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INVESTIGATING THE INTERPLAY OF DIGITAL TRANSFORMATION AND ARTIFICIAL INTELLIGENCE IN ORGANIZATIONS: INSIGHTS FROM A PRELIMINARY QUALITATIVE ANALYSIS

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Abstract
Explore the proximity, differences and intersections among the concepts of digital transformation, digitization and artificial intelligence within organizations
In-field validation of digital transformation
The Grounded Theory (GT) methodology proposed by Strauss and Corbin (1998) was adopted as our method since it describes a systematic approach to data gathering, analysis and theoretical standing (codes)
Empirical validation of proposed theories
Better comprehension of digital transformation
Social perception of the explored concepts

Key words: Digital transformation, Artificial intelligence, Digitization, Grounded Theory, Business leadership

Investigating the interplay of digital transformation and artificial intelligence in organizations: Insights from a preliminary qualitative analysis

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Abstract. As society increases the usage of digital platforms, organizations started creating business models to address the new digital consumer. These changes are associated with the so-called Digital Transformation (DT), which denotes the adoption of technologies to modify the human work configuration. At the same time, Artificial Intelligence (AI) comprises more efficiency and an enhancement for customer experience, as well as for improving business value delivery. In this content, we aim to explore the relationship between DT and AI, and based on that, to understand what would be their key linking elements. To do so, we conducted interviews with digital leadership in organizations and analyzed the transcriptions through qualitative methods. We found that AI is an important driver in DT, although it demands a consolidated level of digital maturity.

1. Introduction

Over the last decades, society has experienced the replacement of physical products and services for digital ones, e.g., music in media streaming or products on e-commerce platforms. As society changes the way it consumes and interacts, companies have to adapt its business models, internal processes, and work configurations to attend to consumer's expectations. More recently, the deep impact of the 2020 Covid-19 pandemic on companies and businesses motivated the migration to digital platforms, as shown by Priyono, Moin & Putri (2020). The organizational changes are often applied to describe the so-called "Digital Transformation". Hinings et al. (2018) describes that Digital Transformation (DT) phenomenon comprises the adoption of new technologies as organizational changes enablers. As described by Solis (2015), it is the realignment of technology and business models to more effectively engage digital consumers.

Together with the digitization of services and products, more and more data has been produced and generated on the day-to-day activities, e.g, clickstreams on online book stores, preferences on music platforms, or traffic jams on navigation platforms. With this massive amount of big data, learning algorithms have been playing a critical role to gain insights about consumers' behaviors. Therefore, although artificial intelligence (AI) has been mainly approached as learning algorithms as pointed out by Aizenberg & van den Hoven (2020), it has also been investigated as a driver for digital transformation, as explained by Baptista et al. (2020), as well as for improving organizational decision-making (Horita et al., 2020). We should go beyond the computer science notion and understand that AI may be a central element in many businesses to improve efficiency and business value delivery in the digital transformation. For example, Xu et al. (2017) notes how customers are turning to social media in pursuit of support and describes chatbots powered with artificial intelligence as an effective solution. Likewise, Ni et al.(2017) presents a chatbot for patients' intake in hospitals called Mandy. Therefore, in this work, we understand that artificial intelligence represents a technology associated with new customer solutions and business models.

Even though AI and digital transformation seem linked to each other at first, the challenge now is to understand the existing elements that bridge the necessities and demands of both concepts. In other words, how can one use AI to improve their digital services, or foster the organization transformations towards a better business delivery. Furthermore, the existing literature still lacks a way to establish the linking itself of how an organization can implement artificial intelligence in a digital transformation context. Based on these challenges, the question here is the following: ***How artificial intelligence is associated with digital transformation within organizations?***

To answer the proposed question, this research aims to bring a better understanding of the existing relationships between digital transformation and artificial intelligence. This research paper is structured as follows. Section 2 describes the theoretical concepts adopted in this work. Section 3 presents the research methodology. Section 4 presents our preliminary results based on the gathered and analyzed data. Section 5 discusses the results. Finally, Section 5 draws conclusions and indicates future lines of work.

2. Theoretical Background

In this section, the concepts covered during the research are elucidated, i.e., the digital transformation and artificial intelligence.

Digital transformation: more comprehensive than digitization

Although similar, the concepts of digital transformation and digitization have fundamental differences. Digital transformation is often used to describe the changing process in organizations to address new behaviors in a more digitized society. These changes are associated not only with technology but also with business models and society shifts, as delineated by Van Van Veldhoven & Vanthienen & Vanthienen(2019). According to Brock & Von Wangenheim (2019), many companies are dealing with these transformations. The number of waves or digital transformation projects conducted seems to be what sets apart the digital transformation leaders from the laggards.

Van Van Veldhoven & Vanthienen & Vanthienen (2019) define digital transformation as the increasing interaction between business transformation, digital technologies transformation and society transformation. As observed by Kotarba (2018), technological progress triggers changes in society and, therefore, results in modification of business models. Likewise, Matt et al. (2015) notes that the adoption and exploitation of new digital technologies frequently affects products, processes and organizational structures. From a social standpoint, Alekseevna et al. (2017) explains how digital transformation changes individuals' communication in means and intensity. Although strongly associated with technological adoption, digital transformation also comprehends organizational and social aspects.

The digital transformation process is described by Baptista et al. (2020) through three orders of effects on organizations: 1) convergent change, 2) transforming work, and 3) transforming organization. In other words, a proper transformation is only achieved with a certain maturity of organizational capabilities. First-order effect is described as changes that increase efficiency through the improvement of established patterns of work. It is also expected greater digital-human interaction across the processes. Second-order effect represents changes, instead of incremental improvement. of the existing working patterns. Third-order effect represents new understanding in the nature of work and deep changes in organizational structure.

Artificial intelligence within organizations

Artificial intelligence (AI) is described by Davenport & Ronanki (2018) as a system - not a specific technology - with automated or supportive decision-making capability. It is often delineated around the application in which it is presented. Reim, Åström& Eriksson (2020) states that companies understand it as a means for improving or addressing challenges in process automation, data analytics and customer engagement.

The decision-making aspects, although seen as its key-concept, raises questions regarding the ethics behind the algorithms. The unadvised usage of pattern finding, input-output models increase the harming-risk of human individual values - freedom, equality, solidarity, right to life, non-discrimination, privacy, transparency and safety. Companies must carefully address this socio-ethical matter in order to reach sustainable development as Aizenberg & van den Hoven (2020) and Weissbrod & Bocken (2017) presented in their work.

According to Rai, Constantinides and Sarker (2019), the Human-AI relation in the digital labor context can be leveraged in three main forms: 1) substitution, 2) augmentation, and 3) assemblage. The second type describes task performance augmentation enabled by the relationship, i.e., both parts have the same objective and together the execution is enhanced. With the increase of execution capability business development is expected.

3. Methodology

This study applies qualitative research methods to explore the proximity, differences and intersections among the concepts of digital transformation, digitization and artificial intelligence within organizations. The Grounded Theory (GT) methodology proposed by Strauss and Corbin (1998) was adopted as our method since it describes a systematic approach to data gathering, analysis and theoretical standing (codes).

3.1. Participants sampling

As described by Tong, Sainsbury & Craig (2007), purposive sampling allows the selection of individuals who share particular and relevant characteristics pertinent to the research question. Since this work is strongly associated with Digital Transformation, some characteristics and background are required for proper comprehension and discussion of the theme. The first one is a leadership position, as Al-Ali et al. (2017) elucidates leaders play a fundamental role in changing environments - such as those under digital transformation. The second one is past professional experiences in IT, development, digital marketing or correlated relevant markets, due to what Van Van Veldhoven & Vanthienen (2019) exposes - technology and organizational processes are strongly associated. Last but not least, availability to participate in a synchronous interview and fulfill the questionnaire.

In short, the participants were invited through email or instant messaging app (Whatsapp), sampled through a purposive method using as selection criteria: (1) leadership position, (2) past professional experiences and (3) availability.

The interviewed professionals are representative since they: (a) work at different companies; and (b) have different and extensive professional backgrounds. Therefore, we have confidence in the accuracy and validity of the data we collected, and as a consequence of our results. In next sections, the data collection and analysis approaches are presented in further detail.

3.2. Data collection

The data collection occurred digitally in two phases and two different formats. Prior to the interview, the participants were asked to fill a digital form containing characterization questions (Appendix B). At the agreed date, an interview was conducted synchronously using a videoconference tool (Google Meet). The interviews were recorded with the interviewee's formal consent using the same videoconference tool (Google Meet).

For guiding the interviews, open-ended questions (Appendix A) were asked in order to induce the conversation towards the topics and concepts approached in the theoretical background. Once engaged in the conversation, the interviewees had total openness to express their opinions and share their professional experiences. Eventually, the participants' answers led to new questions, made to disambiguate concepts and explore assumptions. Therefore, the interviews varied in time, between 15 and 60 minutes, and number of absolute questions. A total of five interviews were conducted in January and February 2021.

3.3. Data analysis

After the interviews, the recorded meetings were manually transcribed to enable the GT approach proposed by Strauss and Corbin (1998). GT traditionally consists of the following steps: open coding, axial coding and selective coding. Here, we employed the first two steps of GT (open coding and axial coding) as GT Techniques, mainly, because they are able to answer the proposed research question as endorsed by Strauss and Corbin (1998). In the first, "open coding", meaningful quotes are identified and marked in the transcriptions as codes. A code, as defined by Strauss and Corbin (1998), is a manifestation of a concept and their properties and dimensions in the collected data. Later, Saldaña (2021) complements the definition stating that a code is a word or a sentence that is essence-capturing that possesses meaning on its own. In that sense, by "meaningful quotes" we mean any concept that belongs or even is remotely associated with the universe of this work.

In the second, “axial coding”, each code is analysed individually and collectively to establish relations i.e., identify whether they belong to the same conceptual category or not. Strauss and Corbin (1998) defines axial coding as the act of relating categories along the lines of their properties and dimensions. The “axial” on the name is a reference to the coding process that occurs around the axis of a category. This is an iterative process and requires constant reviews until meaningful relations are established.

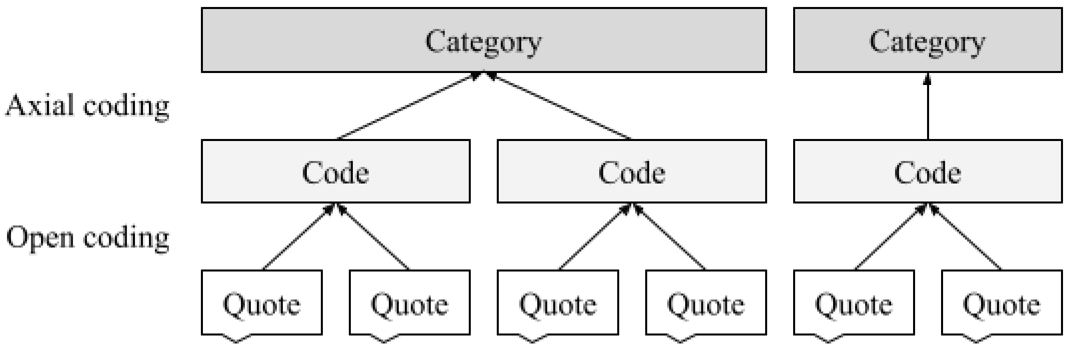

Figure 1: Grounded Theory steps and relations.

For all three steps we used ATLAS.ti (version 7.5), a dedicated software for qualitative analysis, to support our qualitative analysis. The data was analysed textually and also with the generation of support graphical networks, explaining visually the association of the codes and the categories.

4. Preliminary results

In this section, we explore the interviewees’ answers, in Section 4.1 we discuss the professional profile of participants from a quantitative perspective, in Section 4.2. we discuss the organizational characteristics also from a quantitative perspective. The following sections explore possible correlations between the quantitative and qualitative approach of data.

4.1. Characterization of participants

As previously mentioned, all the participants are at leadership positions, this was a requisite due to the conceptual-depth expected and themes approached. The participants were between 28 and 42 years old. Most participants are experienced professionals, with more than 10 years of career and experience in the information technology field. Table 1 presents the characterization of the participants in further details.

Table 1: Participants professional characterization

#	*Age*	*Job position*	*Company type*	*Total professional time*	*Technology professional time*	*Current company time*

1	28	UX Designer specialist	Private	5 - 10 years	5 - 10 years	Less than 1 year
2	39	System analyst	Private	More than 10 years	More than 10 years	1 - 3 years
3	42	IT Coordinator	Public	More than 10 years	More than 10 years	More than 10 years
4	33	IT Manager	Self-employed	More than 10 years	More than 10 years	5 - 10 years
5	28	Innovation Leader	Private	More than 10 years	5 - 10 years	1 - 3 years

It is important to notice that neither of the interviewees works at the same company.

4.2. Characterization of organizations

To assess the digital transformation maturity in each organization, we asked the participants about the adoption of artificial intelligence and digital transformation scenarios. Both questions were put in Likert-scale, where 1 represented “Not being used in any means” or “Not occuring” and 5 represented “It is incorporated in the processes” or “Occurs and exists a strong digital culture”, respectively. Table 2 presents the organization's characterization in further details.

Table 2: Organization’s characterization

#	***Artificial intelligence adoption***	***Digital transformation scenario***
1	2	3
2	5	5
3	1	2
4	2	4
5	4	3
Average	2.8	3.4

In most cases, the interviewees perceived a higher degree of digital transformation (average: 3.4) than the adoption of artificial intelligence (average: 2.8). This can indicate that artificial intelligence is more likely to be adopted in companies that have higher digital maturity. It is important to notice that the participant #5 works at a dedicated artificial intelligence software provider.

4.3. Coding Scheme

Figure 2 shows the coding scheme defined from the analysis of the gathered data. From the bottom of the figure to the top, we first show the codes derived from the quotes of participants, which then provide a basis to coding key categories. This in turn supported the high-level theme. For example, the code "Technology" represents one of the codes that grounds the category "Drivers".

We define drivers as elements that may lead to digital transformation, i.e. that motivates and triggers society, business and technology in ways that characterize convergent and transformational changes. Technology not only improves processes but increases organizational profit through the enablement of new business models. Digitization is a key aspect since the exchange from analog to digital operation also requires a mindset shift. Lastly, Artificial intelligence is a strong changing agent, enough to promote deep structural changes, since systems are built to operate in similar ways as human workers. Even if there are drivers within an organization, digital transformation does not occur unless there are supportive influence factors. Therefore, we define influence factors as elements that sustain the changing process within an organization. To accommodate new technologies on internal processes, work relations need to be reconsidered and professional trained or reallocated. Organizational culture is directly associated with the way an organization conducts internal changes, such as the work relation previously mentioned. Openness to innovation influences the agility in which technologies are adopted and new business models experimented. Finally, digital maturity is the organizational fit to a digital ecosystem, how much it is connected to new channels which the customer might operate. Together Drivers and Influence factors support the Digital Transformation.

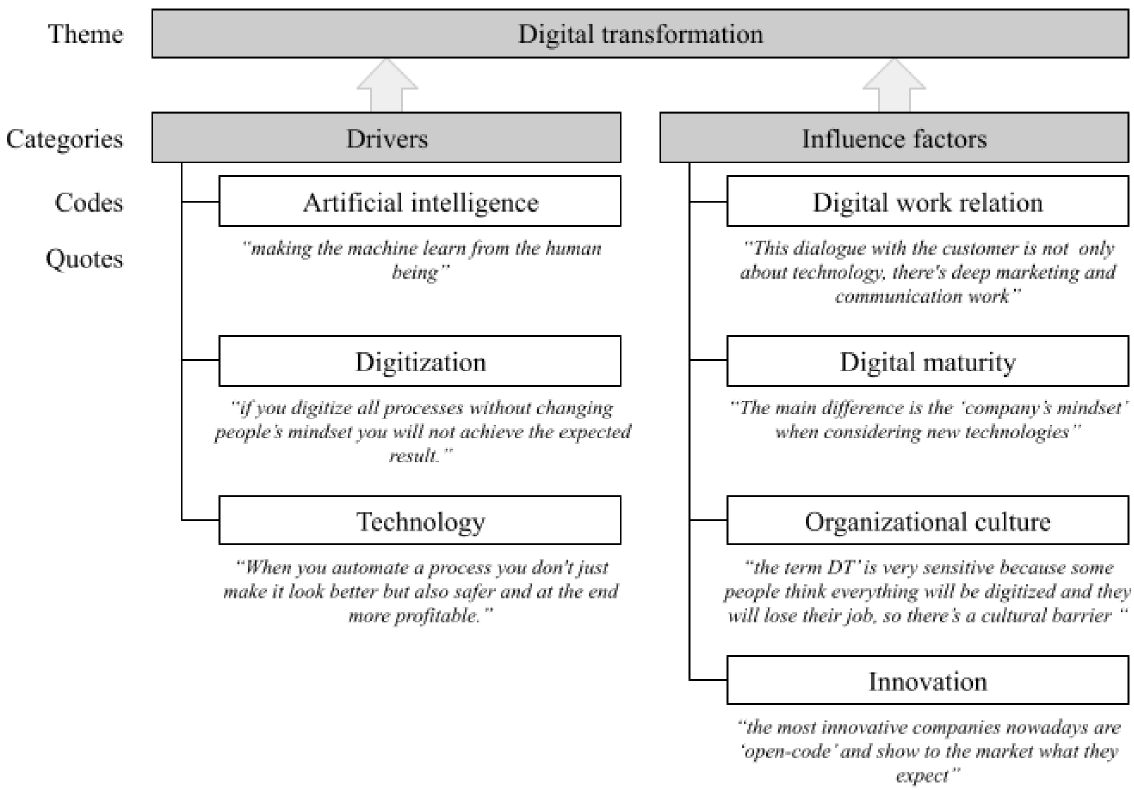

Figure 2: Coding scheme.

5. Discussion

We structured the findings around digital transformation in two themes: drivers and influence factors. As data suggests, drivers are systems implementations, platforms, automations, any tools or technical solutions that serve as foundations for new or redesigned processes and business models. It is intuitive to associate technology adoption as the trigger for the transformation itself, but our results showed that there is a vital and more important element on the spot, i.e., without an appropriate organizational environment, there are no real changes. Organizational culture, level of digital maturity, appetite for innovation and digital work relations are what the data suggests as the fundamental elements of the organizational environment, and, therefore, we call them influence factors.

Drivers and influence factors must coexist and cooperate, as one of the practitioners mentioned during the interviews: "*Some companies seek digital transformation and believe that it occurs through process automation, having more embedded technology but, specially for more traditional companies, if you digitize all processes without changing people's mindset you will not achieve the expected result.*" The continuously increasing interaction between technologies, business and society is how Van Van Veldhoven & Vanthienen (2019) defines digital transformation. This reinforces the importance of a multidimensional approach towards DT and brings more clarification over the concept of technology and business mentioned through empirical evidence.

Another finding indicates the existence of an intrinsec cultural barrier, as one of the practitioner quoted: "*The company in which I work has fifteen thousand employees and thirteen thousand of them are call center operators, the term 'digital transformation' is very sensitive because some people think everything will be digitized and they will lose their job, so there's this cultural barrier related to digital transformation.*". Adding another quote by the same practitioner allowed us to better understand and picture the role of the leader in the DT context: "*You need to invest in people training, so the organizational culture supports digital transformation as one*". Misconceptions should be tackled with training in order to reduce changing resistance, as stated by Al-Ali et al. (2017). This underlines the importance of leaders in the DT context as it is part of the leadership responsibility providing the proper means and knowledge to the team.

Artificial intelligence has countless applications and manifestations, some more obvious and noticeable - like chatbots interacting directly with humans as Ni et al. (2017) presented - and others not so much. All practitioners mentioned chatbot as a known application of AI, this suggests that natural language understanding (NLU) and natural language processing (NLP) are the two most relevant topics in the AI research field. When questioned about the concept, one practitioner answered that AI was about "*making the machine learn from the human being*". That being said, it is inevitable not to think about the future, how AI will interact and work along with humans in organizations. The data of this research suggests that there is a prevalence of one particular human-AI labor relation described by Rai, Constantinides and Sarker (2019), i.e. people associated more often AI with task assemblage - AI and humans working together as an integrated unit. This common perception amongst the practitioners is well represented in the quote: "*Often the questions are basic and the chatbot can provide a quick answer. It is also good to talk to a human and not just the bot, sometimes it gets to a point where the bot can not answer. This dialogue with the customer is not only about technology, there's deep marketing and* *communication work*". As AI becomes more present in the organizational context, we expect to see discussions and works around ethics as the one conducted by Aizenberg & van den Hoven (2019) more often.

This work was not carried out without some limitations, although to the best of our knowledge, it provides relevant contributions to practice and research already mentioned before. The purposive sampling method has an inherent bias risk but still is highly suitable for the proposed methodological approach, since individuals with common particular characteristics (described in Section 3.1 Participants) are required. The interviews were conducted with open-ended questions so the participant could openly share their opinion and eventually add different perspectives. This was used as a risk mitigating strategy for the adopted sampling method. The number of participants were limited by the particular characteristics set as relevant for the depthness of the study, the financial resources dedicated for this research and the socio demographics of the country where the study was conducted. According to de Souza Silva, Rodriguez & Queiroz (2018), about 0,06% of the Brazilian population occupied leadership positions, and therefore we believe there is statistical significance in the size of our sample. We do expect to increase the number of practitioners as this work evolves.

6. Final considerations

Our empirical work provided evidence that artificial intelligence and digital transformation are understood differently but share common two objectives: enhancing customer experience and bringing business efficiency. Interviewees associated digital transformation with cultural changes and offer of digital services. Digitalization that is understood as part of digital transformation was mentioned as a process review mechanism, the transposition of analog data to digital data in ways that increased overall performance.

Digital transformation was strongly associated with systems and platforms modernization (Leon & Horita. 2021), since these are understood as enablers of customers touchpoints. Experimentation, openness to try new technologies and make quick shifts was pointed as Digital transformation enhancers. Likewise, artificial intelligence predictive capability is perceived as its major differential, bringing financial gains and cost avoidance - reduction of losses due to better projections. Also, it has been defined as any practice that tries to mimic human intelligence. Ethical aspects are the major concern, artificial intelligence requires data streams and this raises privacy questions. This matter should be discussed during the solution design or right after its conception, as proposed by the interviewees. It is expected that artificial intelligence handles more mechanical and repetitive labour, specially in first level customer support, so humans will be relocated into more specific or creative activities. This might change the professional specialization level searched by companies and create greater social inequity. These findings are relevant since they established common-ground between digital transformation and artificial intelligence, also clarifying the adoption gap.

Future lines of work could focus on exploring the expected value of artificial intelligence in organizations, exploring pre adoption expectations versus post adoption reality. This could clarify the existence of perception gaps and also elucidate how leaders perceive value. Another interesting work would be the mapping of technical capabilities (hard skills) required for digital transformation and artificial intelligence adoption. When comparing different companies with different levels of digital maturity, this work can help understand what are the skills that differentiate digital leaders.

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Appendix A: interview's base-questions

Base-questions adopted in the interviews conducted during this research:

1. Considering the last year, the company you work at adopted new technologies? If so, what was the objective?
2. Considering last year, the profile or behavior of your final customer changed? If so, how?
3. Considering last year, the company you work at started offering new digital products or services or redesigned products or services that were mainly “offline” (not available digitally)?
4. Have you ever heard about “Artificial Intelligence”? If so, which application are you aware of?
5. The company you work at applies direct or indirectly artificial intelligence on the products or services offered to the customers?
6. Do you believe artificial intelligence can bring economic gains, improve collaborators’ working conditions or improve the environment? If so, which ones and how?

Appendix B: characterization questionnaire

Questions adopted in the characterization form sent to the participants before the interviews:

1. Age: open text field with number validation
2. Professional situation: ratio with the following options: (a) Working at a private company; (b) Working at a public company; (c) Self-employed; (d) Unemployed; (e) Other
3. Job position: open text field
4. Current company time: ratio with the following options: (a) Less than 1 year; (b) 1 - 3 years; (c) 3 - 5 years; (d) 5 - 10 years; (e) More than 10 years
5. Information Technology working experience time: ratio with the following options: (a) Less than 1 year; (b) 1 - 3 years; (c) 3 - 5 years; (d) 5 - 10 years; (e) More than 10 years
6. Total working experience time: ratio with the following options: (a) Less than 1 year; (b) 1 - 3 years; (c) 3 - 5 years; (d) 5 - 10 years; (e) More than 10 years
7. Artificial intelligence usage: likert scale (1 - 5): (1) “Not being used in any means”; (5) “It is incorporated in the processes”

8. Digital transformation scenario: likert scale (1 - 5): (1) "Not occuring"; (5) "Occurs and exists a strong digital culture"

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