Master's thesis

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Study of the effect of choice of organizational culture on artificial intelligence (AI) resources adoption

AI Capabilities and Business Value

Master's thesis in Information Systems
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NTNU
Kunnskap for en bedre verden

To Muhammad Hamza Siddiqui, my loving son...

Summary

Over the last decade, continuous improvement in the high-performance computing systems has provided a significant boost to the inclusion of artificial intelligence (AI) practices to businesses. However, only a handful of organizations truly knows how the transformation affected their business market competition, along with the understanding of the real barriers to its adoption. Many organization finds it hard to oversee the general overview of the present development of AI capabilities. It is understandable to some extent considering the AI technology is complex, and still in its early phase of implementation. While most of the previous work on AI has been conducted from a technical viewpoint, there is a significant gap that still needs to be filled concerning AI impact on business organizations. Usually, the adoption of technology is what each business is willing to introduce through its organizational structure; empirical evidence of its technology adoption on the performance of business firms is still lacking. There is limited scientific literature that helps organizations to understand the real barriers and challenges to firms that have adopted AI. The aim of the present work is to cover the research gap with an empirical study to help identify the main challenges and barriers to businesses facing through the adoption of AI technology. In the present work, a research study is conducted in the form of an online survey aimed at organizations that have adopted AI or in a phase of its adoption into their work routine. The present study conducts the analysis using 242 surveys obtained from professionals working with the technology in established organizations. The results of the survey have been studied through statistical methods of k-means clustering analysis and One-Way ANOVA to find patterns in the obtained data. Particular emphasis has been placed to evaluate how organizations exhibit common strategies of culture and AI resources data. From the analysis of results, a noteworthy finding is that the business organizations having better organizational capabilities of the rationale and hierarchical techniques are better off with handling AI (tangible, intangible, human) resources.

Keywords

Artificial intelligence, organizational culture, artificial intelligence resources, empirical analysis, business capabilities, artificial intelligence adoption challenges

Preface

The work is carried out at the Norwegian University of Science and Technology (NTNU), Department of Computer Science.

I would like to express my sincere gratitude to Professor Patrick Mikalef for his supervision, support, and valuable suggestions. His guidance has been a source of inspiration and motivation for me. I truly thank him for answering questions and broadening my mind.

I would also like to thank my family especially my mother Ghazala Zahid and my father Zahid Latif for their invaluable support during my education years. Special thanks to my brother Zain Latif and my sister Quaratulain for their love and affection. Last but not the least, I want to thank my husband Muhammad Salman Siddiqui for his continued support, encouragement and patience during the course of my masters education. Special love for my son Muhammad Hamza Siddiqui, whose presence around me makes me happy and cheerful.

Trondheim, May 2020

Sidra Tul Muntaha Latif

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Abbreviations

AI	:	Artificial Intelligence
SPSS	:	Statistical Package for the Social Sciences
4IR	:	fourth industrial revolution
IT	:	Information Technology

Chapter 1

Introduction

Recent advancement in the field of information technology (IT) has transformed the economic development scenario for society, economics, and the public sector. The emerging wave of the fourth industrial revolution (4IR) [1] has made it imperative for the business sector to employ artificial intelligence (AI) practices [2] to open new and innovative opportunities to their existing capabilities. AI-assisted analytic, simulation and hypothesis have now become a key for decision making, strategy and innovation throughout the organizations. In short, the introduction has AI has opened unprecedented avenues to enhance the value of existing businesses [3, 4].

At one end, AI has provided exceptional opportunities for revenue by significantly changing the way work has been carried, while at the other end integration's of AI into business models have forced the organization to redefine the underlying principles on which they have been operating from the very beginning [5, 6]. Digital methods are continuously being introduced in the work culture through the employment of AI [7]. The overall change has been more apparent in the business sector (both public and private), which shows that AI integration has led to the transformation of the whole business life cycle [8].

It can be inferred that the integration of AI to business provides numerous benefits to public and private sector organizations [9], the study of AI capabilities in an organizational context is still a young field of research that is gaining much attention at present [10]. We believe that empirical evidence of AI technology adoption on the performance of business firms is still lacking [11]. The present challenges of adoption and barriers are mainly linked to an insufficient understanding of the effects of AI resources on various organizational contexts [12]. Hence it becomes imperative to understand and identify the correlations of organizational culture and AI resources in order to make the integration successful.

1.1 Motivation

The motivation behind the present thesis is to fill the research gap, through an empirical study [13], to identify challenges and barriers current businesses organizations face due to the adoption of AI technology. The idea is to understand and reflect on how organizations can successfully adopt and integrate AI resources and generate value at the same time. One of the primary goals of the present work is particularly to explore how organizations exhibit common strategies of culture and AI resources. The present work generates new knowledge on the subjects and provides meaningful insights through innovative analysis methodology applied to research data.

1.2 Research design and approach

The present thesis employs a qualitative research methodology [14, 15] to analyze and measure complex research constructs. Given the constructs are not designed in a way to have a direct measure (in that case, the quantitative analysis would be appropriate), we believe qualitative representation would help to draw plausible conclusions.

A survey framework has been chosen to gather research data. To conduct the survey, participants have been chosen, which can provide a perspective in a way that helps in creating a holistic view of how organizations exhibit common strategies of culture and AI resources data. More than 350 survey invitations have been sent out to professionals ranging from diverse workgroups operating all over the world. The results of survey data have been scrutinized, and data has been carefully prepared [16] before running qualitative tests and generating conclusions.

1.3 Thesis contributions

The thesis contributes to the present state of the art research in the following way

- The thesis provides key insights into how various cultural and AI resources (tangible, intangible, human) interact.
- It highlights the patterns in the responses of respondents through statistical methods (k-means clustering analysis, One-Way ANOVA) to support conclusions.
- Provide a thorough understanding of how organizations exhibit common strategies of culture and AI resources data.

1.4 Limitations

The present work shows a thorough study of how organizations exhibit common strategies of culture and AI resources through a comprehensive online survey. One of the critical limitations of the present work is that it provides reflections based solely on the results obtained from the survey. Although effort has been made to scrutinize the responses in the best of manner, however, there are possibilities that the survey may still contain few biased answers. Alternatively, there might be other better ways to represents such behavior in the literature. Nevertheless, the present work has been conducted to the best ethical standards of research possible.

1.5 Structure of thesis

The thesis has been outlined as follows:

- In Chapter 2 and 3, we discuss the theory of research methods along with providing details of the existing state of the art research in literature.
- In Chapter 4, we discuss the research methodology and describes a thorough analysis of how the survey has been designed and implemented. It also discusses the model and hypothesis.
- In Chapter 5, we discuss the results and analysis. We present results in the form of demographics data, k-means clustering analysis, One-Way ANOVA, and show how different cultural behavior impact AI resource utilization.
- Chapter 6 discusses the conclusions. While references and appendixes are placed at the very end of the thesis.

Chapter 2

Literature Review

A comprehensive literature review is conducted to explore the use and impact of AI in business in reference to the available scientific literature. Various scientific articles, thesis and case studies have been analyzed to develop a solid foundation to streamline a systematic process for the present research. The literature which we find relevant is studied in detail to develop the conceptual research model and hypothesis.

The understanding of existing literature helped us to devise a solid foundation and clarify the following research question: *challenges and organizational transformations business experience while adopting AI?* and *what is the real definition of term AI in context business value capabilities*. We consider these two as preliminary research questions that are explored in this section, which later becomes the basis for developing and studying AI resource behavior in an overall organizational context.

2.1 Research criterion

The research conducted in the present work originates from both previous experience and motivation of the supervisor as well as an in-depth literature review. In the preliminary phase of the project, after initial motivation from the supervisor, an extensive review of the literature has been conducted. Since AI is a relatively emerging field,

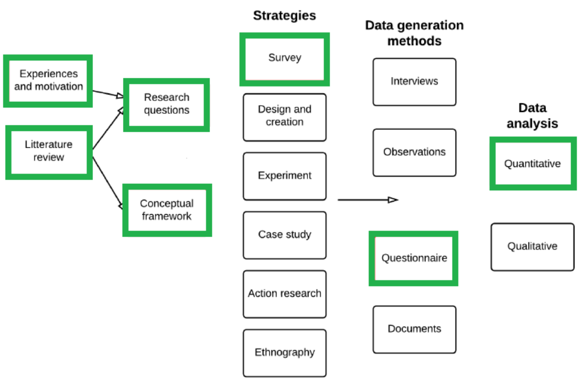

Figure 2.1: Illustration of research criterion [17]

therefore, it has been de-
cided to target research material not older than six years to conduct a literature review of the state of the art research trends in the field. This literature survey built a solid foundation of the subject and help in developing research questions and conceptual framework of the project. All these studies are identified in the first round (specialization report) through an exhaustive literature review, which formed a basis for the present thesis. The present research criterion is depicted in Figure 2.1.

2.2 Methodology

In this section, we have used a literature review strategy, as described in the study of [18]. The literature review has been conducted in systematic stages, which has allowed us to conduct a thorough literature survey keeping all relevant material intact and connected to the main theme of the present report. To begin with, we have first selected the review protocol. In the following stage, we have developed rules to allow inclusion or exclusion of published articles based on a predefined criterion. In the next stage, we analyzed the articles and extracted relevant data. We now provide details of each criterion along with the set of rules identified to conduct an in-depth literature survey.

2.2.1 Protocol development

We have first developed a protocol to allow a systematic and comprehensive review of available literature. We have used guidelines described in the Handbook of [19]. It has formed the basis to identify the research question and driven the way we have selected relevant articles, search strategy, inclusion and quality criteria, and the analysis method. The research agenda has formed the true basis for subsequent research identification of the topic explored ahead in the analysis (section 5).

2.2.2 Inclusion and exclusion criteria

To search for the most relevant material against established research questions, few initial criteria are defined. We have first selected to study the most recent publication on our topic from 2012 on-wards since the AI revolution is fairly new, and business communities are in the process of its adoption. We consider this a wise choice to explore recent articles that were published on the subject after the year 2012. We have mainly focused on research articles that have been published in journals and conference proceedings. Although we also found relevant literature on various blogs, however, we decided to stick to academic literature rather than reports whose authenticity is generally hard to establish. Among the literature, we have put a strong focus on the case studies as we believe that they were an excellent way to extract information concerning current trends in the business community towards the adoption of AI.

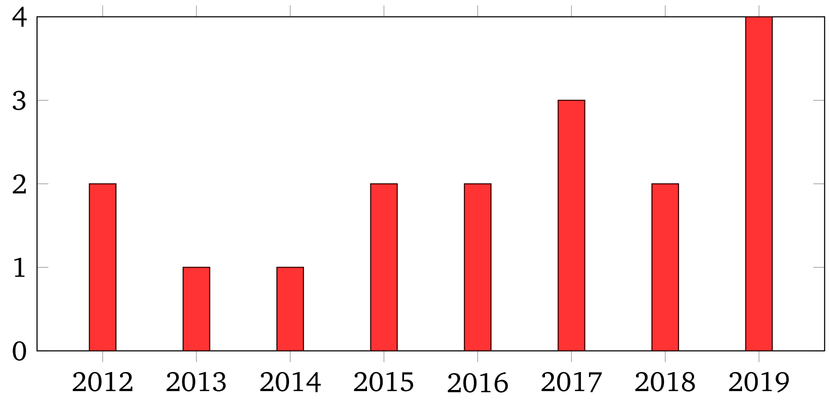

Figure 2.2: Publication timeline of the literature

2.2.3 Data sources and search strategy

We have first started using relevant keywords that are considered closer to the present theme of research work. The search strings are selected with *Artificial Intelligence* as the reference, while the other ten words have been chosen in consultation with the mentor to allow searching for a broad set of relevant literature. The words included are: cognitive intelligence, business digital services, business-government innovation, business organizational learning, business manipulation, business competitive advantage, business dynamic capabilities, business organizational agility, business dynamic capabilities, business operations, business transformation, business big data analytics/management, business operational capabilities, business resource-based view, business values, business uncertainty. These keywords are used to search the fields of manuscript titles, abstract, and keyword selection. We have targeted journals such as Scopus, Business Source Complete, Emerald, Taylor & Francis, Springer, Web of Knowledge, ABI/inform Complete, IEEE Xplore, and the Association of Information Systems (AIS) library. The search has been conducted mainly on the Google Scholar search engine. We have used 25 days to search rigorously for relevant articles starting from 2 August 2019. At the end of the search, we end up collecting 203 papers. From this repository, we began to determine relevant articles through a systematic literature review. For example, we have shortlisted pertinent articles of stage 2 and excluded the articles which were technical or not coherent with the subject of study. This way, we have reduced articles form 203 to 43. In the next stage, we have further segregated articles based on reading their abstracts to identify if topics discussed in the articles overlap the domain of research question we have defined at the beginning. We reduced the number of articles to 22 by excluding the ones which were not relevant or too technical for the present topic.

#	Journal title	Acronym
1	Information Systems Research	ISR
2	Business Horizons	BH
3	California Management Review	CMR
4	International Journal of Information Management	IJIM
5	MIS quarterly	MISQ
6	Futures	F
7	The Journal of Strategic Information Systems,	IJSIS
8	International Journal of Accounting Information Systems	IJAIS
9	Business Intelligence	BI
10	Procedia - Social and Behavioral Sciences	PSBS

Table 2.1: Names of journals explored in the literature review

2.2.4 Quality assessment

The articles collected at this final stage are then further assessed against a rigorous and thorough review. Each paper was studied to evaluate the type of analysis conducted, the research methodology used, relevance to our research question, and we have thoroughly studied if the topics reflect the AI barriers in adoption to the business community. During this process, 5 articles were not found directly matching with our criterion, and after this stage, we have left with 17 articles. Table 1 constitutes the list of journal names corresponding to these 17 articles, while Figure 2.2 show grouping in terms of year of their publication. After the end of these rounds, we manage to collect articles focused on our initial research question described. The stages of literature screening performed in each stage are presented in Figure 2.3.

2.2.5 Data extraction and synthesis of findings

To determine a thorough investigation of findings and scope of scrutinized articles, a spreadsheet has been developed that breakdowns articles in the following criteria. Title, author names, journal names, year of publication, keywords, definitions, research questions, research context, theories, important factors, research methods framework/model, results, analysis method, future research potential, limitations, and conclusions. This allows us to develop a blueprint of all articles and identified key concepts while organizing comparisons across studies and translating findings into higher-order interpretations. We have also tried to record the type of research conducted (e.g., qualitative, quantitative, case study), the sample size, the instruments used (e.g., surveys, interviews, observations). This procedure allowed us to identify key concepts presented in all 17 papers in detail.

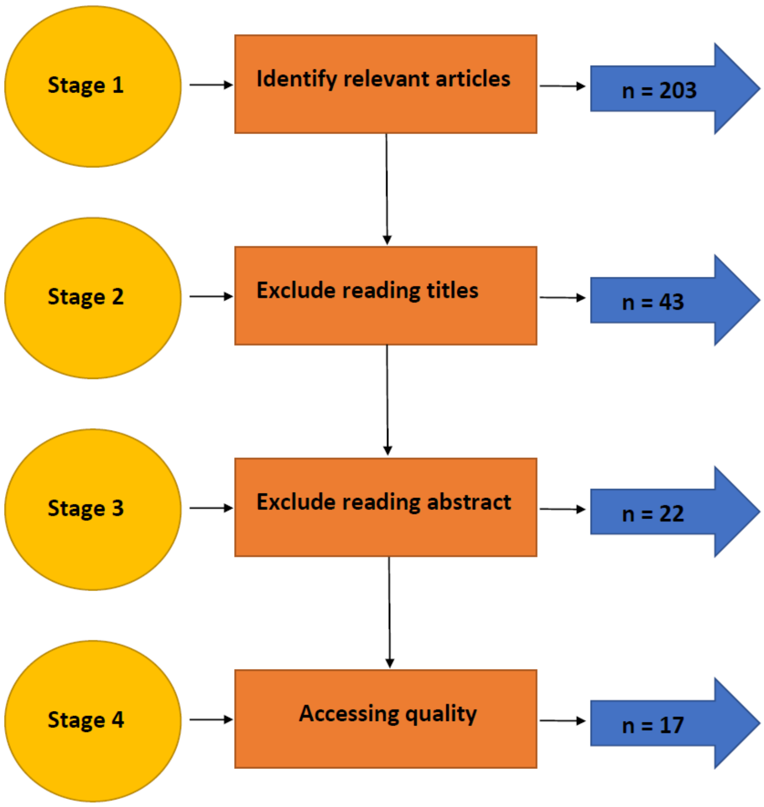

Figure 2.3: Stages of the study selection process

2.3 Defining AI in the business context

We explore the literature to identify the meaning and description of the term AI. We also highlight the attributes and integral concepts that have been discussed. In the segregated literature, we have seen many definitions of the terms described in a broad context, which are summarized in Table 2.2. From a traditional standpoint, AI has been generally perceived as a combination of systems that mimic cognitive functions commonly associated with humans [20]. Where the attributes are typically considered as learning, speech, thinking and problem-solving. In a few studies, the term has been characterized from the perspective of developing systems endowed with the intellectual processes characteristic of humans [21]. In general, the system's ability of humans for a reason, discover meaning, generalize, or learn from past experience. Also, a handful of studies have described the terms form an application point [22], while some have generically discussed the term that can be integrated into any field of study [23]. One of the pivotal

Author(s) & date	Definitions
Russell [24]	Artificial intelligence allow machines and processes to mimic cognitive functions that humans associate with a mind such as learning and problem-solving
Russell [24]	Artificial intelligence involves mimicking cognitive functions generally associated with human attributes to process and behavior
Miller [25]	Artificial intelligence in a typical organizational context is refers to as unique technology that rapidly transforms business and manufacturing, extending their reach into what would normally be seen as exclusively human domains of expertise

Table 2.2: Sample definitions of AI

points discussed in articles shows that AI systems in a business context should take information from its environment and takes necessary actions that maximize its chances of success [12, 30]. In an organizational context, the AI system has been identified as one that leads to improving an organization's ability to use data from previous systems and predict the future decisions in a way that substantially reduced the cost of making predictions [9]. While according to few, the recent emergence of AI in aid in decision making and collection for data has certainly improved business and transformed competitiveness. It has undoubtedly become a key player to identify and enable fast decision making and win business over competitors.

The discussion related to key definitions of AI enables us to understand that AI is not limited to a particular application. Instead, they are considered as simple collection definitions as depicted in [24] to more complicated systems, processes,

Author(s) & date	Definition
Kaplan and Haenlein [26]	Artificial intelligence in the context of business enterprise is defined as the ability to independently interpret and learn from external data to achieve specific outcomes via flexible adaptation
Makridakis [27]	Artificial intelligence in a business perspective include learning (the acquisition of information and rules for using the information), reasoning (using rules to reach approximate or definite conclusions) and self-correction
Adadi and Berrada [28]	Artificial intelligence is the ability of a digital computer/computer-controlled robot to perform tasks commonly associated with intelligent beings
Loebbecke and Picot [29]	Artificial intelligence is the capability of a business model to imitate intelligent human behavior without a human intervention
Wirtz *et al.* [9]	Artificial intelligence behaves as an intelligent agent where a business process perceives its environment and takes actions which maximize its chances of success.
Shah and Chircu [30]	Artificial intelligence represents the collection of technologies, systems, and processes that able to sense their environment, think, learn, and take action in response to what they're sensing and their objectives
Duan *et al.* [12]	Artificial Intelligence systems have improved an organization's ability to use data to make predictions and have substantially reduced the cost of making predictions

engines, etc.

Chapter 3

Theoretical foundation

After successfully investigating the general definition of AI terminologies in the organizational context, we now explore how different viewpoints are critical in the literature corresponding to the use of AI resources. We have defined and studied the underlying organizational culture and identified potential AI resources. Through this systematic approach, we developed a solid foundation for building our research methodology and hypothesis of the research. We mainly adopted novel studies from literature [31] to devise the framework outlined in the present section. The present constructs are also being adopted from studies of big data analytic, a sub-domain of AI [10].

3.1 Tangible AI resource

To measure AI capabilities in a business context, tangibles AI resources are segregated into three sub-constructs, namely data, basic resources, and technology. As reported by [31] these assets are defined to be the ones that can be sold or bought in a market. Herein we provide a brief idea about the constructs and their implication concerning AI resource utilization.

3.1.1 Basic resource

This resource comprises of time and amount of funding the organization own concerning AI initiatives. While organizations have enough funds, this construct measure the strength of basic resources both in terms of time and investments the organization can invest in extracting the benefits out of AI integration to their business model.

3.1.2 Data

Data is considered one of the primary features of AI resources in an organization. It composes of collection of data, its connectivity and ease of access. The constructs based on data allow us to understand the accurate idea about the capabilities of organizations to store, access, integrate, and analyze the data while providing a realistic estimate to obtain meaningful insights [32]. One of the prime concerns could be to seek an answer if the organization has access to large, unstructured, or fast-moving data for analysis? Do they have storage capabilities, the capacity to perform the high-value analysis? Or if the organization has enough AI data available and has the right to assess data for error estimation? [33]

3.1.3 Technology

Technology has a lot of significance when it comes to the integration of AI resource capabilities to an organizational level. The main idea of construct related to technology is to find if the organizations are equipped with state of the art cloud-based services for storage and integration [34]. Do they have access to smart GPUs and if the organization is willing to invest in networking infrastructure (e.g., enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low-latency). It is important to analyze that the organizations that want to or have been integrating AI have scalable data storage infrastructure. Another aim could be to evaluate if the data is secured from to end with state-of-the-art technology for the successful integration of AI infrastructure [35].

3.2 Human AI resource

The human resource in the present context consists of human workforce technical and managerial skills. This can be further categorized with the ability of employees to deal with problems, teamwork, knowledge about work, experience, ownerships, etc. Mainly constructs based on this are aimed to understand the relation of technical skills and managerial skills towards AI resource utilization.

3.2.1 Technical skills

It generally belongs to the class of idea to evaluate how much the human workforce has the knowledge and capacity to deploy solutions based on AI resources in the business model [32]. These include employees, technical skills to operate systems, understanding of machine learning, natural language processing, deep learning, data analysis, processing, and security. They also include information about formal training to deal with AI applications and the kind of work experience they require to full fill their jobs.

3.2.2 Managerial skills

These sets of constructs are developed to understand the experience and skillsets of experienced employees generally working at higher managerial positions related to business problems and to direct AI initiatives for the solution [34]. To further identify the issues, one of the key things is to evaluate if the managers are able to work with data scientists, other employees and customers to determine opportunities that AI might bring to the organization [31]. It would also be interesting to explore if the managers have a sense of where to apply AI or have adequate leadership skills. Another interesting aspect could be to identify managers who can design AI solutions to support customers needs while showing adequate commitment to AI projects [36].

3.3 Intangible AI resource

These resources are not something that can be physically or practically described in an organizational manifesto [5]. These have a broad meaning and is highly dependent on the context they have been used. These can be categorized into inter-departmental coordination, organizational change capacity, risk proclivity.

3.3.1 Inter-departmental coordination

It is the ability and capacity within the organization to engage amount different departments such as marketing, R&D, manufacturing, information technology, and sales for active cooperation. Collaboration, collective goals, teamwork, same vision, mutual understanding, shared information, shared resources. Related to AI integration of resources, it becomes important from a strategic point to analyze such cooperation in greater detail [37].

3.3.2 Organizational change capacity

It is the ability of an organization to anticipate and plan for change both within the organization and outside among competitors. Concerning AI integration in the business model, this becomes apparent to understand how AI could provide strategic changes for the organization and to help it to adapt to changing market conditions [38]. It could be interesting to seek in-depth reflective questions to anticipate how change has been communicated among members of the organization and how senior members commit new values.

3.3.3 Risk proclivity

It referees to account how well organizations are able to handle the risk associated with various projects by taking bold steps to achieve overall objectives. This may require taking bold, aggressive posture in order to maximize the probability of exploiting potential opportunities [39]. The idea is to evaluate through reflective questions to understand the impact of a strong proclivity for high-risk projects. The constructs measure directly organization ability to undertake bold and wide-ranging decisions.

3.4 Organizational culture

The culture is a significant part of organizational decision-making [40] and is a direct measure of principles which binds people and technology together. The true sense of these constructs measures how the culture affects the performance of the organization in general and how it will affect AI integration. We describe details of culture based on four values of the group, developmental, rational and hierarchical.

3.4.1 Group

It is considered to be a measure of the capacity of organizational culture and reflects on the critical aspects of how the employee interacts through essential pillars of an organization. One of the measures could be to understand if loyalty and tradition is the central pillar on which employees effectively work in an organization. Another interesting aspect could be to identify if the organization nurture its human resource in a way that would lead to a shorter distance among people working in the organization.

3.4.2 Developmental

In the context of organizational culture, it represents the way how organizations behave against the dynamic and ever-changing cultural situation in the market concerning the technology. Since the AI market is rapidly evolving, one of the interesting aspects could understand for a given organization, how are the dynamism and entrepreneurial nature of its work [41]. Another direction would be to seek commitment to innovation and development and to evaluate if the organization reshapes itself against ever-changing market scenarios through the acquisition of new resources.

3.4.3 Rational

It depicts how the organization has been structured to accomplish its goals. This measure will help identify if the emphasis is placed in the organization to tasks and goal accomplishment [42]. In addition, it could also be important to measure if an organization emphasizes competitive actions, outcomes, and achievement while remaining a very production-oriented place.

3.4.4 Hierarchical

It refers to the organizational structure, both in terms of defining rules and human resources. This helps measures if organizations' culture is formal and structured and if formal rules and policies glue the human workforce together. Another essential aspect would be to identify how much emphasis has been placed on permanence and stability.

Chapter 4

Research methodology

4.1 Conceptual Model

In the light of research model identified in the literature review study and theoretical foundation section, we have created a conceptual research model [43]. The aim of the model is to identify the key constructs that we wanted to explore in the present research. Based on the conceptual model as shown in Figure 4.1 we developed the hypothesis which ultimately leaded us into a set of questionnaire for online survey.

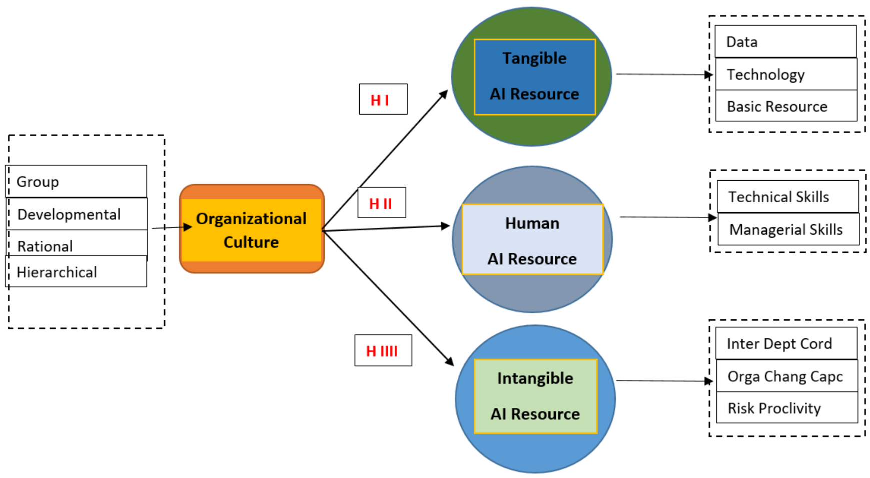

Figure 4.1: Conceptual model of hypothesis

4.2 Hypothesis

From a detailed study of literature, we have identified that the organization culture has direct implications on the amount of AI resource utilization [42]. In order to develop and validate a relationship between culture and how organizations consume AI resources (tangible, intangible, human), we have developed three hypotheses that we wanted to test through the online survey.

- Hypothesis I: We consider a positive correlation between culture and use of tangible AI resources
- Hypothesis II: We consider a positive correlation between culture and use of AI human skills resources
- Hypothesis III: We consider a positive correlation between culture and use of intangible AI resources

4.3 Research approach

In order to test the hypothesis against real data, we decided to transform the research in the form of an online survey. We agreed to contact respondents from organizations that have already implemented AI or in the phase of its implementation in their business model. In consultation with the supervisor, we have decided to select respondents from every possible part of the world and to use every resource which can provide us meaningful data sets for analysis inline with the aims and objectives of present work.

Name	**Questions**
Background Questions	Please answer the following questions
BQ1	Indicate the size-class of your organization.
BQ2	Select the industry in which your organization conducts its business.
BQ3	When did your organization start using ‘artificial intelligence’ solutions?
BQ4	Indicate how many years you have been working in current organization.
BQ5	Indicate your current role in your organization.

Table 4.1: Survey basic questions

4.4 Survey design

We have developed the survey in software tool SurveyGizmo (SurveyGizmo, 2019). In order to find the right persons, people have been identified on the webpages of various businesses. The contacts are established by a convenient sampling method and were based on a network of people that had experience in using AI through a practitioner group. They were initially contacted in early January 2020. We have sent the invitations to the participants over the email via a questionnaire link and ask them to fill out the survey, which approximately takes 10mins to be filled. We also sent three reminders at 10-day intervals to allows the participants to fill the survey. We asked the participants to respond to the survey by marking on a 7-point Likert scale, with 1 denoting a very low intention to adopt, while 7 indicates a very high intention to implement AI for the particular task.

4.4.1 Survey target organizations

In terms of the organizations that we have targeted for this survey, they range from bank and financial, trading, education, media, consulting, oil and gas, property, consumer goods, health care, construction and industrial good, technology, ICT and telecommunications, utilities, shipping, transport, trading. We mainly targeted participants having an active role as data scientists, software engineers, technical consultants, system analysts, IT directors, operation managers, technology officers, business managers, project managers working in the aforementioned target business areas. In general, most of the organizations that have been targeted in the survey are a well-established business with a fairly large amount of IT departments, which has more likely hood of large integration of AI resources.

4.4.2 Survey basic questions

In the first questions of the survey, the emphasis has been made to ask the basic question concerning AI, as summarized in Table 4.1. The main idea is to identify if the organization is using AI solutions and for how long they have been using it. We also ask the participants to respond to how much is the size of their organization. The size has been measured in accordance with European Commission (European Commissions, 2012), with the following values: micro (0-9 employees), small (10–49 employees), medium (50–249 employees) and large (250+ employees). Besides, we also seek information on the present role and the mode of business of their organization. We then followed on in which capacity the organization is using AI solutions and for how long the employee has been working in the organizations (number of years).

4.4.3 Survey culture and AI resources measures

After opening round of questions, we have divided the rest of the sections mainly into AI resource management and cultural behavior, as identified in section 3.1. We have segregated questions for AI resources into tangible, human resources, intangible resources and organizational culture into the group, developmental, rationale, hierarchical. Table 4.2 - Table 4.5 provides a description of questions that has been asked to respondents in the survey to measure our constructors related to present research.

Name	Questions
Data	Please answer how much you agree or disagree with the following statements (1 - totally disagree, 7 - totally agree).*
D1	We have access to very large, unstructured, or fast-moving data for analysis.
D2	We integrate data from multiple internal sources into a data warehouse or mart for easy access
D3	We integrate external data with internal to facilitate high-value analysis of our business environment
D4	We have the capacity to share our data across business units and organizational boundaries
D5	We are able to prepare and cleanse AI data efficiently and assess data for errors
D6	We are able to obtain data at the right level of granularity to produce meaningful insights
Technology	Please answer how much you agree or disagree with the following statements (1 - totally disagree, 7 - totally agree).*
TE1	We have explored or adopted cloud-based services for processing data and performing AI and machine learning
TE2	We have the necessary processing power to support AI applications (e.g. CPUs, GPUs)
TE3	We have invested in networking infrastructure (e.g. enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low-latency)
TE4	We have explored or adopted parallel computing approaches for AI data processing
TE5	We have invested in advanced cloud services to allow complex AI abilities on simple API calls (e.g. Microsoft Cognitive Services, Google Cloud Vision)
TE6	We have invested in scalable data storage infrastructures
TE7	We have explored AI infrastructure to ensure that data is secured from to end to end with state-of-the-art technology
Basic Resources	Please answer how much you agree or disagree with the following statements (1 - totally disagree, 7 - totally agree).*
BR1	The AI initiatives are adequately funded.
BR2	The AI project has enough team members to get the work done.
BR3	The AI project is given enough time for completion.

Table 4.2: Survey questions for tangible AI resource

Name	Questions
Technical Skills	Please answer how much you agree or disagree with the following statements (1 - totally disagree, 7 - totally agree).*
T1	The organization has access to internal and external talent with the right technical skills to support AI work
T2	Our data scientists are very capable of using AI technologies (e.g. machine learning, natural language processing, deep learning)
T3	Our data scientists have the right skills to accomplish their jobs successfully
T4	Our data scientists are effective in data analysis, processing, and security
T5	Our data scientists are provided with the required training to deal with AI applications
T6	We hire data scientists that have the AI skills we are looking for
T7	Our data scientists have suitable work experience to fulfill their jobs
Managerial Skills	Please answer how much you agree or disagree with the following statements (1 - totally disagree, 7 - totally agree).*
M1	Our managers are able to understand business problems and to direct AI initiatives to solve them
M2	Our managers are able to work with data scientists, other employees and customers to determine opportunities that AI might bring to our organization
M3	Our managers have a good sense of where to apply AI
M4	The executive manager of our AI function has strong leadership skills
M5	Our managers are able to anticipate future business needs of functional managers, suppliers and customers and proactively design AI solutions to support these needs
M6	Our managers are capable of coordinating AI-related activities in ways that support the organization, suppliers and customers
M7	We have strong leadership to support AI initiatives and managers demonstrate ownership of and commitment to AI projects

Table 4.3: Survey questions for Human AI resoruces

Name	**Questions**
Inter-departmenta Coordina-tion	Please indicate to what extent do departments (e.g., marketing, R & D, manufacturing, information technology, and sales) within your organ-ization engage in the following activities: (1 - To a very small extent, 7 - To a very large extent).*
IDC1	Collaboration
IDC2	Collective goals
IDC3	Teamwork
IDC4	Same vision
IDC5	Mutual understanding
IDC6	Shared information
IDC7	Shared resources
Organization Change Capacity	Please answer how much you agree or disagree with the following statements (1 - totally disagree, 7 - totally agree).*
OCC1	We are able to anticipate and plan for the organizational resistance to change
OCC2	We consider politics of the business reengineering efforts
OCC3	We recognize the need for managing change
OCC4	We are capable of communicating the reasons for change to the mem-bers of our organization
OCC5	We are able to make the necessary changes in human resource policies for process re-engineering
OCC6	Senior management commits to new values
Risk Pro-clivity	Please answer how much you agree or disagree with the following statements (1 - totally disagree, 7 - totally agree).*
R1	In our organization we have a strong proclivity for high risk projects (with chances of very high returns)
R2	In our organization we take bold and wide-ranging acts to achieve firm objectives
R3	We typically adopt a bold aggressive posture in order to maximize the probability of exploiting potential opportunities

Table 4.4: Survey questions for Intangible AI resources

Name	Questions
Group	Please indicate the extent to which you agree or disagree with the following statements (1 - completely disagree, 7 - completely agree)*
G1	The glue that holds the organization I work in together is loyalty and tradition.
G2	The organization I work in is a very personal place
G3	The organization I work in emphasizes human resources.
Developmen	Please indicate the extent to which you agree or disagree with the following statements (1 - completely disagree, 7 - completely agree)*
DE1	The organization I work in is a very dynamic and entrepreneurial place..
DE2	The glue that holds the organization I work in together is commitment to innovation and development.
DE3	The organization I work emphasizes acquiring new resources and meeting new challenges.
Rational	Please indicate the extent to which you agree or disagree with the following statements (1 - completely disagree, 7 - completely agree)*
RA1	The glue that holds the organization I work in together is the emphasis on tasks and goal accomplishment.
RA2	The organization I work in is a very production-oriented place.
RA3	The organization I work in emphasizes competitive actions, outcomes and achievement.
Hierarchical	Please indicate the extent to which you agree or disagree with the following statements (1 - completely disagree, 7 - completely agree)*
H1	The organization I work in is a very formal and structured place.
H2	The glue that holds the organization I work in together is formal rules and policies.
H3	The organization I work in emphasizes permanence and stability.

Table 4.5: Survey questions for the cultural effect of AI

4.5 Ethics of survey

As the participants are selected from different regions for the present research, we have made a set of guidelines from [44] in order to safeguard data-keeping ethical perspectives intact. In the theme page of the survey, when the survey has been sent out, a complete guide for the participant has been written, as depicted in Appendix A. This page outlines the reason for conducting the survey, along with basic definitions that are important for participants to respond to before starting the survey. This way, before even starting the survey, the participant already knows the reason (for the purpose of scientific evaluation) as well as the definition of scientific terms that may appear while filling the survey. The status bar continuously appeared at the bottom of the page, which allowed participants to track the progress of their survey. In the end, we asked for the optional email address of the participants if they would like to receive the final results of the research and would like to compare the progress of their organization in comparison to other international partners. It has been assured that the information of the survey has been kept strictly confidential and we have not distributed any information to a third party, which may violate terms of ethical perspectives.

4.6 Research analysis techniques

4.6.1 k-means analysis

We have adopted the k-means clustering analysis procedure [45], as a statistical tool to gain an in-depth analysis of the obtained data from the survey. K-means cluster analysis is a procedure that converts the group of data into a cluster whose characteristics are not yet known but are based on a set of specified variables. At present, it has been considered as one of the most advanced tools to classify and distinguish big data. For analysis using k-mean to be efficient and effective following two conditions should be incorporated into the analysis

- **Efficient**. It requires the user to group data into a compact cluster as possible
- **Effective**. It requires to capture the most important clusters which exactly represents the statistical variation in the data

4.6.2 Clustering principle

In theory, the k-mean analysis starts with identifying and building clusters based on the cluster centers [46]. One has a choice to use his own number of clusters or choose among a class of k well-spaced observations of cluster centers. Given the accurate estimate of the cluster center, the k-means follow the below-mentioned procedure as described in [45]

- It first assigns cases to clusters in connection to the distance from the centers of each cluster (set of k center-points (μ), observations x).

$$S_i^{(t)} = \left\{ x_p : \left\| x_p - \mu_i^{(t)} \right\|^2 \leq \left\| x_p - \mu_j^{(t)} \right\|^2 \; \forall j, 1 \leq j \leq k \right\} \tag{4.1}$$

- It then updates the position of the center of the cluster from the mean of specific cases present in the respective cluster.

$$\mu_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{x_j \in S_i^{(t)}} x_j \tag{4.2}$$

K-means is an iterative procedure meaning that the algorithm keeps on repeating itself iteratively reassignment until center-points would not be updated anymore.

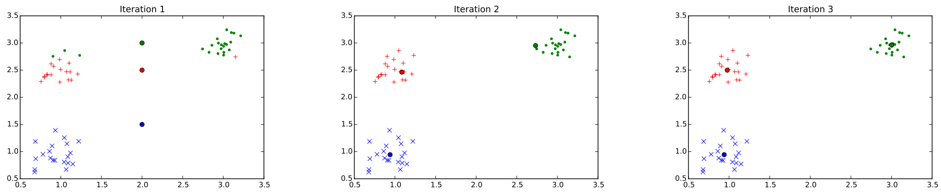

Figure 4.2: Illustration of steps of k-means cluster analysis

The k-means algorithm is designed such that it optimize the objective function 4.3. As there is only a finite number of possible assignments for the number of centroids and observations available and each iteration has to result in a better solution, the algorithm always ends in a local minimum (see Figure 4.2.

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} r_{nk} ||x_n - \mu_k||^2 \tag{4.3}$$

$$\text{with } r_{nk} = \begin{cases} 1 & x_n \in S_k \\ 0 & \text{otherwise} \end{cases}$$

The main problem of k-means is its dependency on the initially chosen centroids. The centroids could end up in splitting common data points whilst others and separated points get grouped together if some of the centroids are more attracted by outliers.

4.6.3 One-Way ANOVA

In this research work, based on the research ideas given in [47], we choose to conduct a one-Way ANOVA in order to study the survey data. This analysis is important to determine the relation of two independent groups and provide statistical evidence that the associated population means are significantly different. This analysis can be conducted on independent groups in order to determine the results. The ANOVA analysis computes and analyzes the following important statistical parameter to compare the significance.

The first quantity that is calculated in the ANOVA is the calculation of of variance between independent group's using the following equation [48]

$$SS_{between} = \Sigma\, n_j\, (\overline{X}_j - \overline{X}^2 \tag{4.4}$$

where

- $\overline{X}_j$ denotes a group mean
- $\overline{X}$ is the overall mean;
- n_j is the sample size per group.

Given m groups are analyzed the ,

$$df_{between} = m - 1 \tag{4.5}$$

so $df_{between}$ is found using the following equation

$$MS_{between} = \frac{SS_{between}}{df_{between}} \tag{4.6}$$

Once the vaiance information is computed among the groups, the variance with-in the same groups can be computed as,

$$SS_{within} = \Sigma\, (X_i - \overline{X}_j)^2 \tag{4.7}$$

where

- $\overline{X}_j$ denotes a group mean
- $\overline{X}_i$ denotes an individual observation

given the analysis is conducted for n independent observations and m groups,

$$df_{within} = n - m \tag{4.8}$$

Hence

$$MS_{within} = \frac{SS_{within}}{df_{within}} \tag{4.9}$$

Hence *F-statistic* can be determine using following

$$F = \frac{MS_{between}}{MS_{within}} \tag{4.10}$$

While the p statistic or the significance factor can be computer as a function of F-statistic

$$P = P(F) \tag{4.11}$$

4.6.4 Statistical significance

Statistical significance is of great interest while studying One-Way ANOVA as it provides the probability of obtaining an underlying deviation from a particular hypothesis. In the literature [49], statistical significance has often been referred to as the p-value. The p-value is normally considered as the probability value. Or, more often, it is called simply p in various research papers [50]. For a given data set, a low p-value inherently means that the data is unlikely to some (null or self-declared) hypothesis. If the value is low ($p < 0.05$), the normal convention is that the data set is statistically significant.

Chapter 5

Survey analysis and Results

In this chapter, we show results from the analysis that has been conducted on the obtained data. We have made an attempt to keep the results direct and straightforward as possible to determine clear understanding. To analyze data, we have used the descriptive statistics along with k-means cluster analysis using the commercial software by IBM SPSS [51]. To begin with, we show the results of the survey in general by showing demographic details. We then show from the analysis of how organizational culture influences the choice of AI resources. We further comprehend this coupling with quantitative and qualitative analysis data [15].

5.1 Data Preparation

We have initially contacted more than 350 companies located in different parts of the world. Before running the analysis, we segregated the data based on the following questions to prepare data for analysis [16].

- Is the data complete?
- Does it have any outliers?
- Does the data need cleansing?
- Does the data required to be filled in missing values

We have received a filled survey of 242 respondents. In the process of the data preparation stage, based on the aforementioned points, we run each data segregation stepwise. We find that out of the total response we received 105 respondents did not fill in the complete data sets. In the next stage, we look for outliers are find that 19 respondents fill in the same values for each answer, which we somewhat find not an exact representation of the given survey questions. After that stage, we conducted data cleansing and replaced the missing values. We find that some respondents poorly understood some questions while some other misinterpreted Likert scales. For correct statistical analysis, we have further removed 9 responses, which eventually left us with 110 responses out of a total of 242 initial responses. We have, therefore, chosen 110 responses for further analysis to measure our research objectives.

5.1.1 Data averaging

In order to analyze the data with the utmost reliability and validity, we have performed averaging of the values of the responses. For instance, we have several responses to the questions asked for human skills and thus have many columns of data. We have calculated the average of all similar questions and used that as an overall representation of respondents' behavior. We have performed this step to all the resources that have been analyzed in the present study (e.g., data, technology, managerial skills, etc.) as well as for the different types of culture (e.g., hierarchical).

5.1.2 Data analysis

To show a thorough review of the choices made by participants in the survey, we create and establish methodologies to establish and deduce hidden patterns in the data. In the following sections, we provide a description of the results obtained after the analysis and discuss the findings in close relation to available scientific literature.

5.1.3 Demographics data

We show the results obtained by the survey in the form of a demographics data in Table 5.1 and Table 5.2. In terms of the size of the sample and number of employees of the organizations, 88% reported that they belong to considerable large organizations having 250+ employees, while only 10.6% reported that they belong to a company that has 25-50 employees in their organization. This represents that respondents of the survey generally belong to a class of well established and big companies.

From the survey results as summarized in Table 5.1, it can be seen that 9.7% of the participant's organizations have deployed AI within last year while 18.8% have been using AI for a period of 1–2 years. The rest of the participants reported that their organizations had deployed AI for 2-3 and 3-4 years 19.5% and 12.4%, respectively. The 38.9%respondents said that their organization had employed AI solutions for over 4 years. This essentially means that majority of respondents belong to organizations having already good experience of working and integrating AI into their business model. The highest percentage of respondents who undertake the survey belong to technology companies with a proportion of 32%. While respondents from the bank and financial companies stand at second place with a score of 20%. The same trend is observed in the respondents job description, where 24% reported they are working as a role in data scientists position, which has a direct link to technology. Overall, we notice the right mix of organizations and professionals who have responded to the survey making it a diverse and insightful data collection campaign.

5.2 k-means cluster analysis of organization culture

5.2.1 Standardisation of data

Although the Likert scale of data is set to 1-7 (1 - totally disagree, 7 - totally agree), however, it remains imperative to standardize the mean and variance before performing k-means analysis. We have performed this through a descriptive analysis of each variable separately. This, in turn, produces standardize values that have been incorporated into the original data set as separate new columns. The new standardized values have been differentiated from original values through a Z, and we now call them Z standardized values of each variable.

5.2.2 Convergence test

The iteration history depicts the path of the clustering process at each subsequent analysis step. We have presented the results of our convergence analysis iteration history for a single case of organizational culture in Table 5.3. It can be seen from the table that cluster centers shift significantly in the early iteration. For the present case, we note that from the 5th iteration, the cluster center starts to settle down and approach zero values. In the first 3 iterations, the algorithm calculates the mean and variances of the data set and allocate the final location of each cluster. The algorithm also adjusts solutions centers before moving to subsequent iterations. A converged solution is necessary to draw plausible conclusions from the k-means cluster analysis [45]. If the algorithm does not converge, one might have to increase the iteration count and redo the procedure to obtain a converged solution.

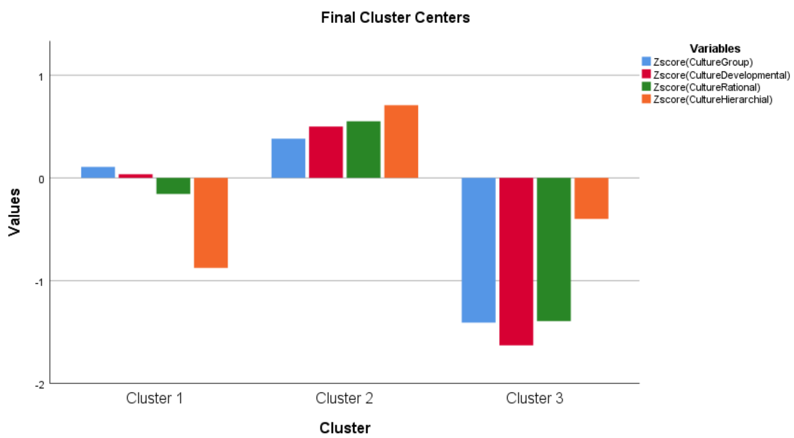

Figure 5.1: k-means clustering analysis of organizational culture

5.2.3 k-means analysis

We have performed the k-means cluster center analysis on the standardized data set of the variables. We have selected 3 clusters to segregate the data based on the count of iteration history, which revealed that the selected cluster number is adequate for the present analysis [45, 52]. We have essentially taken note of iteration count and made sure the solution achieve convergence and monitored maximum absolute coordinate change for cluster centers to approach zero. In this analysis, we have chosen the iteration count as 5. From the results, we found a minimum distance of 4.847 from the initial centers. From Table 5.4, we note that the three clusters are divided into 37, 56 and 18 cases, respectively.

5.2.4 Final cluster centers

We have presented the results of final cluster analysis quantitatively and qualitatively in Table 5.5 and Figure 5.1 . The table quantifies the Euclidean distances between the final cluster centers where greater distances between clusters correspond to greater dissimilarities [53]. We notice that all cluster values are different for the organizational culture, which represents corresponding different mean values.

The result computed from the analysis tries to identify optimum structures/patterns within the data for organizational culture responses filled by the participants [52]. As can be seen that Cluster 1 has both positive and negative homogeneous values; however, the magnitudes are low. This shows that the respondents grouped in this cluster have mixed opinions on a standardized scale. While cluster 2 contains higher and positive values showing a higher and positive reflection of the business overall organizational culture. Cluster 3 represents the lowest values, but show less negative values for hierarchical culture variables as compared to cluster 1. This essentially means here the respondents showed significant negative opinion concerning the organizational culture [54], apart from the hierarchical behavior culture of the organization, which, according to the respondents of cluster 1 is less negative.

5.2.5 Cluster membership information

We also calculated the cluster membership information while conducting the k-means analysis. This is an important feature and becomes integral once we show the comparison of individual AI resource against the overall organizational culture to highlight correlations. The calculation of cluster membership information resulted in a new data set appearing as a new column at the very end of the SPSS work data-sheet [51].

Dimension	**Population**	**Frequency**
BQ1		
1-9	0	0
10-49	1	0.9%
50-249	11	10.6%
250+	100	88.5%
BQ2		
Bank & Financials	23	20.9%
Basic Materials	2	1.8%
Consulting Services	11	9.7%
Consumers Goods	4	3.5%
Consumers Services	6	5.3%
Education	3	2.7%
Health Care	3	2.7%
ICT	12	10.6%
Indsutrials	3	2.7%
Media	3	2.7%
Offshore	2	1.8%
Oil & Gas	2	1.8%
Property	1	0.9%
Technology	37	32.7%
Trading	1	0.9%
Transport	1	0.9%
BQ3		
<1	11	9.7%
1-2	21	18.6%
2-3	22	19.5%
3-4	13	12.4%
4+	44	38.9%
BQ4		
<1	10	8.8%
1-3	21	9.7%
3-5	24	21.2%
5-7	24	21.2%
7-10	22	19.5%
10-15	11	9.7%
15-20	10	18.8%
>20	3	2.7%

Table 5.1: Sample demographics

Dimension	Sample	Frequency
BQ5		
Bussiness Analyst	3	2.7%
Bussiness Manager	6	5.3%
Chief Executive Officer	3	2.7%
Digital Officer	11	9.7%
Data Scientist	28	24.8%
Enterprise Architecture	3	2.7%
Head of IT	5	4.4%
IT Director	5	4.4%
IT Project Manager	7	6.2%
Operation Manager	5	4.4%
Software Engineer	9	8%
System Analyst	6	5.3%
Technical Consultant	7	6.2%
Other	12	10.6%

Table 5.2: Sample demographics contd

Iteration	Cluster		
	1	2	3
1	2.236	2.038	1.866
2	0.092	0.063	0.000
3	0.092	0.058	0.000
4	0.029	0.021	0.000
5	0.000	0.000	0.000

Table 5.3: Iteration history of convergence of k-mean analysis of organizational culture

Cluster	Culture	Intangible	Human Skills	Tangible
1	37	42	12	55
2	56	13	52	9
3	18	56	47	46

Table 5.4: Number of cases in each cluster of organizational culture, intangible, human and tangible AI resource

	Cluster		
	1	2	3
Group	0.10772	0.38152	-1.40837
Developmental	0.03558	0.50037	-1.62984
Rational	-0.15611	0.55128	-1.39420
Hierarchial	-0.87626	0.70740	-0.39960

Table 5.5: Final cluster centers of obtained after k-means cluster analysis of culture. Values depict Zscore of each cluster

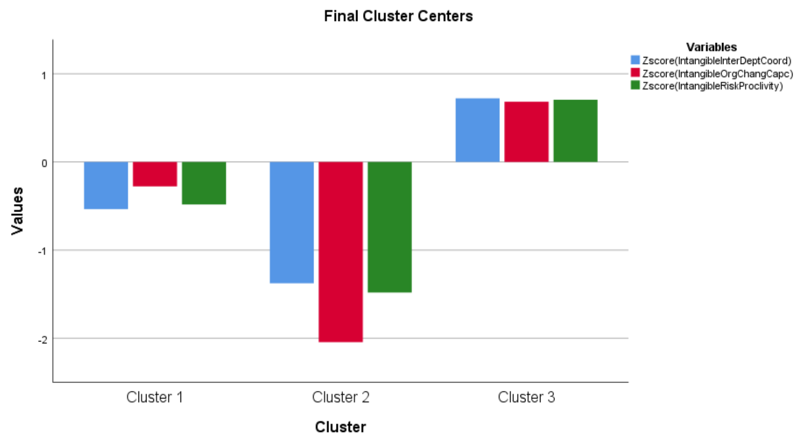

Figure 5.2: k-means clustering analysis intangible AI resource

5.3 k-means cluster analysis of intangible AI resource

We run the k-means cluster center analysis on the standardized data set of the variables for intangible resources. We have selected 3 clusters to segregate the data. For the present case of intangible resource 5 iterations resulted in a converged solution. We achieved convergence by monitoring small changes in cluster centers corresponding to the given iteration [45, 52]. In the present analysis, the minimum distance between the initial centers is found to be 3.74. The final obtained cluster information, as given in Table 5.4 shows that cases have been segregated in three clusters as 42, 13 and 56 cases, respectively.

5.3.1 Final cluster centers

Table 5.6 and Figure 5.2 present the final cluster analysis in a respective quantitative and qualitative manner. Cluster 1 consists of respondents segregated into moderate negative values for all intangible AI resources. Whereas cluster 2 represents the group which gave lowest values for all intangible resources on a standardised scale. In the meanwhile, all the respondents with positive values are segregated into the cluster 3 [45, 51].

5.4 k-means cluster analysis of tangible AI resources

For the k-means cluster analysis of tangible resources, the test has been run on the standardized values. Similar to culture and intangible resources, we decided to divide the data among 3 optimum clusters. 5 iterations are required to achieve converge solutions. The minimum distance between the initial centers and final cluster values is found to be 4,299 for the tangible AI resource data set. As reported in the Table 5.4, the 3 clusters contain 12, 52 and 47 cases, respectively.

	Cluster		
	1	2	3
Inter Dept Coord	0.10903	-2.86339	1.59523
Org Chang Capc	-0.70239	-2.83669	1.68301
Risk Proclivity	-1.29752	-2.09323	1.48749

Table 5.6: Final cluster centers of obtained after k-means cluster analysis of Intangible. Values depicts Zscore of each cluster

5.4.1 Final cluster centers

Table 5.7 and Figure 5.3 show the results for final cluster analysis with respective means. It can be noticed that cluster 1 group consist of data sets of positive values of the variables on the standardised scale. Cluster 2, on the other hand, show large negative values for the tangible AI resource. Similar to cluster 2, the cluster 3 group also show negative values however their magnitudes are significantly lower [45, 51].

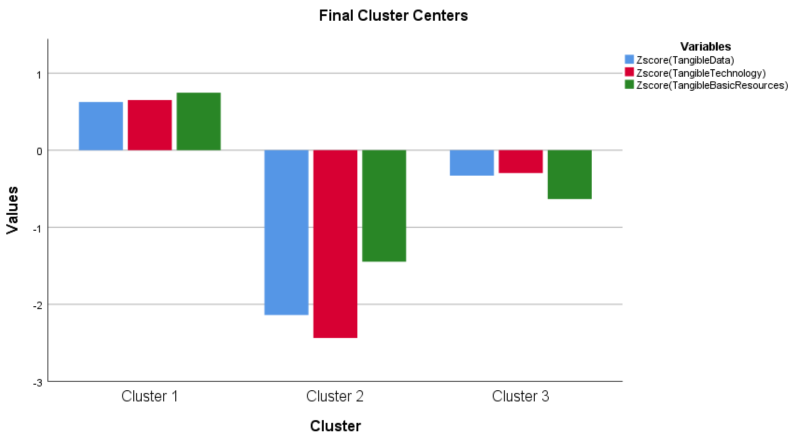

Figure 5.3: k-means clustering analysis tangible AI resource

5.5 k-means cluster analysis of human AI resources

We run the analysis for present data of human AI resource, which is segregated into technical and managerial skills. In the analysis, the convergence criterion is achieved by monitoring small changes in cluster centers. We found the maximum absolute coordinate change for all centers to zero at the iteration level of 5 and 3 cluster values (similar to other AI resources) [45, 52]. In the present analysis, the minimum distance between the initial centers is found to be 3.765. As reported in

	Cluster		
	1	2	3
Data	1.33247	-3.55779	0.51743
Technology	1.22577	-2.87067	-1.31012
Basic resource	1.55214	-2.24367	-1.82192

Table 5.7: Final cluster centers of obtained after k-means cluster analysis of tangible AI resource. Values depicts Zscore of each cluster

	Cluster		
	1	2	3
Technical skills	2.21016	0.64041	-0.14425
Mangegerial skills	-1.34744	0.83808	-0.58321

Table 5.8: Final cluster centers of obtained after k-means cluster analysis of human AI resource. Values depicts Zscore of each cluster

the Table 5.4, the cases are segregated into 3 clusters as 55, 9 and 46, respectively.

5.5.1 Final cluster centers

As can be seen from the Table 5.8 and Figure 5.4, which outline the quantitative final cluster analysis and an overall qualitative representation. Cluster 1 and cluster 3 group contain respondents that provided low scores of the human AI resource. Besides, cluster 1 has more negative values than cluster 3 on a standardized scale. Cluster 2, on the other hand, shows moderately positive values for both technical and managerial resources [45, 51].

5.6 Impact of organization culture on AI resources

The ANOVA table, as described in subsection 4.6.3, indicates the contribution of each obtained cluster solution factored over a given variable. In general, a variables having large F values provide the most significant separation between clusters [48].

The analysis of One-Way ANOVA table calculations show the following information in the form of tables, the formulas used by SPSS to determine present solutions are described in subsection 4.6.3

- **Sums of squares within** show the total dispersion within groups
- **Degrees of freedom within** is (n - k) for n observations and k groups and
- **Mean squares within** represent the variance within groups
- **F-value** basically show evidence of null hypothesis

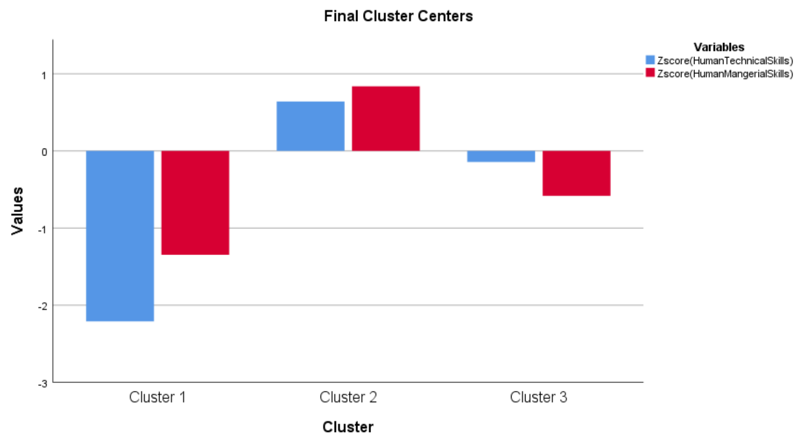

Figure 5.4: K-means clustering analysis of human AI resource

- **Sig.** represents the measure of p-statistic

5.6.1 Role of tangible AI resources

In order to formulate a detailed comparison of obtained clusters after k-mean analysis of tangible AI resources, we have performed one-way ANOVA calculation. To obtain a direct measure of correlation among AI resources and culture and to understand how culture influences the choice of resource, we have first computed the culture membership from the standard k-means analysis of cultural behavior as reported in subsection 5.2.5. We then used this information as a factored variable to compute the ANOVA table and obtained the magnitudes of F-statistic and significance (p-value). The results are summarized in Table 5.9

		Sum of Squ	df	Mean Squ	F	Sig.
Data	Between Groups	8.290	2	4.145	2.847	0.062
	Within Groups	155.793	107	1.456		
	Total	164.083	109			
Technology	Between Groups	2.300	2	1.150	0.532	0.589
	Within Groups	233.684	108	2.164		
	Total	235.985	110			
Basic Resources	Between Groups	13.427	2	6.714	2.774	0.067
	Within Groups	261.415	108	2.421		
	Total	274.843	110			

Table 5.9: One-Way ANOVA of tangible resources factored on the basis of culture membership information

The One-Way ANOVA analysis has provided an opportunity to evaluate the overall representation of the effects of organizational culture on tangible AI resources. We have also compared our results corresponding to devised Hypothesis I for the present ANOVA. We find that the significance of data and basic resource has significance with corresponding values of 0.062 and 0.067, unlike to the technology which has a value of 0.589. This represents that data and basic has been somewhat significant, but not entirely as the significance values are needed to be below 0.05 for the hypothesis to hold ultimately [47, 50].

However, the One-Way ANOVA analysis has only provided an overall representation of the organizational culture based on the cluster membership information. We yet do not have confirmation on how the various subcategories of culture (group, hierarchical, development, rational) have individual impacts. In order to draw realistic estimates, we have performed a one-way ANOVA test for data of tangible resources factored by each of the individual cultural resources. The results of corresponding statistical significance is shown from Table 5.10 - Table 5.13.

From the tables, we can extract some interesting patterns. We notice that the organizational culture group has no significant on the tangible resources, where only data resource is partially found the closes with the significance of 0.052 (hypothesis I not supported for the group). Culture development also shows significance for data with a value of 0.046, which shows a direct significance confirmation. While the culture resource rational and hierarchical have shown high significance for all tangible resources (most of the significance values are less than 0.05), which provide a strong basis that the culture resource has high impacts on the consumption of tangible resource in an organization (hypothesis I supported for rationale and hierarchical)

This, in turn, identifies the k-means cluster of tangible AI resources that has direct significance from the standpoint of the organizational culture of rational and hierarchical, while it is partially significant for organizational culture group and developmental. This could necessarily mean that organizations that have a better rational and hierarchical culture exploit the tangible AI resources adequately in terms of: 1) utilization and assess to data to develop meaningful insights 2) adequate funding and reasonable workforce to successfully accomplish a task [7]. This could be due to the fact that organizations which generally possess a formal and structured culture to accomplish goals are better at making use of tangible AI resource into their business model. Whereas a medium positive correlation of technology against the hierarchical further emphasis that permanence and stability are required to obtain full use of AI resources and infrastructure.

No or less positive correlation among the organizational culture of group and development shows that these organizations behavior becomes a challenge [3] and has less significance than rationale and hierarchical when it comes to making full use of tangible AI resources in a business model.

		Sum of Squ	df	Mean Squ	F	Sig.
Data	Between Groups	25.125	16	1.570	1.741	0.052
	Within Groups	83.875	93	0.902		
	Total	109.000	109			
Technology	Between Groups	16.990	16	1.062	1.073	0.391
	Within Groups	93.010	94	0.989		
	Total	110.000	110			
Basic Resources	Between Groups	21.573	16	1.348	1.433	0.143
	Within Groups	88.427	94	0.941		
	Total	110.000	110			

Table 5.10: One-Way ANOVA of tangible AI resources factored on the basis of organizational cultural group

		Sum of Squ	df	Mean Squ	F	Sig.
Data	Between Groups	26.718	17	1.572	1.757	0.046
	Within Groups	82.282	92	0.894		
	Total	109.000	109			
Technology	Between Groups	9.081	17	.534	.492	0.951
	Within Groups	100.919	93	1.085		
	Total	110.000	110			
Basic Resources	Between Groups	23.122	17	1.360	1.456	.129
	Within Groups	86.878	93	0.934		
	Total	110.000	110			

Table 5.11: One-Way ANOVA of tangible AI resources factored on the basis of organizational cultural development

		Sum of Squ	df	Mean Squ	F	Sig.
Data	Between Groups	33.104	15	2.207	2.733	0.002
	Within Groups	75.896	94	0.807		
	Total	109.000	109			
Technology	Between Groups	17.394	15	1.160	1.190	0.293
	Within Groups	92.606	95	0.975		
	Total	110.000	110			
Basic Resources	Between Groups	26.441	15	1.763	2.004	.023
	Within Groups	83.559	95	0.880		
	Total	110.000	110			

Table 5.12: One-Way ANOVA of tangible AI resources factored on the basis of organizational cultural rationale

		Sum of Squ	**df**	**Mean Squ**	**F**	**Sig.**
Data	Between Groups	31.530	18	1.752	2.058	0.014
	Within Groups	77.470	91	0.851		
	Total	109.000	109			
Technology	Between Groups	30.826	18	1.713	1.990	0.018
	Within Groups	79.174	92	0.861		
	Total	110.000	110			
Basic Resources	Between Groups	26.272	18	1.460	1.604	0.075
	Within Groups	83.728	92	0.910		
	Total	110.000	110			

Table 5.13: One-Way ANOVA of tangible AI resources factored on the basis of membership information of organizational cultural hierarchical

5.6.2 Role of Intangible AI resource

We perform the ANOVA calculation to develop a comprehensive comparison of the data obtained after the k-mean cluster analysis of Intangible resources. We first evaluate the impact of how culture affects the choice of intangible resources by evaluating the culture membership information from the standard k-means analysis and then using the information as a factored variable to compute the ANOVA table to obtain the value of F-statistic and significance (p-value). The results obtained for the intangible resources are summarized in Table 5.14. As we can

		Sum of Squ	**df**	**Mean Squ**	**F**	**Sig.**
Inter Dept Coord	Between Groups	3.052	2	1.526	1.541	0.219
	Within Groups	106.948	108	0.990		
	Total	110.000	110			
Org Chang Capc	Between Groups	5.697	2	2.848	2.949	0.057
	Within Groups	104.303	108	0.966		
	Total	110.000	110			
Risk Proclivity	Between Groups	7.026	2	3.513	3.685	0.028
	Within Groups	102.974	108	0.953		
	Total	110.000	110			

Table 5.14: One-Way ANOVA of intangible AI resources factored on the basis of organizational cultural cluster membership

note from the obtained quantitative values from the Table 5.14, which show a high significance for the organization change capacity (0.057) and risk proclivity (0.028). From the literature [47, 50], we find that the risk proclivity fully completes the significance (0.05) while organization change capacity closely full fills but not completely. While inter-departmental cooperation does show a low value of F-statistics and significance, which negate the hypothesis completely to be valid based on the factored membership cluster information. Nevertheless, the present analysis provides an overall assessment of the effect of culture on the intangible AI resources. To evaluate the realistic details of each culture, i.e., group, hierarchical, developmental, rational, we conduct similar analysis through a one-way ANOVA test for data of intangible resources factored by each of the individual cultural resources. The results of corresponding statistical significance is shown from Table 5.15 - Table 5.18.

As can be seen from the analysis result, which has been calculated using the formula described in subsection 4.6.3, that both culture group and developmental do not impart significance on the intangible resource (hypothesis III not supported for group and developmental). From the tables, we notice significantly low values of F-statistic and significance for each. Whereas, for the culture rationale, we find incredibly high significance where all three resources are found to have a significant impact. Only organization change capacity shows a partial significance with values close to 0.05 (hypothesis III partially supported for rationale). Organizational culture hierarchical again shows a significance for the intangible resources, where both inter-department coordination and organization change capacity are highly relevant with high F-statistics (hypothesis IIII supported for hierarchical). Risk proclivity remains not significant, with low significance values of 0.339.

From the analysis above, it becomes imperative that the k-means cluster of intangible resources show a partial significance, where culture group and developmental do not show significance, while rational and hierarchical, show high relevance and significance. We again notice high significance of organizational culture rationale and hierarchical similar to tangible resources, which also showed positive correlations. With the results we could imply that organizational culture of rationale and hierarchical remain significant in terms of : 1) high meeting organization its goals, show better performance than its competitors. It also help organizations to anticipate and recognise new changes in their business models [7]. 2) Organizations will be able to take bold and wide-ranging acts to achieve targets [39]. In terms of organizational culture of group and development we find less significance which we believe remains low due to low significance against intangible resources. This also shows that these organization culture becomes a challenge while taking full use of intangible AI resource [3].

		Sum of Squ	**df**	**Mean Squ**	**F**	**Sig.**
Inter Dept Coord	Between Groups	19.597	16	1.225	1.274	0.231
	Within Groups	90.403	94	0.0962		
	Total	110.000	110			
Org Chang Capc	Between Groups	18.406	16	1.150	1.181	0.298
	Within Groups	91.594	94	0.974		
	Total	110.000	110			
Risk Proclivity	Between Groups	17.517	16	1.095	1.113	0.355
	Within Groups	92.483	94	0.984		
	Total	110.000	110			

Table 5.15: One-Way ANOVA of intangible AI resources factored on the basis of organizational cultural group

		Sum of Squ	df	Mean Squ	F	Sig.
Inter Dept Coord	Between Groups	19.597	16	1.225	1.274	0.231
	Within Groups	90.403	94	0.962		
	Total	110.000	110			
Org Chang Capc	Between Groups	18.406	16	1.150	1.181	0.298
	Within Groups	91.594	94	0.974		
	Total	110.000	110			
Risk Proclivity	Between Groups	17.517	16	1.095	1.113	0.355
	Within Groups	92.483	94	0.984		
	Total	110.000	110			

Table 5.16: One-Way ANOVA of intangible AI resources factored on the basis of organizational cultural development

		Sum of Squ	df	Mean Squ	F	Sig.
Inter Dept Coord	Between Groups	34.943	15	2.330	2.948	0.001
	Within Groups	75.057	95	0.790		
	Total	110.000	110			
Org Chang Capc	Between Groups	23.007	15	1.534	1.675	0.069
	Within Groups	86.993	95	0.916		
	Total	110.000	110			
Risk Proclivity	Between Groups	29.813	15	1.988	2.355	0.006
	Within Groups	80.187	95	0.844		
	Total	110.000	110			

Table 5.17: One-Way ANOVA of intangible AI resources factored on the basis of organizational cultural rationale

		Sum of Squ	df	Mean Squ	F	Sig.
Inter Dept Coord	Between Groups	29.585	18	1.644	1.880	0.027
	Within Groups	80.415	92	0.874		
	Total	110.000	110			
Org Chang Capc	Between Groups	27.968	18	1.554	1.743	0.046
	Within Groups	82.032	92	0.892		
	Total	110.000	110			
Risk Proclivity	Between Groups	19.895	18	1.105	1.128	0.339
	Within Groups	90.105	92	0.979		
	Total	110.000	110			

Table 5.18: One-Way ANOVA of intangible resources factored on the basis of organizational cultural hierarchical

5.6.3 Role of human AI resource

The ANOVA analysis is conducted on data obtained after the k-mean cluster analysis of human skills. Firstly, the impact of culture is investigated on the choice of human skills through culture membership information obtained from the standard k-means analysis. The results are used as the factored variable to compute the ANOVA table. The analysis of F-statistic and significance (p-value) is checked to analyze the significance of cultural resources on human skills. The results obtained for the intangible resources are summarized in Table 5.19. The Table 5.19 provides

		Sum of Squ	**df**	**Mean Squ**	**F**	**Sig.**
Technical Skills	Between Groups	5.421	2	2.711	2.799	0.065
	Within Groups	104.579	108	0.968		
	Total	110.000	110			
Managerial Skills	Between Groups	9.190	2	4.595	4.923	0.009
	Within Groups	100.810	108	0.933		
	Total	110.000	110			

Table 5.19: One-Way ANOVA of human AI resource factored on the basis of organizational cultural cluster membership

a comprehensive overview of the significance of the human AI resource against the membership information of culture. We notice that the managerial skills are highly relevant with a significance value measure of 0.009, whereas human, technical skills show a medium significance with 0.065. To study the impact of individual culture, i.e., group, the hierarchical, developmental, rational resource on human AI resource, we conducted a one-way ANOVA test and showed results in Table 5.15 - Table 5.18.

While only managerial skills (0.052) are significant for the culture group, we notice no significance for the culture developmental on the human AI resource with low values of F-statistic and significance (hypothesis II partially supported group and not supported for developmental). Whereas, the culture rationale is found to be highly significant for both managerial and technical skills (hypothesis II supported for rationale). The trend of organizational culture rationale is found to be common for all three resources (tangible, intangible, human skills), which show that overall culture rationale has an impact from the standpoint of the present survey. Besides, culture hierarchical again show a low significance for human AI resource (hypothesis II not supported for hierarchical).

From the analysis above, it becomes imperative that the k-means cluster of human AI resources show a high significance for the culture rationale, while low significance is observed for the other resources. The results determine that the organizations with immense potential of better alignment of cultural rationale will be better at talent with the right technical skills to support AI, hiring managers and employees having the right skill set for AI resources [34]. Moreover, there is a good chance that such places will have high-quality managers with strong leadership skills that take organizational business capabilities to a high level with the integration of AI [23]. Interestingly, a medium positive correlation between the organizational group and managerial skills means that the organizations with strong human resource management and principles of loyalty will aid managers in taking direct AI initiatives and will be a better position to transform the way their business moves with the market through AI solutions.

		Sum of Squ	**df**	**Mean Squ**	**F**	**Sig.**
Technical Skills	Between Groups	16.614	16	1.038	1.045	0.418
	Within Groups	93.386	94	0.993		
	Total	110.000	110			
Managerial Skills	Between Groups	25.138	16	1.571	1.740	0.052
	Within Groups	84.862	94	0.903		
	Total	110.000	110			

Table 5.20: One-Way ANOVA of human AI resource factored on the basis of organizational cultural group

		Sum of Squ	**df**	**Mean Squ**	**F**	**Sig.**
Technical Skills	Between Groups	12.477	17	0.734	.700	0.796
	Within Groups	97.523	93	1.049		
	Total	110.000	110			
Managerial Skills	Between Groups	22.426	17	1.319	1.401	0.154
	Within Groups	87.574	93	0.942		
	Total	110.000	110			

Table 5.21: One-Way ANOVA of human AI resource factored on the basis of organizational cultural development

		Sum of Squ	**df**	**Mean Squ**	**F**	**Sig.**
Technical Skills	Between Groups	33.961	15	2.264	2.829	0.001
	Within Groups	76.039	95	0.800		
	Total	110.000	110			
Managerial Skills	Between Groups	41.707	15	2.780	3.868	0.000
	Within Groups	68.293	95	0.719		
	Total	110.000	110			

Table 5.22: One-Way ANOVA of human AI resource factored on the basis of organizational cultural rationale

		Sum of Squ	df	Mean Squ	F	Sig.
Technical Skills	Between Groups	21.393	18	1.188	1.234	0.252
	Within Groups	88.607	92	0.963		
	Total	110.000	110			
Managerial Skills	Between Groups	23.701	18	1.317	1.404	0.149
	Within Groups	86.299	92	0.938		
	Total	110.000	110			

Table 5.23: One-Way ANOVA of human AI resource factored on the basis of organizational cultural hierarchical

Chapter 6

Conclusion

The present research is conducted to explore the capabilities and impact of Artificial Intelligence (AI) in the business and organizational context. The present research work is solely performed for scientific purposes. With the dissemination of results, the objective is to expand existing knowledge already available on the subject.

6.1 Summary of research

The research work is performed via a survey that was sent to professionals having an active role as data scientists, software engineers, technical consultants, etc. in a range of companies such as bank and financial, trading, education, etc. The respondents were asked to answer set of questions designed on the format of a 7-point Likert scale (with 1 denoting a very low intention, while 7 indicates a very high intention) to evaluate how firms exhibit common strategies for organizational culture and AI resources (tangible, intangible, human). We received a filled survey of 242 respondents from various parts of the world. Out of which 105 respondents filled partial survey results, which were excluded from the final analysis. 27 respondents answer were excluded through outliers (same values for all survey questions or misunderstanding of scale), which eventually left us with 110 responses. We have performed an analysis of the final 110 responses to measure our research objectives.

6.2 Summary of analysis technique

We have performed the k-means cluster center analysis on the standardized data set of the variables. We have selected 3 clusters to segregate the data based on the count of iteration history, which revealed that the selected cluster number is adequate for the present analysis [45, 52]. We also performed the One-Way ANOVA to indicate the contribution of each obtained cluster solution factored over a given variable. In the research work, variables having large F values provided the most significant separation between clusters [48]. The quantities **Sums of squares** showed the total dispersion within groups, **Degrees of freedom** showed the (n - k) for n observations and k groups, **Mean squares** represented the variance within groups, **F-value** showed the evidence of null hypothesis and **Sig.** represented the measure of p-statistic.

6.3 Discussion of choice of organizational culture on the adoption of tangible AI resource

The k-means cluster analysis of tangible resources with three clusters resulted in an adequate representation of the data set. The minimum distance between the initial centers and final cluster values is found to be 4.299. For the tangible AI resources, we found that the significance of data and basic resource has significance with corresponding values of 0.062 and 0.067, unlike to the technology which has a value of 0.589. From the results of ANOVA table, we noticed that the organizational culture group has no significant on the tangible resources, where only data resource is partially found close with the significance of 0.052 (hypothesis I not supported for the group). Culture development also showed significance for data with a value of 0.046. While the culture resource rational and hierarchical showed high significance for all resources.

In general, the results obtained showed significant support for the hypotheses established. We found a direct and positive correlation on the choice of organizational culture, such as rational and hierarchical, on the adoption of AI resources. This means twofold possibilities for tangible AI resources. First, it shows the organization with positive rational and hierarchical culture results in enhanced utilization and assesses of data resources, which in turn help in developing meaningful insights. Secondly, the positive correlation also depicts that organizations will have adequate funding and a flexible workforce to successfully accomplish their task. Whereas a medium positive correlation of tangible AI resources such as technology against the hierarchical organizational culture further emphasizes that permanence and stability are required to obtain full use of AI tangible resources and infrastructure. No or less positive correlation among an organizational culture of group and development is representative of the fact that such organization cultural becomes a challenge and have less significance than rationale and hierarchical when it comes to making full use of tangible AI resource [3, 7].

6.4 Discussion of choice of organizational culture on the adoption of intangible AI resource

The k-means cluster center analysis on the standardized data set of the variables for intangible resources showed adequate representation over three clusters. The minimum distance between the initial centers is found to be 3.74. From the results, we noticed a high significance of organizational culture rationale and hierarchical similar to the behavior we have noticed for tangible resources. From the One-Way ANOVA analysis, we noticed a high significance for the organization change capacity (0.057) and risk proclivity (0.028). Whereas culture group and developmental do not impart significance on the intangible resource (hypothesis III not supported for group and developmental). Only organization change capacity showed a partial significance with values close to 0.05 (hypothesis III partially supported for rationale). Organizational culture hierarchical again showed a significance for the intangible resources, where both inter-department coordination and organization change capacity are highly relevant with high F-statistics (hypothesis IIII supported for hierarchical). Risk proclivity remains not significant, with low significance values of 0.339.

The results implied that the organizational culture of the rationale and hierarchical remain significant in meeting organization goals and help it to show better performance than its competitors. It also aids organizations to anticipate and recognize new changes in their business models. This way, organizations will be able to take bold and wide-ranging acts to achieve targets. Whereas, for the organizational culture of group and development, less significance is observed, which again represent organizational challenges for culture are identified as a barrier to unleash the full potential of tangible AI resource [3, 7, 39].

6.5 Discussion of choice of organizational culture on the adoption of human AI resource

The k-means cluster center analysis on the standardized data set of the variables for human AI resources showed adequate representation over three clusters. The minimum distance between the initial centers is found to be 3.765. The One-Way ANOVA showed a high significance for the organization change capacity (0.057) and risk proclivity (0.028). From the literature [47, 50], we also noticed a similar trend for risk proclivity (significance of (0.05)) while organizational change capacity partially full fills. While inter-departmental cooperation does show a low value of F-statistics and significance, which negate the hypothesis ultimately to be valid based on the factored membership cluster information. While both culture groups and developmental does not impart significance on the intangible resource (hypothesis III not supported for group and developmental). Whereas, for the culture rationale, we found high significance where all three resources showed a significant impact. Only organization change capacity showed a partial significance with values close to 0.05 (hypothesis III partially supported for rationale). We also noticed that Organizational culture hierarchical showed a significance for the intangible resources, where both inter-department coordination and organization change capacity are highly relevant with high F-statistics (hypothesis IIII supported for hierarchical). Risk proclivity was not significant, with values of 0.339.

In general, the human-AI resources show a high significance for the culture rationale, while low significance is observed for the other resources. The results determine that the organizations with immense potential of alignment of cultural rationale are better at using technical skills of managers and employees having the right skill set to support AI resources. Moreover, it also represents that such places will have high-quality managers with strong leadership skills that take organizational business capabilities to a high level with the integration of AI. Interestingly, a medium positive correlation between the organizational group and managerial skills means that the organizations with strong human resource management and principles of loyalty will aid managers in taking direct AI initiatives and will be a better position to transform the way their business moves with the market through AI resource solutions [23, 34].

6.6 Research outlook

In the present research work, no or less positive correlation among the organizational culture of group and development at one hand shows that these organizations' culture becomes a challenge and reduce the effective use of AI resources. While from a survey standpoint, there still a chance that these questions remain less precise for respondents, which additionally results in low significance impacts.

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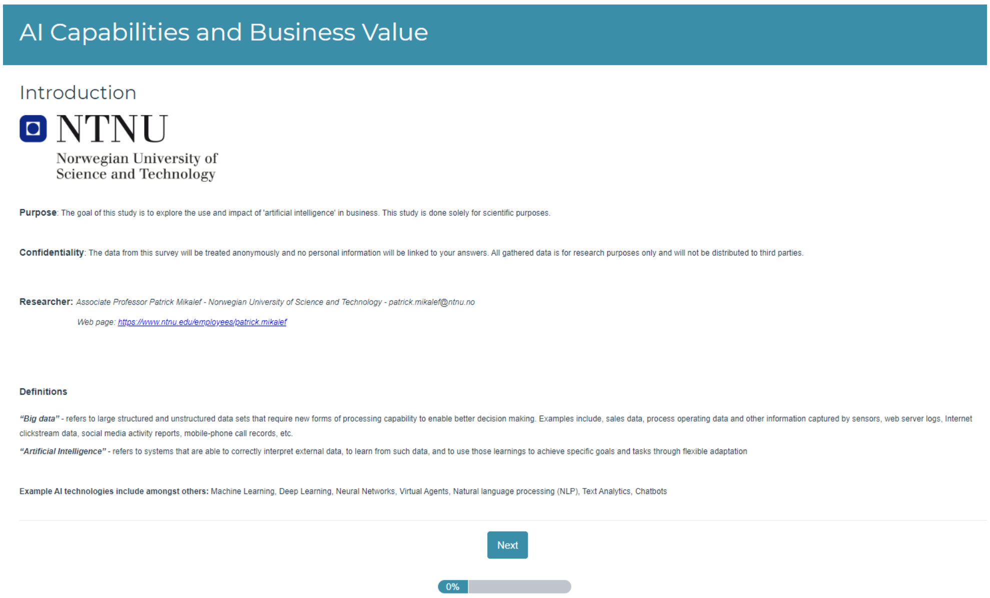
Appendix

Image excerpt of the survey



AI Capabilities and Business Value

Introduction

NTNU
Norwegian University of
Science and Technology

Purpose: The goal of this study is to explore the use and impact of 'artificial intelligence' in business. This study is done solely for scientific purposes.

Confidentiality: The data from this survey will be treated anonymously and no personal information will be linked to your answers. All gathered data is for research purposes only and will not be distributed to third parties.

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Definitions

"Big data" - refers to large structured and unstructured data sets that require new forms of processing capability to enable better decision making. Examples include, sales data, process operating data and other information captured by sensors, web server logs, Internet clickstream data, social media activity reports, mobile-phone call records, etc.

"Artificial Intelligence" - refers to systems that are able to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation

Example AI technologies include amongst others: Machine Learning, Deep Learning, Neural Networks, Virtual Agents, Natural language processing (NLP), Text Analytics, Chatbots

Next

0%

Figure 6.1: Image of online survey form sent to participants

Survey additional questions

Table 6.1: Survey questions for creativity, performance and environment

Name	Questions
Creativity	Please indicate the extent to which your organization has achieved the following outcomes (1 - to a very low extent, 7 - to a very high extent)*
C1	Our organization has produced many novel and useful ideas (services/products).
C2	Our organization fosters an environment that is conductive to our own ability to produce novel and useful ideas (services/products).
C3	Our organization spends much time for producing novel and useful ideas (services/products).
C4	Our organization considers producing novel and useful ideas (services/products) as important activities.
C5	Our organization actively produces novel and useful ideas (services/-products).
Performance	Please indicate the extent to which your organization has achieved the following outcomes (1 - to a very low extent, 7 - to a very high extent)
P1	Compared to our key competitors our organization is more successful.
P2	Compared to our key competitors our organization has a greater market share.
P3	Compared to our key competitors our organization is growing faster.
P4	Compared to our key competitors our organization is more profitable.
P5	Compared to our key competitors our organization is more innovative
Dynamism	With respect to the uncertainty of your environment, please indicate how much you agree or disagree with the following statements (1 - totally disagree 7- totally agree)
D1	Products and services in our industry become obsolete very quickly
D2	The product/services technologies in our industry change very quickly
D3	We can predict what our competitors are going to do next

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