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# Toward Responsible Use Of Digital Technologies In Manufacturing Companies Through Regulation

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**Abstract**

Digital technologies have gained significant importance in the course of the 4th Industrial Revolution and these technologies are widely implemented, nowadays. However, it is necessary to bear in mind that an ill-considered use can quickly have a negative impact on the environment in which the technology is used. For more responsible and sustainable use, the regulation of digital technologies is therefore necessary today. Since the government is taking a very slow response, as the example of the AI Act shows, companies need to take action themselves today. In this context, one of the central questions for companies is: "Which digital technologies are relevant for manufacturing companies in terms of regulation?" This paper conducted a quantitative Delphi study to answer this question. The results of the Delphi study are presented and evaluated within the framework of a data analysis. In addition, it will be discussed how to proceed with the results so that manufacturing companies can benefit from them. Furthermore, the paper contributes to the development of an AI platform in the German research project PAIRS by investigating the compliance relevance of artificial intelligence applications.

**Keywords**

digital technologies; compliance; regulation; manufacturing companies; Delphi study; Artificial Intelligence; 5G, Conversational Interfaces

## 1. Introduction

In today's world, there is a noticeable trend towards mandatory and comprehensive transparency and trust in corporate compliance and governance due to requirements imposed by legislators and regulators [1]. Nowadays, information and information technology (IT) must be considered as part of these compliance efforts in the company [2]. This takes into account the increasing relevance of the operational resource information as a production and competitive factor [3]. In addition, it is to be expected that the legal and regulatory requirements relating to IT will increase for companies in the future [4]. Beyond this assumption, new digital technologies, such as artificial intelligence or edge computing, are among the central building blocks of the digital transformation, in addition to traditional information technology [5]. These must also be taken into account in the future compliance efforts of companies, as they are a central component on the path of digital transformation. In the case of artificial intelligence, for example, the EU Commission has published a regulation on artificial intelligence (AI) with the aim of using the technology in accordance with the values, fundamental rights and principles of the Union. [6]

These developments in the field of artificial intelligence in recent years and months exemplify the need for compliance in the use of digital technologies in companies. Thus, there is a need for support for companies

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to systematically create compliance guidelines for a variety of digital technologies that are used in manufacturing companies.

This paper presents the first model in a series of four models to address the problem of compliance for digital technologies in manufacturing companies. Therefore, the compliance-relevant digital technologies must be identified and structured, as well as a blueprint and guideline for creating regulations must be developed. This paper provides the basic foundation for the project and describes the identification of the compliance relevance of digital technologies by a Delphi study. The overall research goal is to enable companies to formulate compliance regulations for digital technologies in systematic ways. The interim results of the first model, discussed in this paper, highlight the relevance of the topic and provide an assessment of various digital technologies in terms of compliance relevance.

The remainder of this paper is organized as follows. Section 2 reviews the literature regarding compliance of digital technologies and Delphi studies. Section 3 presents the Delphi study design and the study conduction. Then, in section 4 the collected data is described. This is followed in section 5 by an analysis of the data and a presentation of the key findings. Finally, section 6 contains a discussion and section 7 presents a conclusion and an outlook.

## 2. State of the art

This section summarises the previous activities in the field of compliance of digital technologies. It also briefly introduces the scientific basis of the Delphi study.

### 2.1 Compliance of digital technologies

In the literature, there is a two-sided view of compliance of digital technologies. On the one hand, there is the understanding that digital technologies can support the detection of compliance violations in order to counter compliance risks. This understanding is often also found under the keyword digital compliance. On the other hand, there is the understanding that the use of digital technologies must take place under defined rules. [7] The understanding of compliance of digital technologies on which this paper is based corresponds to the second view. A prominent example of this understanding is the AI Act of the EU Commission, which aims to make AI safe, transparent, ethical, impartial and under human control. [6] The EU's proposal establishes a grading of AI application based on risk. In addition to the assessment of risk, corresponding rules are also defined for use depending on the risk. For example, social scoring is to be banned due to the high risk, and chatbots with a low risk will be subject to transparency obligations in order to enable users to decide if they want to take advantage of them. [6] So far, there are no holistic approaches to describe compliance of digital technologies. Only AI as a lighthouse project is being examined with regard to these aspects.

### 2.2 Delphi Study

The Delphi study has been used since the 1950s and has existed in various forms. Available publications offer a broad spectrum of different definitions and interpretations of the Delphi study. [8] Delphi studies aim to solve complex problems and questions with the help of the knowledge of many individual experts [9]. For this purpose, selected experts from different domains are consulted [8]. According to HÜTTNER, the Delphi study can be classified as a more formalised expert survey [10]. Especially in comparison to the method of an open group discussion, the Delphi study, due to its anonymity, does not allow a change of the individual judgement by orientation on the answers of others [8]. However, since several rounds of questioning are carried out, it is possible to communicate the evaluated results of a wave as feedback to the participants, so that they reflect on their answers in a targeted manner [10]. This results in a prognosis or solution for the addressed problem that is superior to an individual performance and brings the advantages of a group performance [9]. HÄDER divides Delphi studies into four different types, each with its own profile.

Type 1: Delphi studies for the aggregation of ideas.

Type 2: Delphi studies for the most accurate possible prediction of an uncertain issue or for its precise(r) determination.

Type 3: Delphi studies to identify and qualify the views of a group of experts on a diffuse issue.

Type 4: Delphi studies to build consensus among the participants. [8]

## 3. Methods

For this paper, a Delphi study was conducted to identify the compliance relevance of digital technologies. In the previous section, the method of the Delphi study was briefly introduced, and in this section the method is explained in more detail, as well as the design and execution of the study.

### 3.1 Delphi study design

The Delphi study was designed as a HÄDER type three study, as the focus is on collecting, determining and qualifying expert opinions on the diffuse topic of compliance for digital technologies. The type three study has specific characteristics. A decisive feature is the quantitative procedure, which was implemented by integrating 22 expert opinions. Furthermore, the experts are selected on the basis of their expertise in the areas of compliance and digital technologies. Moreover, the interdisciplinarity of the experts was taken into account. This means that scientific experts as well as practitioners were interviewed. The expert group is described in detail under Section 5. [8]

In the first step, the question was operationalised by using the facet theory in order to achieve a comprehensible reduction of the complexity of realistic questions [11,8]. In addition, the scope of digital technologies was narrowed down. For this purpose, various technology radars and trend radars were examined. The technology radar and trend radar of the German Federal Ministry for Economic Affairs and Climate is particularly comprehensive and was therefore selected for the study [12]. Based on this, a longlist of 18 technologies was generated, which results in the first facet. Furthermore, in the second facet, different points of view on digital technology were determined. These are data, technology and organization. They were taken from the Aachen Digital Architecture Management and are particularly suitable as they describe the perspectives on digital infrastructure [13]. Moreover, a rating scale for compliance relevance was defined. The exact levels for the evaluation of the relevance can be found in the following mapping sentence (see Formula 1).

$$\textit{The respondent } (p_i) \textit{ evaluates the digital technology } \overbrace{\begin{Bmatrix} 5G \\ \textit{edge computing} \\ \dots \\ AI \end{Bmatrix}}^{F_1} \textit{ regarding to}$$

$$\textit{the viewpoint } \overbrace{\begin{Bmatrix} \textit{data} \\ \textit{technology} \\ \textit{organisation} \end{Bmatrix}}^{F_2} \textit{ as } \overbrace{\begin{Bmatrix} \textit{not relevant at all} \\ \textit{less relevant} \\ \textit{moderately relevant} \\ \textit{sufficiently relevant} \\ \textit{highly relevant} \\ \textit{I don't know} \end{Bmatrix}}^{F_3} \textit{ for compliance.} \quad (1)$$

A decomposition into further facets would be possible, but the pre-test and the study itself showed that the reduction of complexity through three facets was sufficient. The questionnaire was designed with the help of the formulated mapping sentence. This means that for each digital technology (facet one), the points of consideration data, technology and organization (facet two) were queried via the relevance scale (facet three). The questionnaire also contains questions to indicate how confident the respondent is in his/her answer.

### 3.2 Conducting the Delphi study

To finalise the survey document, a pre-test was conducted with a selected expert to check the questionnaire for comprehensibility and to determine the approximate processing time. Subsequently, the actual study was conducted according to the typical procedure as shown in Figure 1.

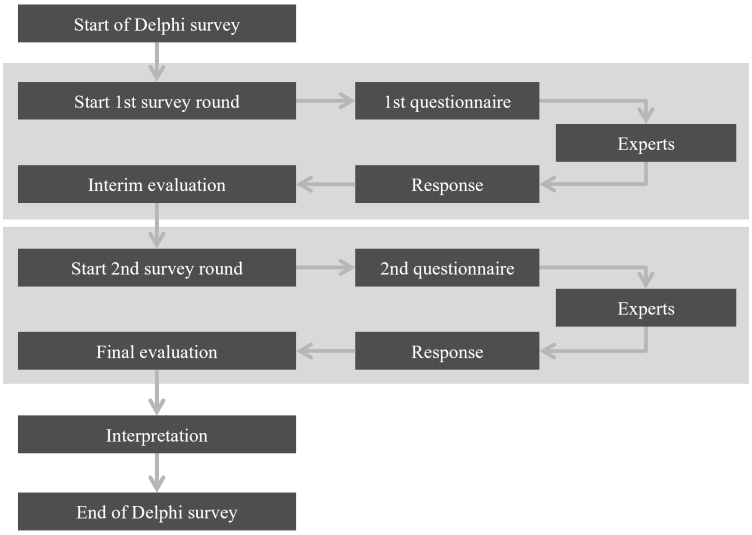


Figure 1: Procedure of the Delphi study

The questionnaire was initially sent to 34 experts as an online survey. 22 of the experts contacted responded within the processing period of four weeks. Subsequently, an interim evaluation of the data was carried out in order to generate feedback for the following round. For this purpose, the number of mentions for each answer option was prepared in the form of a bar chart. An exemplary evaluation for technology 5G can be seen in Figure 2.

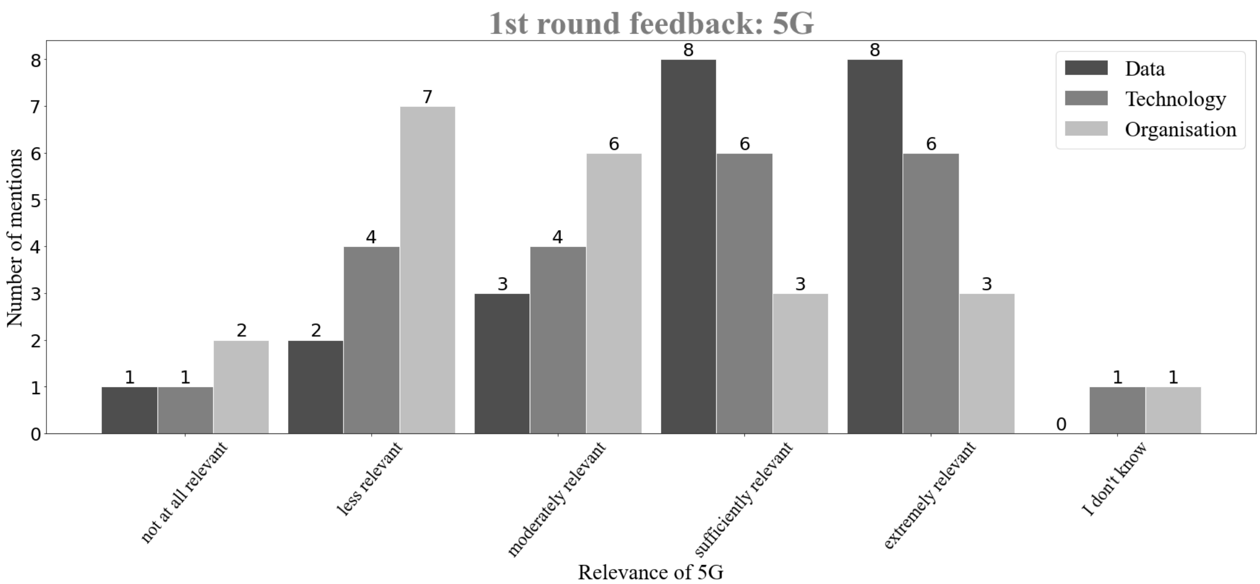


Figure 2: Evaluation example 5G

This feedback was integrated into the second survey and the survey was sent to the 22 participants fromm the first round. The processing period of the second round was four weeks and 16 of the participants sent a response. The number of participants can also be seen in Table 1. This concluded the conduct of the study.

Table 1: Number and participation of the requested experts of the Delphi study

| Field of activity of experts | Quantity of requests | Quantity of Experts | |
|---|---|---|---|
| | | First round | Second round |
| Science | 7 | 5 | 4 |
| Practice | 27 | 17 | 12 |
| Total | 34 | 22 | 16 |

## 4. Data description

The data is divided into the collected head data and the collected core data. The head data of the questionnaire contains general questions. The self-assessment of the expert regarding his expertise should be emphasized here. The self-assessment takes place on an ordinal scale with five response options. These are "don't know" {NaN}, "none" {0}, "low" {1}, "medium" {2} and "high" {3}. The Expertise is assessed for digital technologies in general, as well as for compliance. In addition, at the end of the questionnaire, respondents could once again highlight the digital technology for which the corresponding expertise is particularly high. This results in a list of all 18 digital technologies for each expert, which is binary coded for the evaluation ("no particular expertise" {0}, "particular expertise" {1}). These Boolean truth values can be viewed as weights for individual responses in the later analysis. The core data includes 54 characteristics generated by three observation points for 18 technologies and are each ordinally scaled. Experts could choose between "not at all relevant" {0} and "extremely relevant" {4} on a five-point scale. In addition, the questionnaire contains the option "I don't know" {NaN}. The entire scale can be found in Table 2.

Table 2: Overview of the scale for assessing the relevance of technologies

| Statement | Scale value |
|---|---|
| Highly relevant | 4 |
| Sufficiently relevant | 3 |
| Moderately relevant | 2 |
| Less relevant | 1 |
| Not relevant at all | 0 |
| I don’t know | NaN (Not a Number) |

## 5. Data analysis and finding relevant technologies for compliance

Using the data collected in the Delphi study, the relevance of the individual digital technologies for a compliance guideline will be derived. For this purpose, a data-driven analysis of the head data and a simplified form of hypothesis-driven analysis of the core data will be performed.

First, the head data is analyzed because it provides the basis for the following analysis of the core data and ensures the transparency and validation of the expert group. The spider diagram in Figure 3 shows how the 22 participants assess their own expertise on the two topics of concern, compliance and digital technologies.

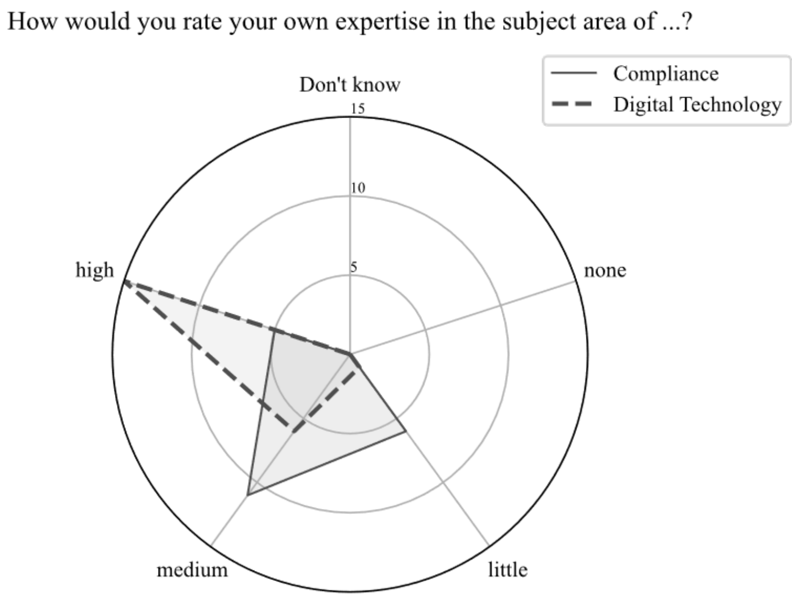


Figure 3: Expertise of the respondents

It shows that both areas are represented in the expert group by correspondingly high or medium levels of knowledge. It can be concluded that the expert group formed for the Delphi study is suitable for the research due to its mixed expertise and mixed backgrounds from business and research (see Table 1).

Before the hypothesis-driven analysis of the core data is presented in the following, a preselection of digital technologies based on particular characteristics is necessary. During the initial examination of the core data, one particular feature of the digital technology thread stood out. Here the participants answered particularly frequently "I don't know" {NaN}. This can be seen in the first as well as in the second survey round. Due to the lack of meaningfulness, this technology is therefore excluded from the evaluation. Furthermore, the core data for the digital technology Brain Computer Interface showed a particularly high demand for compliance. It should be noted, however, that this technology has a very low degree of maturity and has not yet found regular application in manufacturing companies. This can also be borrowed from the technology and trend radar [12]. Consequently, this technology is excluded for the further procedure.

The hypothesis-driven analysis of the core data is presented below. For this purpose, three hypotheses are stated and proven or disproven.

*H1 Based on the compliance relevance determined in the Delphi study, a clear ranking of the digital technologies can be generated.*

The statistical measures median, mode and interquartile range (IQR) are used to determine a ranking in descending order of the compliance relevance of the digital technologies. Only ordinally scaled data is available in the Delphi study, so both the median and the mode are suitable. Since the median reflects the distribution of responses and the mode only shows the most frequent response, it is the more decisive measure. In addition, the IQR is only a measure of dispersion and not a measure of location like the median and mode. Consequently, the median is used as the first criterion. If a respondent indicated that he or she was particularly confident about a digital technology, the median would be weighted twice. Furthermore, the average is taken to combine the dimensions of data, technology and organization. The ranking by using the weighted median leads to the result that there are still a large number of split ranks. Therefore, the mode is additionally introduced as a second criterion. The same principle of weighting and averaging is applied here. After using the mode as the second criterion, the number of split ranks was reduced, but there are still many split ranks. Therefore, IQR is used as the third criterion. Continuing with the application of the explained weighting and averaging. The result can be seen in Table 3.

Table 3: Result ranking by median, mode and IQR

| Rank | Digital technology | Median | Mode | IQR |
|---|---|---|---|---|
| 1 | Deep Learning | 3,3333 | 3,6667 | 1,25 |
| | Machine Learning | 3,3333 | 3,6667 | 1,25 |
| 2 | Natural Language Processing | 3,3333 | 3,3333 | 1,0 |
| 3 | Computer Vision | 3,1667 | 3,0 | 1,1667 |
| 4 | Conversational Interfaces | 3,0 | 3,0 | 0,6667 |
| 5 | 5G | 3,0 | 3,0 | 1,0 |
| 6 | RFID | 2,8333 | 3,3333 | 1,3333 |
| 7 | WiFi-6 | 2,6667 | 3,0 | 1,3333 |
| 8 | System virtualization | 2,6667 | 2,6667 | 1,0 |
| 9 | ZigBee | 2,6667 | 2,6667 | 1,4167 |
| 10 | Virtual Reality (VR) | 2,6667 | 2,6667 | 1,6667 |
| 11 | Distributed Ledger Technologien | 2,6667 | 2,3333 | 1,0 |
| 12 | Edge Computing | 2,3333 | 2,3333 | 1,5 |
| 13 | Augmented Reality | 2,3333 | 2,0 | 1,0 |
| | Bluetooth 5 | 2,3333 | 2,0 | 1,0 |
| 14 | Quantum Computing | 2,0 | 2,6667 | 2,0 |

Using the measures median, mode and IQR, the hypothesis could still not be proven because the ranking of the digital technologies is not clear. The ranks one and 13 are still divided. Nevertheless, it can be stated that it was possible to make the relevance of the digital technologies comparable with one another.

*H2 The generated ranking list enables a systematic identification of compliance-relevant digital technologies.*

To test the hypothesis two, the previously generated ranking list is considered. With a relevance score of at least three, which corresponds to "sufficiently relevant", it is assumed in the following that the compliance relevance is sufficient for consideration in the subsequent models. Moreover, the use of the word "sufficient" in everyday language already indicates the adequacy and appropriateness of the relevance. The scale value below three corresponds to "moderately relevant", which in turn is understood in everyday language as " slightly" relevant and is therefore not sufficient for the further considerations. The minimum relevance of three or "sufficiently relevant" defined in this way is applied to the leading statistical measure, the median. This results in a list of compliance-relevant digital technologies shown in Table 4.

Table 4: Identified compliance relevant digital technologies

| Rank | Digital technology | Median | Mode | IQR |
|---|---|---|---|---|
| 1 | Deep Learning | 3,3333 | 3,6667 | 1,25 |
| | Machine Learning | 3,3333 | 3,6667 | 1,25 |
| 2 | Natural Language Processing | 3,3333 | 3,3333 | 1,0 |
| 3 | Computer Vision | 3,1667 | 3,0 | 1,1667 |

| | | | | |
|---|---|---|---|---|
| 4 | Conversational Interfaces | 3,0 | 3,0 | 0,6667 |
| 5 | 5G | 3,0 | 3,0 | 1,0 |

The six digital technologies identified are all at least sufficiently relevant at the median. This statement is strengthened by the fact that the mode is also three or greater for all six digital technologies. In summary, a system of two position measures was used to identify the top six compliance-relevant digital technologies. Systematic identification has thus been successful and the hypothesis put forward is substantiated.

*H3 There are thematic clusters within the compliance-relevant digital technologies.*

The list of compliance-relevant digital technologies which has already been compiled is used to investigate the third hypothesis. This means a search is made for thematic clusters in the six most compliance relevant digital technologies that are at least sufficiently relevant. First of all, it is noticeable that the ranks one to three are all occupied by digital technologies that are related to artificial intelligence. However, the digital technologies: machine learning, deep learning, natural language processing and computer vision, are also related to each other [14]. In the field of computer science, machine learning focuses on developing efficient algorithms to solve problems using computational power [15]. While machine learning uses approaches from statistics, it also includes methods that are not solely based on previous work by statisticians, leading to new and widely cited contributions in the field [16]. In particular, deep learning is used in these contributions. Deep learning models consist of multiple processing layers capable of learning representations of data with multiple levels of abstraction. Deep learning has dramatically improved machine learning capabilities, e.g., in speech or image recognition [17]. Sub-applications of deep learning such as computer vision and natural language processing exist for this purpose [18]. In the context of artificial intelligence, the described techniques such as machine learning and thus deep learning and computer vision or natural language processing are now applied to mimic human intelligence in machines. [14]. The described connections can also be taken from Figure 4.

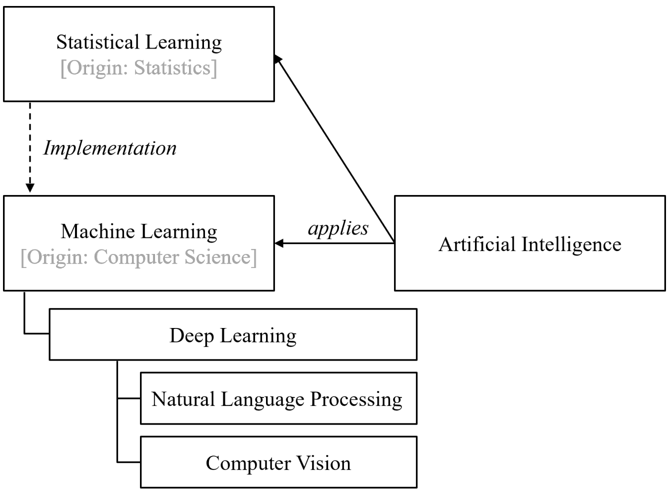


Figure 4: Applications of Artificial Intelligence based on KÜHL [14]

Thus, the identified cluster is named with the overarching term "Applications of Artificial Intelligence" and includes the digital technologies machine learning, deep learning, natural language processing and computer vision. After explaining the proximity in terms of content, it should be further emphasized that the median of all digital technologies in this cluster only varies between 3.3333 and 3.1667. This supports the clustering that was carried out.

The digital technology conversational interfaces is ranked fourth and 5G is ranked fifth. Conversational interfaces is a human-machine interface topic and 5G is a communication technology. No other meaningful content cluster can be formed for 5G. In the case of conversational interfaces, it should be considered whether it would make sense to join the cluster Applications of Artificial Intelligence. However, the authors decided against this because conversational interfaces are based on the technological development of artificial intelligence applications and speech recognition in particular, but interaction with humans has a special role and trust is an important component when using them in manufacturing companies [19]. In summary, the hypothesis set up can be confirmed, as the content cluster Applications of Artificial Intelligence was found.

## 6. Discussion

Digital technologies continue to evolve over time, so the results developed in the paper may change over time. Therefore, the described results of the Delphi study represent a current snapshot that is valid for a limited period of time. When selecting the digital technologies, care was taken to use those that are state-of-the-art today. In addition, the study was structured in a way that is clearly comprehensible. This would allow to reproduce the work at a later time and to update the results. In case of changes, this means that the model has to be adapted or extended.

## 7. Conclusion and Outlook

The aim of the work was to identify the compliance-relevant digital technologies for manufacturing companies. To this purpose, a Delphi study was conducted to integrate the expertise of many individual experts. In analyzing the data obtained, a hypothesis-driven approach was followed and statistical measures were used to derive a ranking of digital technologies in descending order of their current compliance relevance for manufacturing companies. The study showed that the experts were able to narrow down the relevant digital technologies. In order to achieve the overarching research goal of enabling manufacturing companies to write their own compliance for the digital technologies they use, further work is needed, in particular to enable the systematic derivation of compliance rules. For this purpose, a framework has to be developed in the following models to ensure a holistic derivation of compliance rules. In addition, the challenge is to enable companies to do the individual actions themselves and a meta-model has to be developed for this purpose in further work.

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## References

[1] Dietzfelbinger, D., 2008. Praxisleitfaden Unternehmensethik: Kennzahlen, Instrumente, Handlungsempfehlungen. Gabler, Wiesbaden.

[2] Bertele, M., Lehner, F., 2008. IT-Compliance: rechtliche Aspekte des IT-Managements: Darstellung rechtlicher Aspekte - organisatorische, technische und personelle Maßnahmen - Rahmenkonzepte zur Umsetzung. VDM-Verl., Saarbrücken, 126 pp.

[3] Krcmar, H., 2015. Informationsmanagement, 6., überarb. Auflage ed. Springer, Berlin [u. a.], Online-Ressource.

[4] Falk, M., 2012. IT-Compliance in der Corporate Governance. Gabler Verlag, Wiesbaden.

[5] Stich, V., Hicking, J., Stroh, M.-F., Abbas, M., Kremer, S., Henke, L., 2021. Digitalisierung der Wirtschaft in Deutschland: Technologie- und Trendradar 2021.

[6] Europäische Kommission, 2021. Verordnung des europäischen Parlaments und des Rates zur Festlegung harmonisierter Vorschiften für künstliche Intelligenz (Gesetz über künstliche Intelligenz) und zur Änderung bestimmter Rechtsakte der Union.

[7] Bräutigam, P., Habbe, S., Gergen, P., Daum, A., Heckmann, D., Marx, L., Auer, J., Brand Thimo, 2021. Digitalisierung & Compliance: Compliance-Studie 2021.

[8] Häder, M., 2002. Delphi-Befragungen. Springer Fachmedien Wiesbaden, Wiesbaden.

[9] Döring, N., Bortz, J., 2016. Forschungsmethoden und Evaluation in den Sozial- und Humanwissenschaften, 5. vollständig überarbeitete, aktualisierte und erweiterte Auflage 2016 ed. Springer, Berlin, Heidelberg, 1051 pp.

[10] Hüttner, M., 1982. Markt- und Absatzprognosen. Kohlhammer, Stuttgart, Berlin, Köln, Mainz, 196 pp.

[11] Borg, I., 1986. Facettentheorie: Prinzipien und Beispiele. Psychologische Rundschau 37.

[12] Stich, V., Hicking, J., Stroh, M.-F., Abbas, M., Kremer, S., Henke, L., 2021. Digitalisierung der Wirtschaft in Deutschland: Technologie- und Trendradar 2021.

[13] Hicking, J., Wenger, L., Abbas, M., Benning, J., Clemens, F., Bremer, M., Engländer, J., Heimes, P., Henke, L., Kaminski, L., Kremer, S., Niederau, M., Seelmann, V., Stroh, M.-F., Walter, T., 2020. Aachener Digital-Architecture-Management: Wegweiser zum digital vernetzten Unternehmen.

[14] Kühl, N., Goutier, M., Hirt, R., Satzger, G., 2020. Machine Learning in Artificial Intelligence: Towards a Common Understanding. Karlsruhe Institute of Technology.

[15] Mohri, M., Rostamizadeh, A., Talwalkar, A., 2018. Foundations of machine learning, Second edition ed. The MIT Press, Cambridge, Massachusetts, 486 pp.

[16] Sebastiani, F., 2002. Machine learning in automated text categorization. ACM Comput. Surv. 34 (1), 1–47.

[17] He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep Residual Learning for Image Recognition, in: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2016). Las Vegas, Nevada, USA, 27-30 June 2016. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA. 6/27/2016 - 6/30/2016. IEEE, Piscataway, NJ, pp. 770–778.

[18] Russell, S., Norvig, P., 2022. Artificial intelligence: A modern approach, Fourth edition ed. Pearson, Hoboken, N.J., 1115 pp.

[19] Gupta, A., Basu, D., Ghantasala, R., Qiu, S., Gadiraju, U., 04252022. To Trust or Not To Trust: How a Conversational Interface Affects Trust in a Decision Support System, in: Proceedings of the ACM Web Conference 2022. WWW '22: The ACM Web Conference 2022, Virtual Event, Lyon France. 25 04 2022 29 04 2022. ACM, New York, NY, USA, pp. 3531–3540.

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