*. This variable measures how different levels of required digital competence are distributed among all examined advertisements.

Table 4.1-2: Digital Skills Levels

Skills Level		
	Frequency	Percent
none	93	37.2
foundation	70	28.0
intermediate	39	15.6
advanced	39	15.6
specialized	9	3.6

If one considers all 250 cases, the measures of central tendency and variability are skewed based on the influence of the most frequent outcome of the *skills_lvl* variable. The distribution shows that, even though advertisements ask for digital skills more frequently than not, the lack of any skill requirement represents the most prevalent outcome. Without any adjustment to this, the sample mode therefore is “none” (0) and the median is “foundation” (1). This means that, if one considers the entire sample, there is an equal number of cases below and above the most basic level of digital competence. Job advertisements that require no skills are hence as proportionally prevalent as advertisements that require skills on the level of “intermediate” (2) or better. The interquartile range reflects this by designating “intermediate” as the middle group.

The true distribution of digital competence, however, can only be understood by excluding cases that register the outcome “none” (0). The remaining sample group consists of 157 cases with varying levels of skill requirements. The skewness of this group is less large while still significant (0.194, z-value: 2.9) and represents a more accurate reflection of the skill level proportions. With this adjustment, both the median and the interquartile range shift to the level “intermediate” (2) which means that the proportion of “foundation” (1) skills matches the proportion of skills that are “advanced” (3) or better. The number of entries in the category “advanced” (3) equals the number of entries in the category “intermediate” (2). A mean/range of “intermediate” (2) therefore signifies the influence of the large number of the category “foundation” (1). The “specialized” (4) category that counts advertisements that require skills in all relevant competence levels is comprised of only 9 entries out of 250 observed cases (3.6%).



Graph 4.1: Digital Skills Levels

4.2 Function Types

4.2.1 Prevalence of Skills

The nominal variable *fcftype_kmn* assigns 1 out of 22 possible function types to each advertisement based on the structure of the original database. The random sampling process results in the fact that the number of cases (N) is unevenly distributed among these categories. The most frequently counted function types are:

Marketing/PR (49); Administration (35); Project Management (32); Pedagogy (14); Research Assistant (14); Finance/Controlling (13); Event Management (10).

The following categories contain less than 10 entries:

Ensemble & Orchestra Management (8); Curation (7); Artist Management (7); Artistic Director (6); Fundraising/Sponsoring (4); Teaching/Research (4); Editorial Department (5); Dramaturgy (4); Artistic Production (4); Ticketing (3); Consulting (2); Film Director (2); HR (2); Sales/Customer Service (1).

A bivariate analysis of the variable *fcftype_kmn* and the dichotomous variable *skills* reveals whether a relationship between certain advertised function types and the mentioning of a requirement of digital competence can be expected. The Chi-Square Test for (*skills* * *fcftype_kmn*) is significant (.006) but expectedly violates the 20% threshold (65%). This is due to a low amount of entries in some levels of the variable. Filtering out all function types that contain N<10 entries, increases the significance and reduces the cells with an expected count of less than 5 to 25%. The slight violation nevertheless indicates that the approximation of the underlying distribution is not generalizable. The null hypothesis stating that there is no relationship between required skills and function type cannot be rejected. An analysis of individual frequencies can nevertheless be used to demonstrate potential associations. Categories that are likely to pass the test of non-independence can be used in specifically constructed analyses.

In 12 out of 22 cases, the majority of observations mentions digital competence while 4 categories are matched evenly and 6 are dominated by no mention of digital skills. The two categories that count no mentions at all (HR; Sales/Customer Service) are likely to be insignificant based on a very low number of entries.

Table 4.2.1-1: Digital Skills & Function Types

Skills * Type of Function								
		Type of Function						
		Finance/Controlling	Marketing/PR	Project Management	Pedagogy	Administration	Research Assistant	
Skills	yes	Count	10	43	13	6	25	9
		%	76.9%	87.8%	40.6%	42.9%	71.4%	64.3%
	no	Count	3	6	19	8	10	5
		%	23.1%	12.2%	59.4%	57.1%	28.6%	35.7%

Frequent mentioning of digital skills is shown to be prevalent in observations that advertise relevant function types. Among the categories that contain larger sums of entries, the largest proportion of advertisements with a requirement for digital competence is found in Marketing/PR (87.8%), Finance/Controlling (76.9%) and Administration (71.4%). In contrast to this, larger categories that are predominantly filled with advertisements that do not mention digital skills are Pedagogy (42.9%) and Project Management (40.6%). Smaller categories that are noteworthy due to highly positive frequencies are Editorial Department (80%) and Curation (71.4%). The Function Type of Artistic Director represents a sole negative outlier (16.7%).

A first overview of the function types reflects the aforementioned discussion of the distribution of digital skills. Mentions of digital competence occur in advertisements for functions in almost all examined categories but vary in their prevalence. The overall proportion of skill requirements (54.5%) is lower than the sample average (62.8%). This proportion is influenced by large categories at the top of the distribution hierarchy.

Test Case: Marketing/PR

The Chi-Square Tests for (*skills * fcttype_kmn*) and (*skills_lvl * fcttype_kmn*) are not reliable since not all 22 categories are likely to be related to the existence of any skills. However, an examination of the frequencies in the crosstabulation shows that there are certain function types that indicate dependence. The outcome Marketing/PR represents the most promising example for a more detailed examination.

Recoding the outcome Marketing/PR into an individual dichotomous variable and relating it to the *skills* variable yields significant results (.00, 0%). The null hypothesis stating that there is no dependent relationship between both measures can be rejected. The Chi-

Square frequencies suggest that advertisements which fall into the category Marketing/PR are generally more likely to include the mentioning of digital skills which is in line with the rest of the sample distribution.

Table 4.2.1-2: Digital Skills & Marketing/PR

Skills * Marketing/PR					
		Marketing/PR			
			no	yes	Total
Skills	yes	Count	102	42	144
		%	56.0%	87.5%	62.6%
	no	Count	80	6	86
		%	44.0%	12.5%	37.4%

In the logistic regression analysis, the variable is used as a continuous predictor to calculate the probabilities for group membership based on the mutually exclusive outcomes of the dichotomous variable *skills* (yes/no). This prediction can be calculated since the recoded variable *Marketing/PR* is also dichotomous and can thus be treated as a scale or ratio measure.

Table 4.2.1-3: Logistic Regression Digital Skills & Marketing/PR – Step 0

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-0.515	0.136	14.306	1	0.000	0.597

			Score	df	Sig.
Step 0	Variables	Marketing/PR(1)	16.054	1	0.000

Table 4.2.1-4: Logistic Regression Digital Skills & Marketing/PR – Step 1

Variables in the Equation									
								95% C.I. for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1	Marketing/PR(1)	1.703	0.461	13.629	1	0.000	5.490	2.223	13.559
	Constant	-1.946	0.436	19.879	1	0.000	0.143		

The model summary reports that the results for the variables in the equation are significant (.00). The Nagelkerke R Square does not represent the amount of variance explained by the model but the value reduction in log odds which cannot be as intuitively interpreted. Instead, the fit of the model can be tested by using the unstandardized beta weights and the intercept to calculate the predicted probabilities.

The value for β equals 1.703 which represents the logarithmic odds calculated by referring to the levels of the response variable *skills* (1/0) ($1.703 = \ln \frac{P(1)}{P(0)}$). Within the calculation of the logit that is transformed into the final predicted probabilities, the variable levels for *Marketing/PR* (1/0) are multiplied by this factor. The model predicts the probability of group membership for *skills=no*.

$$\text{Predicted_logit}(\text{skills}) = -1.946 + (1.703 * \text{Marketing/PR})$$

The value for $\text{Exp}(\beta)$ equals 5.490 which represents the change in logarithmic odds of group membership caused by increasing the covariate level by 1. Within the logistic calculation, the move from *Marketing/PR=no* to *Marketing/PR=yes*, therefore multiplies the odds by a factor of 5.5.

The equation predicts no mentioning of digital skills for both levels of the marketing variable since the probability for *skills=yes* lies below 50%. In the case of advertisements for *Marketing/PR*, the prediction is based on a probability of 56.1% (43.9% for *skills=yes*) while the probability for other function types is (87.5%) (12.5% for *skills=yes*). Advertisements for *Marketing/PR* functions are thus 28.4% more likely to mention digital skills than advertisements in other categories.

4.2.2 Competence Levels

A bivariate analysis with the variable *skills_lvl* shows that levels of competence are themselves unevenly distributed among function types. The Chi-Square Test for (*skills_lvl* * *fcctype_kmn*) is significant (.002, $N > 10$) but clearly violates the 20%-threshold (65%).

The average proportion of advertisements that do not mention any digital skills of the sample is 37.2%. A count of advertised positions in Project Management and Pedagogy shows that this proportion is more than 50% larger for both function types (59.4%; 57.1%). In contrast, only 12.2% of advertisements in *Marketing/PR* do not require any digital skills.

The average proportion for the competence level of “foundation” (one skill in one competence area) is 28%. In this case, Project Management represents a low outlier (18.8%) while advertisements in Finance/Controlling require skills on this level twice as often as on average (46.2%). Several high outliers in small categories also influence the distribution.

The average proportion for the competence level of “intermediate” (several skills in one competence area) is 15.6%. Large categories such as Finance/Controlling (15.4%);

Marketing (18.4%) and Administration (22.9%) dominate the distribution. No advertisements in Pedagogy require this level of skills. Curation is a noteworthy outlier in a smaller category (32.7%).

The average proportion for the competence level of “advanced” (several skills in several competence areas) is also 15.6%. This level of skills occurs 2.5 times as often in the function type Teaching/Research (40%). In Marketing – the largest category with the highest predicted association to the *skills* variable – this is the most commonly required level of competence (32.7%).

The average proportion for the competence level of “specialized” (skills in all competence areas) is 3.6%. Research Assistants represent an extreme outlier case since they are almost 6 times as frequently required to be specialized in digital skills (21.4%).

Table 4.2.2-1: Digital Skills Levels & Function Types

Skills Level * Type of Function								
Skills Level			Type of Function					Research Assistant
			Finance/Controlling	Marketing/PR	Project Management	Pedagogy	Administration	
none	Count		3	6	19	8	10	5
	%		23.1%	12.2%	59.4%	57.1%	28.6%	35.7%
foundation	Count		6	15	6	3	12	4
	%		46.2%	30.6%	18.8%	21.4%	34.3%	28.6%
intermediate	Count		2	9	6	0	8	1
	%		15.4%	18.4%	18.8%	0.0%	22.9%	7.1%
advanced	Count		1	16	1	3	5	1
	%		7.7%	32.7%	3.1%	21.4%	14.3%	7.1%
specialized	Count		1	3	0	0	0	3
	%		7.7%	6.1%	0.0%	0.0%	0.0%	21.4%

Test Case: Marketing/PR

The regression analysis for the test case Marketing/PR can also be used to investigate whether this function type can be linked to the existence of a certain level of digital competence. In this case, the logistic regression calculates the probabilities for group membership of the recoded dummy variable *skills_advanced* (yes/no).

The model summary reports that the results for the variables in the equation are significant (.000). The logarithmic odds weight β equals -1.456. The model predicts the group membership for *skills_advanced*=yes.

$$\text{Predicted_logit}(\text{skills_advanced}) = -0.693 + ((-1.456) * \text{Marketing/PR})$$

The value for $\text{Exp}(\beta)$ equals 0.233 which represents the change in logarithmic odds of group membership caused by increasing the covariate level by 1. Within the logistic calculation, the move from *Marketing/PR=no* to *Marketing/PR=yes*, therefore multiplies the result by a factor of 0.233

Table 4.2.2-2: Logistic Regression Digital Skills Levels & Marketing/PR – Step 0

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1.718	0.184	87.548	1	0.000	0.179

		Score	df	Sig.
Step 0	Variables Marketing/PR	15.430	1	0.000

Table 4.2.2-3: Logistic Regression Digital Skills Levels & Marketing/PR – Step 1

Variables in the Equation									
							95% C.I. for EXP(B)		
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1 ^a	Marketing/PR(1)	-1.456	0.391	13.903	1	0.000	0.233	0.108	0.501
	Constant	-0.693	0.306	5.125	1	0.024	0.500		

For Marketing/PR advertisements, the equation predicts no group membership of *skills_advanced=yes* based on a probability of 33.3%. In contrast, the probability used in the calculation for other advertisements is only 10.4%. It can therefore be said that advertised functions in Marketing/PR are 31.2% more likely to require advanced digital skills.

4.3 Organization Types

4.3.1 Prevalence of Skills

The nominal variable *orgtype_kmn* assigns 1 out of 14 possible organization types to each advertisement based on the structure of the original database. The most frequently counted function types are:

Music (48); Visual Arts (37); Museum & Cultural Heritage (37); Commercial “Creative Economy” (27); Art Market & Exhibition Space (16); Media & Literature (15); Cultural Policy & Public Administration (15); Interdisciplinary (14); Foundation (14)

Fewer than 10 entries are contained in the following categories:

Education & Society (9); University & Research (7); Library & Archive (6); Social Culture (“Soziokultur”) (3); Cultural Tourism (2)

The relationship between the variables *orgtype_kmn* and *skills* is also tested by referring to the bivariate table. In this case, The Chi-Square Test for (*skills* * *orgtype_kmn*) is not significant. Filtering out all categories that contain $N < 10$ entries reduces the number of cells with low expected counts but does not increase the significance. This means that, in contrast to the analysis of function types, there is no evidence for a meaningful relationship. The frequency analysis is unambiguous in that the null hypothesis cannot be rejected with significant confidence even when the number of cases included is adjusted. The designation of a test case for individual analysis is therefore also not reasonable. The crosstabulation can nevertheless be analyzed in a descriptive way.

Table 4.3.1: Digital Skills & Organization Types

Skills * Type of Organization									
		Type of Organization							
		Visual Arts	Commercial “Creative Economy”	Cultural Policy & Public Administration	Arts Market & Exhibition Spaces	Media & Literature	Museum & Cultural Heritage	Music	
Skills	yes	Count	20	21	9	11	10	22	26
		%	54.1%	77.8%	60.0%	68.8%	66.7%	59.5%	54.2%
	no	Count	17	6	6	5	5	15	22
		%	45.9%	22.2%	40.0%	31.3%	33.3%	40.5%	45.8%

In comparison to the analysis of function categories, advertisements that call for digital skills are less evenly distributed. In 12 out of 14 cases, the majority of observations mention digital competence. The outliers – Cultural Tourism (50%) and Social Culture (“Soziokultur”) (33.3%) – are also the two categories with the lowest count of advertisements. Within the rest of the organization types, the most relevant categories are found at the bottom rather than at the top. Advertisements from organizations in Visual Arts (54.1%), Music (54.2%) and Museum & Cultural Heritage (59.5%) ask for digital skills only slightly more often than not. The three categories represent the three largest counts of observations and make up for a combined percentage of 48% of the sample (122 out of 250).

In contrast to this, the fourth largest category Commercial “Creative Economy” has the second highest score of digital skills requirements overall and the highest among categories with $N > 10$ (77.8%). The function types Interdisciplinary (71.4%), Art Markets & Exhibition Space (68.8%), Media & Literature (66.7%), Foundation (64.3%) and Cultural Policy & Public Administration (60%) represent a broad middle group among larger counts.

The overall proportion of skill requirements (85.7%) is much higher than the sample average (62.8%). Larger categories can be found at the top and at the bottom of the distribution hierarchy. The fact that more than 50% of all entries can be found in the 50th and 60th percentile when it comes to skill requirements, however, reflects the failed attempt to discard non-independence.

4.3.2 Competence Levels

Following from this, the bivariate analysis of the variable *orgtype_kmn* and the dichotomous variable *skills_lvl* can also not be expected to be reliable. The Chi-Square Test for (*skills_lvl* * *orgtype_kmn*) is not significant. The frequency analysis nevertheless shows that digital competence levels are also unevenly distributed among organization types.

The average proportion of advertisements that do not mention any digital skills of the sample is 37.2%. The results of the preceding analysis are reflected in the distribution of advertisements for different organizational categories. Job descriptions that include no digital skills are almost twice as prevalent in Visual Arts (45.9%), Music (45.8%) and Museum & Cultural Heritage (40.5%) as in the Commercial “Creative Economy” (22.2%).

The average proportion for the competence level of “foundation” (one skill in one competence area) is 28%. The distribution of advertisements that require this skill level is relatively balanced even if category size is taken into account. Music (12.5%) and Media & Literature (13.3%) are low outliers, Commercial “Creative Economy” follows the trend (25.9%), and Cultural Policy & Public Administration (40 %) and Art Market & Exhibition Spaces (43.8%) are high outliers.

The average proportion for the competence level of “intermediate” (several skills in one competence area) is 15.6%. Visual Arts (10.8%), Music (14.6%) and Art Markets & Exhibition Spaces (12.5%) can be expected to influence the sample average. The proportion of advertisements from organizations in Cultural Policy & Public Administration, however, is almost twice as low when it comes to this level of digital competence (6.7%).

The average proportion for the competence level of “advanced” (several skills in several competence areas) is also 15.6%. Several larger categories such as Commercial “Creative Economy” (11.1%), Visual Arts (8.1%) and Art Market & Exhibition Spaces (6.3%) score considerably lower. In contrast, Music organizations advertise positions that require advanced skills more frequently (20.8%) and Media & Literature organizations even twice as often (33.3%).

The average proportion for the competence level of “specialized” (skills in all competence areas) is 3.6%. 9 out of 14 organization types such as Visual Arts, Cultural Policy & Public Administration and Media & Literature do not make any mention of specialized skills in the counted advertisements. A single outlier is the Foundation category where the proportion is almost 4 times larger as on average.

Skills Level * Type of Organization									
Skills Level			Type of Organization						
			Visual Arts	Commercial “Creative Economy”	Cultural Policy & Public Administration	Arts Market & Exhibition Spaces	Media & Literature	Museum & Cultural Heritage	Music
none	Count		17	6	6	5	5	15	22
	%		45.9%	22.2%	40.0%	31.3%	33.3%	40.5%	45.8%
foundation	Count		13	7	6	7	2	10	6
	%		35.1%	25.9%	40.0%	43.8%	13.3%	27.0%	12.5%
intermediate	Count		4	10	1	2	3	4	7
	%		10.8%	37.0%	6.7%	12.5%	20.0%	10.8%	14.6%
advanced	Count		3	3	2	1	5	6	10
	%		8.1%	11.1%	13.3%	6.3%	33.3%	16.2%	20.8%
specialized	Count		0	1	0	1	0	2	3
	%		0.0%	3.7%	0.0%	6.3%	0.0%	5.4%	6.3%

Table 4.3.2: Digital Skills Levels & Organization Types

4.4 Reproducibility

4.4.1 Prevalence of Skills

Table 4.4.1-1: Reproducible Output

Reproducible Output			
		Frequency	Percent
Valid	yes	40	16.0
	no	210	84.0

A univariate analysis of the variable *reproduce* shows that only 40 out of 210 advertisements relate to reproducible outputs which represents less than 1 out of every 5 observations.

Among function types, there is no category that is positively associated with the existence of reproducible outputs. Advertisements that most frequently mention this output type (in proportion) connect to functions in Finance/Controlling (23.1%), Marketing/PR (22.4%) and Event Management (20%). The largest category that makes no mention of reproducible outputs is Pedagogy. Smaller categories such as Ensemble & Orchestra Management, Artistic Director, Curation and Artistic Production also do not advertise any positions in this context.

When it comes to organization types, only the category of Media & Literature (73.3%) is positively associated with the presence of reproducible outputs. This represents an extreme outlier case since the proportion for all other organization types with the exception of the Interdisciplinary category (50%) is less than half as large. Advertised positions in Commercial “Creative Economy” organizations are nevertheless more prevalently related to reproducible outputs than on average (25.9%). The overall distribution is even more skewed than the distribution of function types since several large categories such as Music (8.3%) can be found at the bottom of the hierarchy of proportions. In addition to this, several larger categories such as Foundation, Art Market & Exhibition Spaces, Cultural Policy & Public Administration do not mention reproducible outputs at all.

Table 4.4.1-2: Digital Skills & Reproducible Output

Skills * Reproducible Output				
		Reproducible Output		
		yes	no	
Skills	yes	Count	30	127
		%	75.0%	60.5%
	no	Count	10	210
		%	25.0%	39.5%

The frequency table suggests that, within reproducible contexts, advertisements are 50% more likely to mention digital competence than not (75% compared to 25%). However, the fact that the sample size is skewed towards advertisements that do not relate to reproducible outputs indicates that this increase is not significant based on the absolute numbers (20 observations). The Chi-Square Test for (*skills * reproduce*) is therefore expectedly not significant. There is no violation of cell counts (0%) and excluding N<10 for entries in function type and organization type actually decreases the significance level.

4.4.2 Competence Levels

In contrast, when it comes to the relationship between the *reproduce* variable and the *skills_lvl* variable, the Chi-Square Test is significant (.02) and does not violate the threshold (12.5%). If digital competence is mentioned in the counted advertisements, the level of that competence can therefore be expected to be influenced by the presence of reproducible outputs.

Table 4.4.2-1: Digital Skills Levels & Reproducible Output

Skills Level * Reproducible Output				
			Reproducible Output	
			yes	no
Skills Level	none	Count	10	83
		%	25.0%	39.5%
	foundation	Count	10	60
		%	25.0%	28.6%
	intermediate	Count	5	34
		%	12.5%	16.2%
	advanced	Count	13	26
		%	32.5%	12.4%
	specialized	Count	2	7
		%	5.0%	3.3%

Following the preceding analysis, advertisements that do not make mention of any digital skills are 50% more prevalent in the non-reproducible category. When it comes to the first two levels of competence, however, the proportions do not deviate significantly from the sample average. Instead, the influence of the factor can be explained by referring to the third category: most of the advertisements that relate to reproducible outputs demand advanced digital skills (32.5%), while the most frequent level for the sample is none (39.5%). The proportion of advanced level skills is 2.5 times larger when the factor reproducibility is present.

In order to test whether this relationship can be replicated in a significant model, the variable *reproduce* is used as a continuous predictor to calculate the probabilities for group membership based on the mutually exclusive outcomes of the recoded dummy variable *skills_advanced* (yes/no).

Table 4.4.2-2: Logistic Regression Advanced Digital Skills & Reproducible Output – Step 0

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1.718	0.184	87.548	1	0.000	0.179

			Score	df	Sig.
Step 0	Variables	Reproducible Output(1)	8.804	1	0.003

The model summary reports that the results for the variables in the equation are significant (.003). The logarithmic odds weight β equals 1.178. The model predicts the group membership for *skills_advanced*=yes.

$$\text{Predicted_logit}(\text{skills_advanced}) = -1.718 + (1.178 * \text{reproducible})$$

Table 4.4.2-3: Logistic Regression Advanced Digital Skills & Reproducible Output – Step 1

Variables in the Equation								
		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)
								Lower Upper
Step 1	Reproducible Output(1)	1.178	0.412	8.166	1	0.004	3.246	1.448 7.280
	Constant	-1.988	0.222	79.991	1	0.000	0.137	

The value for $\text{Exp}(\beta)$ equals 3.246 which represents the change in logarithmic odds of group membership caused by increasing the covariate level by 1. Within the logistic calculation, the move from *reproduce*=no to *reproduce*=yes, therefore multiplies the result by a factor of 3.246.

The equation predicts no mentioning of advanced digital skills for both levels of the reproducible variable which is in line with the frequency analysis. When reproducible outputs are not present, this prediction is based on a probability of 87.9% (12.1% for *skills_advanced*=yes). When reproducible outputs are present, the probability is 69.2% (30.8% for *skills_advanced*=yes). Advertisements that relate to reproducible outputs are consequently 39.14% more likely to mention advanced digital skills.

Test Case: Marketing/PR

Adding the recoded Marketing/PR variable as a continuous predictor in the binary logistic regression reveals how the presence of reproducible outputs changes the previously

calculated probabilities for this function type. The model is significant for *Marketing/PR* (.00) and *reproducible* (.003).

Table 4.4.2-4: Logistic Regression Advanced Digital Skills & Reproducible Output – Step 0

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1.718	0.184	87.548	1	0.000	0.179

			Score	df	Sig.
Step 0	Variables	Marketing/PR	15.430	1	0.000
		Reproducible Output	8.804	1	0.003

Table 4.4.2-5: Logistic Regression Advanced Digital Skills & Reproducible Output – Step 0

Variables in the Equation									
		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1	Marketing/PR	1.416	0.399	12.568	1	0.000	4.120	1.883	9.012
	Reproducible Output	-1.118	0.430	6.747	1	0.009	0.327	0.141	0.760
	Constant	-0.157	0.777	0.041	1	0.840	0.855		

The equation predicts group membership for *skills_advanced*=yes.

$$\text{Predicted_logit}(\text{skills_advanced}) = -0.978 + (1.118 * \text{Marketing/PR}) + ((-1.416) * \text{reproducible})$$

This regression demonstrates that the combined influence of both variables is significant enough to switch the group membership prediction. The results reflect the fact that both variables increase the chance of an advertisement requiring advanced skills even though the strength of the influence is not equally strong for both factors.

When none of the two factors are present, the model predicts only a 8.4% chance of advanced level skills being required. When only one factor is present, the regression still predicts no mentioning of this skill level even though the function type marketing is associated with a higher chance (27.35%) than the factor of reproducibility (21.83%). Only when both factors are present is the probability high enough for the group membership to be switched to *skills_advanced*=yes (53.5%).

5 Discussion

The findings from the empirical analysis can be used to evaluate specific assumptions about the prevalence and distribution of digital competence among organizations and functions in the creative industries. In some cases, the analysis supports the assumptions that have been derived from theoretical characteristics while in other cases, the evidence is not perfectly consistent with the literature. In the latter case, the findings represent the basis for further discussions about other potential influence factors.

5.1 Assumption Test

5.1.1 Organization Types

Assumption (1a) states that all organizations within the creative economy require at least some level of digital competence rather than none. However, not every single observation can be expected to register digital skills. In order for this statement to be proven as true, the analysis has to demonstrate that the non-existence of digital competence represents an outlier case. However, the findings do not provide a stable foundation for this claim. Even though almost all organization types require digital skills more often than not, the distribution of these skills is much less one-sided than expected. Within the three organization types that represent 48% of the sample (Visual Arts, Music, Museum & Cultural Heritage), the average proportion of counted advertisements without any digital skill requirements is 45%. However, the fact that the frequencies of the organization type variable are not significant with regard to skills prevalence or distribution means that the assumption cannot be completely disproven by the analysis.

Assumption (1b) states that organizations that focus on reproducible outputs generally require a higher degree of digital competence than suppliers of non-reproducible outputs. In the analysis, advertisements that mention digital skills are shown to be 50% more prevalent when they also mention reproducible outputs. Media & Literature organizations (that are 73% linked to reproducible outputs) call for advanced digital competence twice as frequently as the sample average while organization types as Art Market & Exhibition Space (0% reproducibility) match the average proportion. The assumption cannot be proven based on this alone since the frequencies lack significance. In this case, however, the regression analysis demonstrates that the presence of reproducible outputs can be used as a positive predictor for the requirement of advanced level digital skills. Advertisements for all organizations and functions are roughly 40% more likely to require digital skills in more than one competence

area when this factor is present. This proves the assumption that the factor of reproducibility increases the requirement of digital skills.

5.1.2 Function Types

Assumption (2a) states that all humdrum inputs require a base-level of digital competence. Advertisements for almost 50% of all function type categories predominantly do not mention any required digital skills which is enough to demonstrate that this expectation is also not fulfilled. In contrast to organization types, however, the frequency analysis is significant in this case. It can therefore not be ruled out that the findings are generalizable and individual function types which call for digital skills more frequently (Marketing/PR) or less frequently (Project Management) are the result of a dependent relationship. The individual examination of the category Marketing/PR shows that, at least for one function type, the existence of a meaningful relationship can also be demonstrated. Advertisements for Marketing/PR are 28.4% more likely to require any digital skills and 31.2% more likely to specify advanced digital skills. The assumption that all functions require digital competence can thus be disproven but the analysis suggests that individual function types can be used as predictors themselves.

Assumption (2b) states that humdrum inputs require more digital competence when reproducible outputs are involved. The analysis of Marketing/PR shows that the influence of reproducibility on all advertisements can be altered by including or excluding certain function types as variables. When reproducible outputs are present and no function type is specified, advertisements are 40% less likely to mention advanced digital skills as opposed to when the function type is Marketing/PR. Advertisements for positions in this category have been shown to require digital skills more frequently than the average sum of all reproducible observations. The assumption that reproducibility also increases the requirement for digital competence among function types can therefore be proven. However, the analysis also suggests that certain function types have a larger influence when they are themselves used as factors.

5.1.1 Summary of Main Findings

The research question that guides this thesis asked: to what extent is digital competence required in the creative industries? The sub-questions asked whether the demand of competence is dependent on the characteristics of functions and/or organizations. The test of assumption results in three major conclusions that pertain to these questions:

(1) The demand for digital competence articulated in job advertisements for creative organizations is limited. Job descriptions commonly do not mention a requirement for digital skills at all or only outline a single application. The case of a position requiring more than one competence area or even competence indicator has to be regarded as uncommon for most function types and organization types.

(2) When it comes to the question of whether digital skills are required at all, the results of the analysis show that referring to a specific type of organization is not likely to provide a consistent answer. Selecting a specific function is likely to be effective for some cases but not for all. Considering the factor of reproducibility, however, proves to be highly useful.

(3) When it comes to the distribution of different competence levels, specific organization types also do not represent a useful indicator. In this case, however, referring to function types is more effective since the analysis proves that there is an underlying relationship for the majority of the examined categories. Selecting a specific function type can even be shown to be a more important predictor for certain competence levels than the factor of reproducibility.

5.2 Theoretical Perspective

When it comes to digital competence, the hiring demand of the creative industries can be said to be influenced by their unique input and output characteristics. The creative economy comprises a variety of different organizations and functions which means that assumptions based on shared characteristics are more difficult to define than assumptions that differentiate between specific inputs or outputs. This is reflected in the results of the analysis.

Firstly, The findings underline that it is difficult to derive generalizable statements about the creative industries solely based on the fact that they all produce outputs with a certain type of symbolic and subjective value. Many of the agreed-upon properties of the creative industries may be not true for all of the organizations in question as Rozentale and Lavange have pointed out (2014). For example, it is possible that the “symmetrical ignorance” described by Caves (2000, p.14) that follows from phenomena such as demand uncertainty and product differentiation is not equally problematic for all organizations or does not necessarily lead to a focus on technology. On the other hand, it could also be assumed that there is a lack of awareness when it comes to the possibilities that digital technology offers to diminish this uncertainty and provide useful information.

Secondly, the research also shows that organizations which focus on reproducible outputs are more likely to require human capital with digital skills. This supports theoretical considerations based on the connection between durable, informational products and the digital attention economy. The distinction between reproducible and non-reproducible outputs represents a useful heuristic that complements the arguments of Bekar and Haswell (2013) and supports Blaug's view that the famous cost disease theorem has to be situated in a new context of outputs (2001).

Thirdly, when it comes to functions, the findings of the analysis suggests that the theoretical literature is already useful but an even more detailed consideration of the properties of certain inputs promises to be rewarding. The fact that humdrum functions are more likely to require digital competence in reproducible contexts reflects the explanatory power of the concept of reproducibility. An equivalent distinction on the level of functions could be found in the concept of technology resistance (Bekar and Haswell, 2013). However, Blaug's notion that the arts are ever-changing also has to be remembered in this context (2001). Visual artists or performers may well consider the reproduction of their works to be a part of the artistic process even though it does not constitute their primary artistic output. The degree of resistance to technology in their production processes could define the amount of value that cannot be replicated in the process of digitization. Referring to this concept on the level of inputs reflects a view of reproducibility on the level of outputs that is not dichotomous but exists on a spectrum that allows for varying degrees. In this way, the idea of technology resistant creative inputs could help to differentiate between suppliers of reproducible outputs in a more detailed and effective way.

Finally, the fact that a large number of humdrum functions does not require any digital skills reveals a need for further research. The explanation that potential applications are non-existent seems to undermine the assumption of Digital ICT as a General Purpose Technology (Bekar and Haswell, 2013). The alternative interpretation that potential applications are not advertised by the organizations again leads to the question of what influences this decision. Further research could investigate a lack of awareness even though it is important to underline that an internal perspective on functions and organizations alone is not sufficient to draw conclusions about the decision-making processes of the creative industries. Analyses that takes the influence of the external environment on the hiring process into account are necessary to provide a holistic overview of the research context.

5.3 Review of Individual Functions

There are several other potential explanations for the superior influence of individual functions (as opposed to organizations) on digital competence. It is possible, for example, that the platform structure results in a more suitable categorization for function types when it comes to this specific analysis. Another potential reason is that the findings reflect the distinctively broad spectrum of organizations defined by the term creative industries. Specific explanations for the relationship between functions and digital competence can be directly derived from the observations. They provide a starting point for further investigations based on more detailed research questions.

Function types that predominantly mention no digital skills disprove the assumption that a base-level of digital competence exists for all functions which can be interpreted in different ways. It is possible that these observations represent a certain group of tasks that has been underestimated with regard to its resistance to technology. However, a review of the advertisements shows that it is difficult to find common properties between the advertised functions to support this claim. This can be illustrated by the fact that, even within a single category where the majority of job descriptions do not mention digital skills (Project Management), the list includes positions with titles as diverse as “Museum Staff”, “Festival Assistant”, “Tour Manager” and “Network Manager”. An alternative explanation for what unites these advertisements could be a lack of awareness for potential applications of digital skills. This lack of awareness on the part of advertising organizations within the creative industries promises to be a fruitful research context for further investigations.

Missing awareness could also explain another finding with potentially significant implications that concerns the question of skill diversity. The count of observations in the competence levels “foundation” and “advanced” suggests that 44% of all advertisements only require a single application of digital competence or fewer, and, that 70% of all functions require skillsets within only a single competence area. However, reviewing individual function categories demonstrates that this imbalance can partly be explained by the fact that some functions simply require a narrower application of digital competence than others.

For example, the function type Finance/Controlling predominantly lists advertisements that require “foundation” level skills. The simplest explanation for this is that applications are similar in all organizations and relate to industry standards. This is supported by the example of three different job descriptions seeking a “Financial Administrator” that all list the single

requirement of handling cost-accounting and bookkeeping software. The organizations in question include a media & entertainment company, a foundation acting as the responsible body for an ensemble group and a cultural event center.

The example of the function type Curator can be used to illustrate a similar tendency for competence areas. Curators often require “intermediary” skills which may be surprising at first glance but can be explained by the fact that the digitalization process in museums entails a large number of related and overlapping applications within a single competence area. Applicants have to be competent enough to develop, maintain and research databases and digital inventories which represents more than enough diversity to warrant the “intermediary” level.

The remaining 30% of all advertisements that require a diverse set of skills in the area of digital technology are populated by a small number of categories. This supports the hypothesis that a lack of awareness cannot generally be stipulated for all functions. When it comes to the requirement of “advanced” digital competence, for example, a closer examination of the category Marketing/PR promises to be rewarding. Almost all advertised positions within this function type require a wide range of digital skills in competence areas such as, for example, content creation (Blogs, Social Media), information (Online Analytics) and communication (E-Mail). In comparison to other categories, Marketing/PR advertisements are also more likely to fall into this category since they often explicitly ask for proficiency with specific applications such as platforms (Facebook, Instagram), enterprise software (Slack), design tools (InDesign) and SEO tools (Google Analytics).

Finally, only 5% of all observations in the analysis point towards a need for “specialized” digital competence which entails knowledge and skills in all competence areas. The small number of advertisements can be grouped into two categories. The first group is aimed at research assistants that are expected to explore the potential of digital technology for the organization. In the example of a renowned museum foundation, a department has been designated to research how the power of Digital ICT can be harnessed to serve the goals of “mediation, communication, interaction and participation” within a newly built institution. Job descriptions in advertisements of this sort are phrased in general terms and require a strategic and conceptual understanding of digital technology rather than specific expertise.

In contrast, the second group consists of specialists who are required to manage software development projects or handle a large number of unrelated tasks that pertain to the

internet and information technology. For example, the role of an “Online Project Manager” in a performing arts center includes, among other things, responsibility for mobile applications, the internal customer-relationship-management system as well as marketing and community management tasks. Advertisements that utilize digital competence in this way do not generally mention strategic implications but instead refer to specific skill applications such as agile methods (Scrum, Kanban), program languages (CSS, Java), databases (WebStorm, Sublime), developer tools (Eclipse, NetBeans) and content management systems (Typo3).

5.4 External factors

This research projects is focused on the influence of internal characteristics on the hiring processes of the creative industries. However, every creative organization or entrepreneur also exists within a complex sphere of external influences that could be examined with the same research object in mind. This section will therefore give a brief overview of external factors that are likely to influence digital competence.

5.4.1 ICT Infrastructure

Fundamental infrastructural characteristics are largely dependent on macro-economic and geographic factors. The Digital Economy and Society Index (European Commission, 2018) which considers various dimensions in order to measure these differences shows that considerable discrepancies can be found when it comes to the aspect of connectivity, a core resource that underlies all digital applications: The speed and performance level of digital communication networks varies between different countries and a connection to the web in the form of fixed and mobile broadband is not equally affordable. This naturally influences the potential that the creative sectors in different countries can exploit by investing in concepts and applications that require digital competence (DESI, 2018).

Characteristics of a country’s ICT infrastructure can further be divided into factors that influence this potential to different degrees. Sociological categories such as the notion of citizen internet use could be investigated to capture the influence of applications pertaining to content consumption, communication, or financial transactions. A EUROSTAT survey of ICT uses for cultural purposes provides the basis for a discussion of this with a specific focus on the creative industries (EUROSTAT, 2017).

In contrast, business-based factors such as the measure of technology integration hold information about the distribution of activities along organizational value chains. The fact that DESI considers the factor “social media” to be independently relevant next to the level of technology availability and absorption, for example, underlines the finding of this research that marketing and communication functions are inherently connected to the application of digital skills (DESI, 2018).

5.4.2 Policy

The creative industries are influenced by various different policy goals and perspectives. This is not only because they can produce different types of value but also because they comprise a heterogeneous spectrum of organizations that includes traditional arts institutions next to for-profit firms. An analysis of policies therefore could, for example, differentiate between policies directed towards “subsidizing the cultural sector” and “stimulating the creative sector” (Nijzink, van den Hoogen and Gielen, 2017, p. 598).

Other factors could be derived from the differentiation between cultural and economic policy objectives. Cultural objectives (e.g. diversity and participation) and economic objectives (e.g. export and investment) can be expected to result in different constraints and expectations when it comes to the hiring decisions of organizations (Braun & Lavanga, 2007). This does not have to mean, however, that subsidy-dependent organizations are generally less encouraged to invest in digital skills. The policy objective of innovation, for example, can be regarded as relevant in this context and has been found to be associated less with economic contexts than with cultural agents and funding (Braun & Lavanga, 2007). Instead, it is generally acknowledged that “innovation policies are particularly popular for high-tech sectors” (p.10).

Finally, useful conclusions may be drawn based on the presence of a digital agenda that informs, guides or influences the policies that influence the creative industries. For example, The European Digital Library project (Europeana) indicates that, on the international level, the process of digitalizing analogue information has been identified as a method to preserve different forms of cultural heritage (Council of Europe/ERICarts, 2018). The resulting adaption processes within the countries are likely to require specific types of digital skills in specific types of organizations that could reveal the impact of EU guidelines of the digitization potential of the creative industries (Council of Europe/ERICarts, 2018).

6 Conclusion

The results of the research project show that the creative industries represent a productive context for the investigation of organizational adaption processes with regard to the increasing relevance of digitization. The research questions can therefore be answered by referring to the most important findings.

To what extent do the creative industries require digital competence? The research shows that, insofar as this requirement can be captured by the contents of job advertisements, it is relatively limited. Potential explanations for this could be found in a lack of awareness on the part of organizations or simply a lack of potential applications even though it is likely that both factors play a role. In order to arrive at alternative explanations, a similar research project with a focus on external characteristics promises to be fruitful.

Is the requirement of digital competence dependent on the features of organizations or functions? The determinants of digital competence probably transcend the distinction between functions and organizations even though it can be said that a focus on functions is more beneficial in the analysis of digital skills (and especially useful when it comes to certain function types). Instead, the factor that determines whether a creative project or enterprise requires digital competence or not most likely pertains to the act of creation or artistic production itself.

The digital reproduction process and the competitive advantages that it affords in the digital economy create a clear separation between organizations that require digital competence sporadically and those that have integrated the use of digital ICT into their business models. If inputs at the production stage resist the application of technological tools and methods, the reproduction process entails a loss of value and becomes less economically advantageous. The investigation of what determines this resistance to technology in the first place represents a suitable challenge for the field of Cultural Economics. With the technological progress in mind, the question whether economic value can ever be perfectly related to the value that we associate with human contributions (whether they be cultural, aesthetic, socially symbolic or in other ways distinctly human) will most likely become more pressing in the near future.

7 References

- Bekar, C. and E. Haswell. 2013 (2014). 'General Purpose Technologies', in R. Towse and C. Handke (eds.) Handbook of the Digital Creative Economy, Cheltenham.
- Blaug, M. (2001). Where are we now on cultural economics. *Journal of economic surveys*, 15(2), 123-143.
- Braun, E. & Lavanga, M. (2007). An International Comparative Quick Scan of National Policies for Creative Industries. Rotterdam: Euricur for the Ministry of Education, Culture and Science of the Netherlands.
- Caves, R. (2000). *Creative Industries: Contracts between Arts and Commerce*, Cambridge, MA: University Press
- Cooke, P. & Lazzaretti, L. (2008) *Creative cities, cultural clusters and local economic development*, Cheltenham, UK: Edward Elgar Publishing.
- Council of Europe/ERICarts. (2018). *Compendium of Cultural Policies and Trends in Europe. Country Profiles*. Retrieved from: <https://www.culturalpolicies.net/web/countries.php>
- Davenport, T., & Beck, J. (2001). *The attention economy: Understanding the new currency of business*. Boston: Harvard business school Press.
- DCMS (Department of Culture, Media and Sport). (1998). *Creative industries mapping document*. London: DCMS.
- European Commission. *Digital Economy and Society Index 2018*. (2018) Brussels: European Commission.
- European Commission. 2018. *DESI 2017. Digital Economy and Society Index 2018. List of indicators. Country profile*. Brussels: European Commission.
- EUROSTAT. (2017). *Digital economy and society statistics - households and individuals*. Retrieved from: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Digital_economy_and_society_statistics_-_households_and_individuals
- Frey, B. S., & Jegen, R. (2001). Motivation crowding theory. *Journal of Economic Surveys*, 15, 589–623.
- Handke, C. (2010). *The Creative Destruction of Copyright*. Rotterdam: Erasmus University: 108-151
- Harper, R. (2012). The collection and analysis of job advertisements: A review of research methodology. *Library and Information Research*, 36(112), 29-54.

- International Trade Centre (ITC) and Unesco. (1997) Final report of the International Symposium on Crafts and the International Market: Trade and Customs Codification. Retrieved from: <http://uis.unesco.org/en/glossary-term/craft-or-artisanal-products>
- KEA. (2006). The economy of culture in Europe. Brussels: KEA European Affairs.
- Kelly, K. (2018, January 31). Better Than Free. Retrieved from: <https://kk.org/thetechnium/better-than-fre/>
- Kelly, K. (1999). New rules for the new economy: 10 radical strategies for a connected world. Penguin.
- Klamer, A. (2017). Doing the right thing. Ubiquity Press.
- Kretschmer, M. , Klimis, G. M. and Choi, C. J. (1999), Increasing Returns and Social Contagion in Cultural Industries. *British Journal of Management*, 10: 61-72.
- Kurekova, L., Beblavý, M., & Thum-Thysen, A. (2013). Online job vacancy data as a source for micro-level analysis of employers' preferences. A methodological enquiry. First International Conference on Public Policy (ICPP), Grenoble, France.
- Mohan, N. & Kyncl, R. (2018, January 16) Additional Changes to the YouTube Partner Program (YPP) to Better Protect Creators. Youtube Creator Blog. Retrieved from <https://youtube-creators.googleblog.com>
- NESTA & Arts Council England. (2017) Digital Culture 2017. Retrieved from: <https://www.nesta.org.uk/report/digital-culture-2017/>
- Nijzink, D., van den Hoogen, Q. L. & Gielen, P. (2017). The creative industries: conflict or collaboration? An analysis of the perspectives from which policymakers, art organizations and creative organizations in the creative industries are acting. *International Journal of Cultural Policy*, 23(5): 597-617.
- Rozentale, I. and Lavanga, M. (2014) The “universal” characteristics of creative industries revisited: The case of Riga. *City, Culture and Society* (Special issue: Creative industries & creative policies: A European perspective?), 5(2): 55-64.
- Scott, M. (2012). Cultural entrepreneurs, cultural entrepreneurship: Music producers mobilizing and converting Bourdieu’s alternative capitals. *Poetics*, 40(3), 237-255
- Shiller, R. (1995). Conversation, information, and herd behavior. *The American Economic Review*, 85(2), 181-181.

- Throsby, D. (2008). Modeling the cultural industries. *International Journal of Cultural Policy*, 14(3), 217-232
- Throsby, C. (2013). *The economics of cultural policy*. Cambridge: Cambridge University Press.1. Elsevier B.V.
- Townley, B. & Beech, N. (2010). *Managing creativity: Exploring the paradox*. Cambridge University Press.
- Towse, R. (2010). *A Textbook of Cultural Economics*. Cambridge University Press.
- Towse, R. & Handke., C. (2013). *Handbook of the Digital Creative Economy*. Cheltenham: Edward Elgar.
- Towse, R. (2011). *A Handbook of Cultural Economics*. Cheltenham: Edward Elgar.
- UNCTAD. (2008). *Creative Economy. Report 2008*. Geneve-New York: UNDP, UNCTAD.
- Vuorikari, R., Punie, Y., Gomez, S. C., & Van Den Brande, G. (2016). *DigComp 2.0: The digital competence framework for citizens. Update phase 1: The conceptual reference model* (No. JRC101254). Joint Research Centre (Seville site).
- Xu, H. (1996) The impact of automation on job requirements and qualifications for catalogers and reference librarians in academic libraries, *Library Resources and Technical Services*, 40(1), 9–31.
- WIPO. (2004). *What is Intellectual Property*. WIPO Publication No.450(E). Retrieved from: http://www.wipo.int/export/sites/www/freepublications/en/intproperty/450/wipo_pub_450.pdf

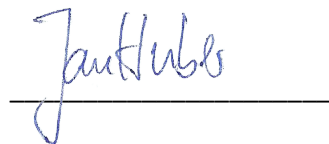
Statement of Originality

I hereby confirm that I am the sole author of the written work here enclosed and that I have compiled it in my own words. Exceptions are corrections of form and content by the supervisor.

With my signature I confirm that

- I have committed no form of plagiarism described in the thesis guidelines.
- I have documented all methods, data and processes truthfully.
- I have not manipulated any data.
- I have mentioned all persons who were significant facilitators of the work

I am aware that the work may be screened electronically for plagiarism.

A handwritten signature in blue ink, reading "Jan Huber", is written over a horizontal line.

Rotterdam; June 11, 2019