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THE RELATIONSHIP BETWEEN ARTIFICIAL INTELLIGENCE AND COLLECTIVISTIC LEADERSHIP

Master's Thesis

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I have written this Master Thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

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Abstract

This thesis investigates the relationship between Artificial Intelligence (AI) and collectivistic leadership within Estonian Information Technology (IT) sector small and medium-sized enterprises (SMEs). For this study, a mixed-methods approach was used, combining quantitative survey data obtained from 104 individuals and the qualitative interviews from six SMEs. The study applied the Kruskal-Wallis H test to identify significant differences across companies in collectivistic leadership dimensions and used thematic analysis to understand the role of AI in the selected organization’s practices. The research findings propose a negative association between high AI intensity and collectivistic leadership traits such as shared decision-making, informal communication, and decentralized control. As opposed to this, companies with strong collectivistic leadership traits showed calmer and more collaborative approaches to AI integration, viewing it as a supportive rather than a directive tool. While the selected sample size limits the generalizability of the research, the findings bring out useful suggestions for leaders guiding AI adoption without weakening collectivistic leadership traits. This study contributes to the growing research between technological tools and modern leadership theories.

Introduction

With the increasing demands within the work environment, new approaches to leadership are a must. This is required to go beyond the traditional leader-focused view (Yammarino & Dansereau, 2009). In traditional research, leadership science and practice has generally focused on the behavior and the perception of leaders. In today's organizations, with the introduction of technological tools, the increased complexity of organizations, as well as with the need to stay competitive, it is difficult for one individual acting alone or in a limited interaction with formal units, to display effective leadership. Interactions that involve a higher level of analysis, and more complex leadership approaches require multi-person forms of engagement. These types of leadership approaches are referred to as "collectivistic" in nature. (Yammarino et al., 2012)

In recent years, more and more attention has been pointed towards the capabilities of a new technology: artificial intelligence (AI). Artificial intelligence has come up as a modern technology capable of revolutionizing the ways companies compete and operate as well as implement new solutions. (Brynjolfsson & McAfee, 2014). According to Benbya et al. (2020), artificial intelligence is typically referred to as the ability of machines to perform human-like cognitive processes such as problem-solving, decision-making, and manipulating amongst other things. Artificial intelligence encompasses a wide range of technologies, including computer vision, natural language processing, and machine learning. These allow machines to carry out tasks that have historically required human intelligence. Artificial intelligence has the potential to significantly improve cooperation, strategic management, and decision-making within organizations. (Daugherty & Wilson, 2018). The integration of AI into organizational leadership has attracted a lot of interest from academics and businesses as the field develops in the twenty-first century however AI projects within organizations remain largely experimental (Benbya et al., 2020). Although there have been a few studies which include the possible effects of AI on leadership, there have not been any previous studies on the relationship of AI and collectivistic leadership. For example, Benbya et al. (2020) and Faraj et al. (2018) state that machine learning algorithms can change the management styles of workplaces, however they fail to mention if and what the exact implications are. The aim of this thesis is to answer the question of what the relationship between artificial intelligence and collectivistic leadership is.

1. Literature review

1.1. Leadership

Traditional and contemporary leadership science as well as practice has been typically viewed as a leader-follower interaction process. This process takes place in small groups and teams, and sometimes situations that take place in a particular context, where a leader (superior or supervisor) and followers (subordinates) share a common vision or mission and jointly accomplish tasks or goals. Leadership is often viewed as an interaction between individuals where there is an authority structure in place (e.g. superior and subordinate reporting) (Yammarino et al., 2012). Leadership is present at both the collective as well as individual level and these two combined formulate organizational leadership (Kivipõld, 2011).

Comparing both Bass (2008) and Yukl (2009) findings on leadership then it is stated that leadership is set in place by the precursors of current holders of applicable positions, which in return leads to actions in a variety of scenarios. Most traditional approaches to leadership consider similar reasons for leadership. These are tied to rudimentary human processes. (e.g. personality, attraction, affection). Leadership outcomes are essentially leadership effectiveness indicators - both soft (e.g. loyalty, satisfaction, commitment) and hard (e.g. performance, turnover, stress). This applies to both the leaders and to their followers. Leadership processes in traditional leadership view take place within a certain context that includes the general climate of the company or unit, as well as the organizational culture and values. (Yammarino & Dansereau, 2009) As such, traditional leadership works have strictly focused on the views and behaviors of individual leaders (Yukl, 2009). According to Kivipõld (2011) traditional leadership is described as a model that is tied to hierarchical authority where leadership is most often concentrated in the hands of an individual or limited number of people at the top of the organizational structure. This means that the leader is considered as the originator and the main conductor of leadership. Both competence and decision-making are concentrated at the individual level. Traditional leadership looks at the interaction between a leader and the followers, more specifically the top-down influence of the leader on its followers. It assumes that effective leadership stems from the leader’s formal position and skills. This approach to leadership highlights personal responsibility for goal achievement (Kivipõld, 2011).

According to Yammarino, in today’s complex, competitive and challenging business landscape, it is difficult for one individual to display effective leadership. This applies to both public, non-profit and governmental sectors. For a single individual it is challenging to keep up with the pace of technological change and the risks involved with decision-making. To tackle the changing business landscape, all-inclusive leadership approaches are needed. These all-inclusive leadership models, which are capable of higher levels of analysis, require multi-person interactions. These approaches to leadership are referred to as “collectivistic”. (Yammarino et al., 2012) This thesis will rely on the definition of collectivistic leadership defined by Yammarino et al.

According to Yammarino (2012) there are five main types of collectivistic leadership approaches: team leadership, network leadership, shared leadership, complexity leadership and collective leadership. Team leadership is a process in which different functions and tasks are determined to make the team more efficient. The precursor to this is that the team shares a common vision and the team members affect each other. The assumption is that the team can achieve more together as a collective rather than the leaders as individuals (Yammarino et al., 2012). The increase of interest in collectivistic leadership approaches can be traced to the 1990s (De Brun et al., 2019). De Brun et al (2019) states that there is noticeable evidence pointing at the positive impact of the different collectivistic leadership approaches in a variety of scenarios.

Network leadership is described by Brass and Borgatti (2019) as a complex combination of strings which include the connections between people. These various connections including friendship, conflicts, and cooperation are often connected between each other. In social sciences these strings are represented by individuals, groups or organizations that are capable of both breaking existing connections and establishing new ones. (Brass & Borgatti, 2019)

Shared leadership divides the responsibilities among all teammates. The primary assumption is that leadership is a combination of various roles which can be filled in by various teammates. The leadership should be divided equally among the teammates and the tasks as well as decisions are not on one individual’s shoulders (Yammarino et al., 2012). In contrast to top-down leadership models, shared leadership has been found to be a better indicator of team performance and organizational outcomes (De Brun et al., 2019).

Complexity leadership is a non-linear dynamic which primarily involves interactions through a period. The primary assumption is that leadership is a socially constructed phenomenon. This socially constructed phenomenon emerges naturally and is not consciously directed by any individual. Leadership is seen as a process of social influence through which change is brought about. (Yammarino et al., 2012)

Collective leadership emphasizes the capabilities, collaboration, and shared dynamics of teams, units and networks rather than focusing on a single individual in a leadership role. It is a fluid and context driven approach where leadership functions are distributed based on the expertise that is required for the specific problem at hand. This model evolves over time and can change depending on the needs of the organization or team. The core assumption of collective leadership is that effective problem-solving benefits from leveraging specialized knowledge of different teammates. Both formally designated and informally emerging leaders adaptively share responsibilities depending on what the situation at hand demands. Over time these individuals build and maintain relationships that contribute to the group's ability to respond effectively to changing circumstances. Collective leadership distributes authority and decision-making however it does not eliminate the importance of formal leadership roles. Those that fill in these roles may shift depending on context, allowing for further readiness and flexibility. (Yammarino et al., 2012). According to Margolis et al. (2016) in the collective leadership model, the importance of a formal leader is significant. The formal leader can either encourage collective strategic vision on the team or the leader can resist sharing power with their subordinates. According to Margolis et al. (2016) the impression (i.e. behavior and job satisfaction) that is left on the leader by their subordinates greatly influences the leader's way of acting.

Collectivistic leadership does not only occur in formal groups and teams, but it can also be found in larger, formal collective structures. These structures can be departments, functional areas, strategic businesses, units, networks of various types, and multiteam systems. In addition, the roles can include numerous informal relationships, networks, and connections that involve personal contact with the organization and the parties interacting with the organization. (Yammarino et al., 2012). The collective structures can change drastically over time, and thus are not static in nature, but rather dynamic and respond to organizational and environmental demands as well as the individuals involved. According to Earley and Gibson (2002), some of the advantages of collectivistic leadership can be found in multinational teams. Collective approaches to leadership become apparent in situations where leadership roles and responsibilities are shared, distributed or switched between team members (De Brun et al. 2019). This type of leadership can lead to these teams finding unique and innovative solutions to the problems that organizations face. O'Leary et al (2011) states that the benefits of multiple teams working together in knowledge-based industries, such as IT, can facilitate better knowledge sharing as well as cross-functional collaboration.

Collectivistic leadership requires new types of leadership methods and interventions for understanding and developing leadership science and practice. This makes it a dynamic leadership process in which a defined or focal leader, or a set of leaders, selectively use the skills and expertise within a particular network and across levels, to efficiently distribute leadership according to what the current issue at hand requires (Yammarino et al., 2012). However, this is more than multiple members sharing different roles and responsibilities. Instead, this is a complex system where both the needs of an organization as well as the individual come into play. Perrow (1967) states that collective leadership traits help organizations adapt and learn because it makes it possible for them to react more skillfully to shifting environmental demands. In a more recent study, networks' importance in fostering collectivistic leadership was noted by Carter and Dechurch (2012). They suggested that networks may operate as a platform for information exchange, action planning, and the encouragement of group decision making, all of which can improve team performance. An article written by Goldstone and Janssen (2005) explains how collectivistic behavior can lead to better decision making, problem solving and better coordination within organizations. At the same time Goldstone and Janssen argue that collectivistic behavior can lead to negative outcomes such as social loafing. During the investigation on the effects of burnout and job engagement on teachers' performance, Hakanen, Bakker, and Schaufeli (2020) found that collectivistic engagement had a good impact on organizational performance. According to the study, group participation reflects favorable feelings, common objectives, and interpersonal support. All of these improve work performance in return.

1.2 AI and Technological Advancement

From the early years of computer science, researchers like Alan Turing have been considering the possibility of a computer playing chess as a test of the machine's intelligence. Alan Turing published "Intelligent Machinery" in 1948 and "Computer Machinery and Intelligence" in 1950. These works have become the inspiration source for current Artificial Intelligence researchers (Turing, 2009). In short, artificial intelligence refers to the application of technological instruments meant to replicate human brain functions in order to reach goals independently. This technology should take into consideration any obstacles that may come their way. (Benko and Lanyi, 2009; Haenlein and Kaplan, 2019; McCorduck et al., 1977)

Artificial intelligence (AI) is a quickly evolving field. It has gained significant interest in the past few years due to its potential to revolutionize various industries as well as aspects of human life. At its base core, AI has two subfields: machine learning (ML) and deep learning (DL). Artificial intelligence refers to the advancement of sophisticated computational systems capable of executing tasks that have traditionally required human intervention. These tasks encompass a range of activities, including but not limited to speech recognition, natural language processing, decision-making, problem-solving, and visual perception. AI should be capable of recognizing patterns, Artificial intelligence assimilates the information it receives, adjusts to new inputs and attempts to enhance its efficacy as time progresses. (Brynjolfsson and McAfee, 2014)

Machine learning is a subset of artificial intelligence. Machine learning focuses on the development of algorithms that allow computers to acquire knowledge and formulate predictions or decisions which are derived from the data provided. Machine learning algorithms figure out patterns and relationships within data autonomously, without the necessity of explicit programming. The capacity for learning is fundamentally linked to the notion that an increase in the volume of information we input correlates with greater precision in the information we subsequently acquire. Furthermore, the ability to derive insights from data enables machine learning systems to generate predictions and make decisions autonomously. This leaves out the necessity of being explicitly programmed for every conceivable situation (Mitchell, T.M., 1997). Machine learning can fundamentally be divided into two distinct categories: supervised and unsupervised machine learning. This applies to both machine learning and deep learning. In short, machine learning can be defined as the process of solving practical problems by first gathering data and then algorithmically constructing a statistical model based on that data (Zohuri et al., 2019). This statistical model that is constructed is then applied by machine learning to solve these practical problems. Machine learning has become an integral part of many commercial applications in both medical and commercial fields within both small and medium sized enterprises as well as larger corporations (Zohuri et al., 2019).

Deep learning is a specialized subset of ML that involves algorithms, also known as artificial neural networks, which are inspired by the structure as well as the function of the human brain. Deep learning is capable of discovering difficult structures within large sets of data. The key factor of deep learning is that it is capable of automatically learning from the raw input that it is being given (Janiesch et al., 2021). This is opposed to the traditional way of machine learning as it does not require extensive human interaction (LeCun, Bengio, & Hinton, 2015). Deep learning enables computers to build complex concepts out of simpler concepts (Goodfellow et al., 2016). Deep learning enables computers to solve more specific and complex problems. Zohuri et al (2019) have described deep learning as the ability to learn on multiple levels at once. For example, these levels can be in the forms of images, sound or text.

1.3 Previous findings on AI and leadership

The speed of change in technology in recent years has been challenging for all businesses. To manage these changes, a lot of businesses are looking at AI to take advantage of new opportunities while also keeping costs under control. (Zohuri et al., 2019). Brynjolfsson and McAfee (2014) state that AI has the potential to make decision-making processes in top-down leadership structures better. This can be done by providing predictive analytics, automating time-consuming tasks, as well as providing data-driven insights. Despite Artificial Intelligence being around for the last couple decades, it has become the center point of attention lately due to the growing availability of data, scalability of cloud computing, and the rising complexity of machine learning and deep learning algorithms (Zohuri et al., 2019). AI can also have some potential negative effects on the traditional top-down leadership claimed by Davenport and Kirby (2016). According to them, organizations can run into potential overreliance on algorithmic decision-making, which may lead to less human input and therefore to the lack of innovation. Davenport and Kirby argue that it is important to balance AI input with human interactions. Schatsky et al. (2015) suggest that AI can force companies to move from the traditional top-down leadership to a more collaborative and adaptive leadership style. This can be due to the complexity of AI and as a result it requires more human interactions. Taddy (2018) in his research mentions that AI can bring challenges to the traditional top-down leadership, including the need for managers to develop new skills for fully enabling the potential of the software. Typically, these types of leaders include having a data-driven mindset, they can continuously adapt as well as learn on the go.

Adoption of new technology in companies is sometimes seen as a necessary driver of innovation, efficiency, and competitive advantage. Structural, cultural, personal and contextual elements can all limit the integration of new tools or systems into current processes and business models. One of the most often reported challenges is employee opposition to new technology adoption. It is typically brought on by ignorance of the technology's purpose, uncertainty or fear of being replaced by the technology. (Choi, 2011) Employees might find it challenging to break long-standing habits, especially if the claimed benefits of the technology are not clear or justified. As stated by Venkatesh and Davis (2000) the two important constructs in technology acceptance are perceived usefulness and perceived ease of use. The influence of organizational culture and leadership within the organization is another important factor for user acceptance. If the organizational culture and leadership does not support the employees during the technological adoption, the teams may become confused and misaligned (Kane et al. 2015). Resource limitation is another common obstacle in successful technology implementation. This does not only include financial resources but also a lack of technological infrastructure and not suitable technological skills (Besson & Rowe, 2012).

With previous studies, there is a lack of evidence pointing at the possible relationship between Artificial Intelligence on collectivistic leadership level. Artificial Intelligence is still evolving and the implications on management are still widely unknown (Benbya et al., 2020). Similarly to this, Faraj et al. (2018) claims that machine learning algorithms have the possibility to transform workplaces and decision-making differently than the previous technological innovations have. However, within the research conducted by Faraj et al. (2018) they fail to mention how or in what way these transformations will happen. Benbya et al. (2020) claim that the introduction of AI will have significant changes on how organizations are managed. The researcher claims that there will be significant restructuring taking place in organizational decision-making due to the use of AI and managing work algorithmically. This means that the tasks will be divided based on certain algorithms, and these tasks will then be given to the workers by the management (Benbya et al., 2020). This refers to the organizations becoming more individualistic. In research about the impact of AI and Reciprocal symmetry on organizational culture and leadership, Maddula S.S. (2018) explains that the adoption of Artificial Intelligence fosters innovation and data-driven decision making, which in return drives organizational cultural changes. According to Maddula S.S. (2018), Organizations utilizing AI make collaboration more accessible for people from different teams and places. This creates a more inclusive environment, which also motivates leaders to seek openly communicated various viewpoints from different internal teams, automate routine tasks and enable employees to concentrate on value-added work. These terms can often be associated with collectivistic leadership traits. Although the aforementioned research points towards the possible impacts that AI has on leadership, no direct research has been conducted on the relationship between Artificial Intelligence and collectivistic leadership. Previously conducted researches most often mention learnings based on top-down leadership structures. Taking all this into consideration, this research aims to answer the following research questions:

RQ: How do Artificial Intelligence and collectivistic leadership relate to each other?

2. Methodology

The primary objective of this study is to explore the relationship between Artificial Intelligence Intensity and collectivistic leadership. The research focused on Estonian SMEs in the Information Technology (IT) sector, specifically targeting organizations with 20-50 employees. The size range was selected to ensure a manageable organizational complexity, while still being likely to adopt AI-driven tools and non-traditional leadership models. Survey respondents include members from across the selected companies. All interview participants were selected from commercial departments, which include sales, account management and marketing teams. These are typically the frontline adopters of AI tools for customer engagement and analytics. (Daugherty & Wilson, 2018).

For this study the researcher has adopted a mixed-methods approach, integrating qualitative interviews and quantitative survey data to analyze the relationship between AI and collectivistic leadership. The design enables both in-depth insights from professionals and a broader organizational-level analysis through statistical trends. The mixed-methods approach enables capturing the multifaceted dynamics between AI and leadership. According to Creswell (2014), a mixed methods approach is particularly suitable when a researcher seeks to both generalize results to a certain population (quantitative) and explore in-depth participant perspectives (qualitative). Through combining both methods, the researcher can gain a more comprehensive understanding of complex social phenomena. This approach is effective in situations where neither the quantitative nor qualitative methods alone are sufficient to capture the full scope of the research problem (Creswell, 2014).

2.1. Sample description

The study was conducted with six companies. The total questionnaire sample size across 6 companies is n = 104 (Table 3). This sample was collected through convenient sampling techniques. To ensure anonymity of the organizations and participants, the organization names are coded from “A” to “F”. The highest number of respondents were from Company A and Company B with n = 23, the lowest number of respondents was from Company D with n= 8.

The research utilizes the Organizational Leadership Capability model and questionnaire developed by Kivipõld and Vadi (2010) as the basis of the quantitative research. This tool is used to assess the presence and strength of collectivistic leadership practices within organizations. The aforementioned Organizational Leadership Capability (OLC) model consists of three main factors and two sub-factors. The main factors include “Alignment and cohesion”, “Control-feedback system”, and “Architecture of the internal network”. The third factor consists of two lower factors, which include “Informal communication” and “Extent of centralization” (Kivipõld & Vadi, 2010). Separately from the five OLC constructs, the survey also includes a measurement “Organizational Performance”. This is treated as a separate construct as this is used to evaluate the effectiveness, impact and relevance of OLC rather than being a component itself (Kivipõld & Vadi, 2010). The original questionnaire consisted of 6 different categories and 22 questions in total (APPENDIX 2). Demographics category was included to record basic demographic data (Table 1): participant gender (male, female, other/prefer not to specify), participant age range (up to 30 years, 31-50 years, over 50 years), participant level of highest education (secondary education or equivalent, Bachelor’s degree, Master’s degree or higher), and the participants level of work experience in the IT field (1-5 years, 5-10 years, more than 10 years). The 22 questions were closed-ended with a seven-point scale (strongly disagree=1, strongly agree=7).

Table 1

Participant demographic information

Category	Answer	Number of respondents	Percentage of all respondents
Gender	Male	44	42.3%
	Female	39	37.5%
	Other/prefer not to specify	21	20.2%
Participant age	Up to 30 years	46	44.2%
	31-50 years	50	48.1%
	Over 50 years	8	7.7%

Highest level of education	Secondary education or equivalent	22	21.2%
	Bachelor’s degree	50	48.1%
	Master’s degree or higher	32	30.8%
Experience in IT sector	1-5 years	57	54.8%
	5-10 years	29	27.9%
	More than 10 years	18	17.3%

Note: (n=104)

Source: prepared by the author

The responders were relatively evenly split between male and female. Most participants were between 31-50 years of age, and most of the respondents have a bachelor’s degree with 1-5 years of IT sector experience.

The qualitative part of this research was performed with the commercial teams of the selected six companies. From each commercial team two participants were interviewed. The selected participants were the team leaders of sales and marketing teams and their substitutes. Through selecting two members from each organization, the researcher tries to eliminate the bias that a single interviewee might have against their company’s AI usage and its perceived impact on their leadership capabilities. Each interview took approximately 30-40 minutes, depending on the conversation flow. During all interviews notes were taken and later transcribed as well as thematically analyzed (APPENDIX 1). Interview transcripts were analyzed using thematic analysis: familiarization with the data, initial coding, theme generation, reviewing themes, defining and naming themes, and writing up. Coding was conducted manually, with each transcript examined line-by-line to extract insights related to AI integration and leadership structure. The resulting themes informed both the AI Intensity Index scoring and the Perrow model classification.

In total the interview consisted of 26 semi-structured questions (APPENDIX 3); each question is designed to correspond with one of the five AI dimensions. The questions are divided through the following logic: “AI in internal workflows” - 7 questions, “AI in decision-making” - 6 questions, “AI in products/services” - 4 questions, “AI autonomy level” - 4 questions, “Perceived impact of AI” - 5 questions (Table 5). For evaluating how Artificial Intelligence (AI) is integrated into the selected companies’ operations, this study uses the AI Intensity Index which has been created for this thesis. The goal is to identify relationships between commercial team’s AI usage and collectivistic leadership traits. AI Intensity Index provides a systematic and comparable way to measure AI presence, functionality, and perceived impact based on qualitative interviews. The index evaluates five dimensions of AI integration, each scored on a 5-point scale ranging from 0 (no usage) to 4 (fully integrated). Scores were assigned based on qualitative interview results.

2.2.Results and analysis

All recorded data was analyzed using the statistical software platform IBM SPSS Statistics version 30.0.0. Prior to analyzing the data, the researcher employed Cronbach's alpha multiplier to validate the reliability of the Organizational Leadership Capability questionnaire (Kivipõld ja Vadi, 2010). This will also let the researcher know if all 5 questionnaire categories are measuring the same phenomenon. Table 2 indicates Cronbach's alpha values and the sufficient reliability levels, as the recommended criteria of ≥ 0.70 is surpassed with four categories (Alignment and cohesion, Informal communication, Extent of centralization, Control-feedback system) and by Organizational Performance α = 0.81. Architecture of internal network had a Cronbach's α of 0.69 which means the results of this research should be interpreted with caution. (Table 2).

Table 2

Reliability coefficients of Organizational Leadership Capability

Measurement	Category	Cronbach's α
Organizational Leadership Capability	Alignment and cohesion	0.83
	Informal communication	0.71
	Architecture of Internal Network	0.69
	Extent of centralization	0.77
	Control-feedback system	0.79
Organizational Performance		0.81

Note: (n=104)

Source: prepared by the author

Although "Organizational performance" is included in the Cronbach reliability analysis (Table 2) and further statistical comparisons across companies, it is not part of the Organizational Leadership Capability construct. This serves as a dependent variable according to Kivipõld and Vadi (2010) and is used to measure the potential impact of leadership practices. In this work, this is analyzed alongside the five OLC categories, however it is treated independently to assess how perceived leadership capability relates to perceived organizational success and competitiveness. Table 3 brings out information regarding the mean and standard deviation factors involving the 6 companies interviewed. These companies are coded from A-F.

Table 3

Means, sample size, and Standard Deviations for each Organizational Leadership Capability category

Category	A n=23	B n=23	C n=16	D n=8	E n=22	F n=12
Alignment and cohesion	4.59 (1.30)	4.35 (1.12)	5.02 (1.22)	4.75 (1.85)	4.19 (1.20)	5.81 (0.39)
Informal communication	4.03 (1.16)	3.90 (0.94)	4.69 (1.09)	4.63 (0.96)	3.85 (1.03)	4.65 (1.29)
Architecture of internal network	4.64 (1.21)	4.05 (1.01)	4.78 (0.92)	4.88 (0.94)	3.95 (0.95)	5.13 (0.90)
Extent of centralization	4.64 (1.39)	4.18 (1.10)	5.03 (0.94)	5.13 (1.45)	4.31 (0.97)	5.44 (0.63)
Control-feedback system	4.10 (1.51)	3.76 (1.22)	4.56 (1.02)	4.72 (1.54)	3.90 (1.24)	5.58 (0.62)
Organizational performance	4.61 (1.16)	4.01 (0.97)	4.55 (1.07)	4.94 (1.27)	3.91 (1.21)	5.35 (0.45)

Source: Compiled by the author, Notes: values in parenthesis represent standard deviations, n= sample size, lettering A-F indicates the company coding

Company A showed moderate collectivistic leadership outcomes, with “Alignment and cohesion” (M= 4.59, SD= 1.30) and “Organizational Performance” (M=4.61, SD= 1.16) scoring relatively high. The control-feedback system category seems to have more variability (M= 4.10, SD = 1.51), indicating a potential inconsistency in how leadership processes might be implemented or perceived by the respondents. Company B scored low in the “Control-feedback system” (M=3.76, SD= 1.22) and “Organizational performance” (M=4.01, SD=0.97) suggesting that the respondents perceive to have a weak structural support and low organizational adaptability in the future. Company C presented strong and balanced collectivistic leadership scores across all categories, strongest being "Alignment and Cohesion (M= 5.02, SD= 1.22) and "Extent of centralization" (M=5.03, SD=0.94). This suggests that the people perceive leadership to be well distributed, well aligned with organizational goals and is collaborative. Low SD values point to consistency within the respondents. Company D showed high scores in "Extent of centralization" (M=5.13, SD=1.45) and "Organizational Performance" (M= 4.94, SD= 1.27) pointing to a strong decentralization and a forward-thinking leadership logic. The high standard deviation values suggest that the respondents might have experienced differing leadership experiences across departments or roles. Company E had the lowest scores across all five categories, suggesting that there might be a lack of communication or more of a top-down leadership approach, while high standard deviation numbers indicate that there is a lack of cohesion in employee experiences. Company F displayed strong collectivistic leadership characteristics with consistently high scores across all categories. "Alignment and Cohesion" (M= 5.81, SD = 0.39) and "Control-feedback system (M=5.58, SD= 0.62) are the highest out of all the six companies. This implies that the company has a well-established collectivistic leadership model, and the survey respondents seem to agree due to low standard deviation.

Conducted survey had an additional "Demographics" section added to receive respondents' demographic data. This data included gender (male, female, prefer not to specify), age (up to 30 years of age, 31-50 years of age, 50+ years of age), highest level of education (secondary education, bachelor's degree, master's degree or higher), and level of IT field work experience (1-5 years, 5-10 years, 10+ years).

To evaluate if there are any statistically significant differences in how the selected six companies (Company A- Company F) scored on the questionnaire, the Kruskal-Wallis H test was performed. This test was chosen to compare the median scores of the Organizational Leadership Capability (Table 4) across multiple independent groups (our selected six companies) and to identify the areas where there are significant differences present. Each of the categories (Table 4) records a critical dimension of the collectivistic leadership as described by Kivipõld & Vadi (2010). This non-parametric test is appropriate for comparing three or more independent groups when the data is not normally distributed.

Table 4

Kruskal-Wallis test

Category	Kruskal-Wallis H	p-value
Alignment and Cohesion	17.73	0.00*
Informal Communication	12.13	0.03*
Architecture of Internal Network	15.36	0.01*
Extent of Centralization	14.51	0.01*
Control-feedback system	18.94	0.00*
Organizational Performance	19.3	0.00*

Note: n=104, p<0.05 significant, p>0.05 not significant

Source: Prepared by the author

The Kruskal-Wallis test revealed statistically significant differences between the companies in several key organizational leadership capability areas. There were significant differences in Alignment and Cohesion (H= 17,73, p=0,003) and Architecture of Internal Network (H= 15,36, p=0,009). The significant differences were also spotted in the two subcategories: Extent of Centralization (H-14,51 p=0,01) and Control-feedback system (H=18,94, p=0,002). These findings suggest that employees' views on the leadership significantly differ between the selected organizations.

Alignment and cohesion displays how unified an organization is around different strategic goals and vision, the significant variance here implies that some companies are more successful in creating shared purpose and employee commitment

Architecture of the internal network shows how information is processed and how information flows through formal and informal channels. The variation here shows that companies have a different level of responsiveness, coordination between departments and varying communication efficiency.

The extent of centralization shows how decision-making authority is distributed. The significant differences in this section indicate that some companies might operate more hierarchically while others take advantage of distributed decision-making.

Control-feedback system measures how organizations self-regulate through different feedback mechanisms. The differences point to a variation in how companies learn, adapt and maintain operational control.

The variations in responses highlight that although all companies in the sample operate in the same sector and within a similar size range, their internal leadership dynamics and organizational cultures differ. The Kruskal-Wallis H test confirms that these are not random differences but statistically significant ones.

In total, 12 interviews were conducted between six companies. Each participant was chosen from the commercial teams (sales, account management and marketing) and they responded to 26 semi-structured questions (APPENDIX 3). To evaluate how deeply Artificial Intelligence systems are integrated into the selected IT companies' operations, AI Intensity Index was developed. The developed Index helps the researcher identify relationships between commercial team's AI usage and collectivistic leadership traits, as it provides a systematic and comparable way to measure the presence of AI, its functionality, and perceived impact based on qualitative interviews. The index evaluates five categories of AI integration. Each category is scored on a 5-point scale ranging from 0= no AI usage to 4= fully integrated into the company's procedures (Table 5). Although each category contains a different number of interview questions, the scoring approach ensures that all categories contribute equally to the total score (maximum 20 points). The number of questions was designed to gain rich qualitative information, however the final score for each category was assigned holistically based on the overall pattern of responses. This was done as opposed to averaging or summing the answers. By doing this, the researcher attempts to gain a good understanding of the nature of AI adoption within the selected companies. For example, if AI was used consistently in key workflows and described as a critical component, the category received a higher score. These scores were assigned by the author of the research. For this research, no secondary reviewers were assigned.

Table 5

Measured AI categories, number of questions, scoring logic

Category	Questions	Scoring Description (0-4)
AI in internal workflows	7	0=Not applied; 1=Minimal; 2=Supportive; 3= Regular; 4= Core
AI in decision-making	6	0= Not used; 1= Conceptual use; 2= Supports decisions; 3= Reoccurring use; 4= Drives decisions
AI in products and services	4	0= No integration; 1=Pilot stage; 2=Limited use; 3=Value-adding, 4=Essential part

AI autonomy level	4	0= Fully manual; 1= manual use; 2= Assistive; 3= Semi-autonomous; 4=Fully autonomous
Perceived impact of AI	5	0= None; 1= Minor; 2= Moderate; 3= Significant; 4= Transformative

Source: prepared by the author

Each company received a total score ranging from 0 to 20, being the sum of all categories combined. Total scoring logic (Table 6) allows the researcher to categorize the companies into 3 different categories: Low= 0-9, Moderate=10-14, High=15-20. Based on the results, the researcher can assess the level of AI usage, integration and perceived impact on leadership models.

Table 6

Company AI Index scoring

Company	Total Score (0-20)	AI Intensity Category
Company A	12	Moderate
Company B	10	Moderate
Company C	12	Moderate
Company D	7	Low
Company E	16	High
Company F	9	Low

Note: (Total Score 0-9=Low, 10-14=Moderate, 15-20=High),

Source: Prepared by the author

Based on the scoring, the highest score was for Company E with a score of 16 out of 20. This puts Company E in the “high” AI Intensity category. The lowest scoring company was Company D with a score of 7 out of 20 and second lowest was Company F, which puts them in the “Low” AI Intensity Category. Company A and Company C scored 12 out of 20 respectively, which puts them in “Moderate” AI Intensity Category.

To test the statistical significance of the AI Intensity Index (Table 6) and the Organizational Leadership Capability questionnaire (Kivipõld and Vadi, 2010) results, a Spearman correlation analysis was conducted. This is required to get an understanding of if there is a correlation between the qualitative and quantitative analysis performed.

Table 7

Spearman correlation between AI Intensity Index and OLC questionnaire analysis table

	Variable	**1**	**2**	**3**	**4**	***5***	***6***
1	AI Intensity Index						
2	Alignment and cohesion	-0.55 (0.26)					
3	Informal communication	-0.41 (0.43)	0.94** (0.01)				
4	Architecture of internal network	-0.75⁺ (0.08)	0.94** (0.01)	0.83* (0.04)			
5	*Extent of centralization*	-0.58 (0.23)	0.89* (0.02)	0.77 (0.07)	0.94** (0.01)		
6	*Control-feedback system*	-0.58 (0.23)	0.89* (0.02)	0.77 (0.07)	0.94** (0.01)	1.00** (0.00)	
7	Organizational performance	-0.75 (0.08)	0.83* (0.04)	0.66 (0.16)	0.94** (0.01)	0.89* (0.02)	0.89* (0.02)

Notes. Values represent Spearman's ρ (top row) with corresponding p-values (bottom row). Correlation is considered highly significant at $p < 0.01$ level (**) or significant at $p < 0.05$ level (*), $p < 0.10$ level ($^{+}$). Sample size: n = 6.

Source*:* Prepared by the author

The Spearman's analysis revealed a consistent negative association between AI intensity and the 6 categories or Organizational Leadership Capability results. Although none of the relationships were at a statistically significant level of $p < 0.05$, the correlation between AI intensity and Architecture of internal network (ρ= -0.75, p= 0.08) as well as the correlation between AI intensity and Organizational performance (ρ= -0.75, p=0.08) indicate marginal significance ($p < 0.10$) and can display a potentially meaningful negative trend. This can suggest that organizations with higher levels of AI integration can show lower levels of collectivistic leadership practices. In particular, how internal structures are managed and how the organizational performance might be perceived by the employees. The negative correlation between Architecture of internal network may show how AI systems affect decision-making hierarchies. In collectivistic leadership, internal networks are often characterized by decentralized communication, informal information change or organic collaboration. If the AI tools are used for internal monitoring or for predictive decision-making, they may reduce these collectivistic leadership traits, leading to more algorithmically driven processes that value less the engagement of each employee. As mentioned by

Yammarino et al. (2012), collectivistic leadership is often linked to increased motivation, satisfaction and a sense of shared purpose. These qualities can be lost in a poorly managed high AI usage environment. Alignment and cohesion (ρ= -0.55), Informal communication (ρ= -0.41), Extent of centralization (ρ= -0.58) and control feedback system (ρ= -0.58) also display a negative correlation with AI intensity. However, none of these findings reached statistical significance and due to the conservative sample size (n=6), these findings should be interpreted with caution.

Charles Perrow's (1967) technology variable model classifies organizational work according to two key dimensions: task variability (how predictable or unpredictable tasks are) and problem analyzability (how structured or complicated are the solved problems). According to Perrow, there are 4 distinct technology types: routine, craft, engineering and non-routine. To apply Perrow's model to this research, the selected 6 companies' AI intensity score was used as a measurement for technological complexity. As higher AI intensity score indicates a shift towards more complex, it is possible to align it with the "engineering" or "non-routine" technology categories. The analysis revealed that four of six companies fall under the "engineering" category which is characterized by high AI usage and a mix of structured and creative tasks. Company E with the highest AI intensity score (16) was classified as "non-routine" due to its use of AI in complex, personalized and dynamic services. Company D was categorized as "routine" due to the low complexity and variability of tasks performed with AI.

Table 8

Perrow Classification Based on AI Intensity Index Score

Company	AI Intensity Index Score	Task Variability	Problem Analyzability	Perrow Category
Company A	12	Medium	High	Engineering
Company B	10	Medium	Medium	Engineering
Company C	12	Medium	High	Engineering
Company D	7	Low	High	Routine
Company E	16	High	Low	Non-Routine
Company F	9	Medium	Medium	Engineering

Notes: Classification is based on Perrow's (1967) model, which categorizes organizations by task variability and problem analyzability

Source: prepared by the author

Compiled table points out that higher AI complexity is connected to more fluid organizational structures. Companies which were categorized as either “engineering” or “non-routine” in the Perrow Category section showed stronger alignment with collectivistic leadership traits. These include shared decision-making, autonomy, planning. None of the companies was categorized as “craft” by the Perrow categorization logic. This can be seen as the nature of AI integration in modern SMEs where low intensity AI usage still supports structured and data driven processes. Based on this Perrow’s framework, the selected companies with higher AI intensity and less structured problems (Company E) fall into Non-Routine category, which typically requires adaptive and less centralized forms of leadership.

2.3 Discussion and findings

The practical part of this thesis focused on the examination and analysis of the relationship between artificial intelligence and collectivistic leadership. Specific focus was on the selected six Estonian SMEs operating in the Information Technology sector.

RQ: How do Artificial Intelligence and collectivistic leadership relate to each other?

As seen on the Spearman correlation analysis, AI intensity was negatively related to all Organizational Leadership Capability categories. Spearman’s correlation values ranged from -.41 to -.75. Although these values are not statistically significant ($p > .23$), and the current selected company sample size is small $n=6$, it still shows a negative trend. This can be seen as a higher AI adoption is related to lower perceptions of collectivistic leadership. In the case of Company E, interview results provided the highest AI Intensity Index score (16), however the OLC scores across all five categories were the lowest out of the six companies interviewed (Table 3). Company F with low AI Intensity score (9) showed the highest levels of collectivistic leadership out of the 6 companies interviewed (Table 3). Based on this study’s mixed-methods results, the relationship between AI and collectivistic leadership traits appears to be moderately negative, which gives an indication that higher levels of AI intensity may correlate with lower levels of collectivistic leadership.

Perrow (1967) states that when task variability is high, and analyzability is low (non-routine tasks) organizations must rely more on mutual adjustment, informal communication and judgement rather than hierarchical control. In the example of Company E, which according to the Perrow technology model operates in the non-routine section due to high variability of tasks and low analyzability, should benefit from less formal, more adaptive and decentralized structures. These structural traits are also assimilated to collectivistic leadership, however their relative OLC scores (Table 3) were lower than all the other respondents. This might suggest that as AI systems become more complex, companies are having a difficult time adjusting their leadership styles. Instead of moving towards more decentralized and supportive of team collaboration, companies might become more centralized with a top-down leadership approach.

Thematic analysis from the interviews provided us with an insight that companies with higher collectivistic leadership traits (Table 3) seemed to approach AI adoption more carefully (Table 6). In Company C and Company F, AI is seen as a tool to support, not replace human-centered processes. This approach is mostly characterized by team-driven decision-making, gradual integration of AI strategies, and long AI evaluation times. Companies that had a high score on the OLC questionnaire results (Table 3) mainly described AI as a supportive tool for collaboration. These companies viewed this tool as something that will assist them but will not replace human judgement. Companies that exhibited strong collectivistic leadership traits may influence the ways in which AI is introduced to the companies and in which areas it is implemented, however based on the analysis, companies with strong collectivistic leadership are not looking at AI as a replacement tool for human decision-making.

These findings are familiar to the theoretical arguments made by Yammarino et al. (2012) who emphasizes that collectivistic leadership is most effective in environments characterized by shared responsibilities, informal communication and adaptive decentralized structures. The empirical evidence aligns with this view, as Companies C and F explained that they use AI as a supportive tool instead of a controlling mechanism. These companies also demonstrated stronger collectivistic leadership traits than the rest of the four interviewed companies. Furthermore, Company E, which demonstrated the highest AI intensity, scored lowest across collectivistic leadership categories. This is similar to the concerns raised by Davenport and Kirby (2016) who stated that overreliance on AI can result in diminished human input and lower collaborative leadership. The findings about Company E can also be connected to the claims made by Benbya et al. (2020) who noted that while AI enables algorithmic management, these structures can unintentionally reintroduce centralization by making decision-making processes more systematic. Studies conducted by Maddula (2018) and Carter & DeChurch (2012) show the positive role of AI in enhancing group collaboration if it is embedded in a context that values inclusivity and shared vision. This is evident with Companies D and C, where AI tools were seen as communication improvers across various departments.

2.4 Limitations and recommendations for further research

While this study has offered useful insights for the researcher, it is necessary to bring out the limitations and recommendations for future research. This study focused solely on selected six Estonian IT sector SMEs. As the selected company sizes ranged from 20-50 employees it gave the researcher a relatively small sample size to work with for both the quantitative analysis as well as the qualitative analysis part. This means that the research cannot be used to generalize the results to a wider population of Estonian IT sector SMEs. To address this restriction, future research should use a wider selection of companies to improve the overall sample size for both the quantitative and qualitative analysis parts. By involving more companies in the research, it is possible to get more diverse samples and a better representation of the target population. Furthermore, the study's focus is on certain businesses and only on Estonian companies, which limits the findings application to only Estonia. To improve external validation, future research should investigate the relationship between AI and collectivistic leadership in other industries as well as other geographical regions. Current quantitative and qualitative data was collected within a 60-day period which limits the ability to observe changes within selected companies over a period. Future research should focus on measuring the relationship over a selected period, as the world of artificial intelligence is continuing to evolve. Although the qualitative interview data was carefully thematically coded, the applied AI Intensity Index, which was used for measuring the extent of artificial intelligence integration within the company's commercial team's procedures, the scoring is based on the researcher's interpretations of qualitative interviews. This can introduce a potential researcher bias. For future research, it is recommended that the AI usage information is also included in the quantitative questionnaire. This would allow for analyzing the AI usage and integration perception across the organization. Qualitative interviews can then be used for validating questionnaire perceptions as well as analyzing the emerging key differences.

Conclusion

In conclusion, this study explored what is the potential relationship between Artificial Intelligence (AI) adoption and collectivistic leadership in the context of Estonian IT small and medium sized enterprises. The researcher combined both qualitative and quantitative questionnaire methods, utilizing mixed methods approach. During the research, 104 questionnaire responses and 12 qualitative interviews were analyzed. Through the Organizational Leadership Capability (OLC) model built by Kivipõld and Vadi (2010), the AI Intensity Index and Perrow's technology framework, the study provided a nuanced understanding of how different levels of AI application relate to leadership traits such as decision-making, autonomy, feedback and internal communication. The research findings contradict the assumption that advanced technological solutions equal in more open and agile organizations. The research results suggest that there is a moderate but consistently negative relationship between AI intensity and collectivistic leadership views. Although this study sample was not statistically significant due to the sample size of 6 companies, the negative correlation between the AI Intensity and OLC scores show that high internal AI usage may reduce the collectivistic leadership traits within companies. This is illustrated by Company E, which recorded the highest AI Intensity but reported the lowest OLC scores out of the six interviewed companies. On the other hand, Company F questionnaire respondents displayed strong collectivistic leadership traits, but are not actively pursuing AI as a critical component in their decision-making or workflows. These findings are backed by the interview thematic analysis results which show that companies with a well-established collectivistic leadership traits have adopted AI as a supportive tool which assists with already existing team-based processes and decision-making.

Although this thesis provided valuable insights, it has many limitations which should be explored in future research. This study's small sample size in combination with the research taking part in Estonia, limit the generalization to a wider audience. Further studies should extend the research to a larger sample size to provide results that can be generalized to a greater spectrum of companies.

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APPENDIX 1

Interview categories coding

Company name	Question Category	Answer	Categorization
Company A	AI in internal workflows	AI used for lead generation; automatic sales tasks, reaching out to contacts	Core
	AI in decision-making	AI lead suggestion, employees maintain final decision making	Supports decisions
	AI in products and services	web shop product with AI assistance for customers	Limited use
	AI autonomy level	AI is an assistant, employees have full control over accepting or rejecting AI	Assistive
	Perceived impact of AI	AI increases efficiency, supports teamwork, does not change leadership styles	Moderate
Company B	AI in internal workflows	AI used for SDR tool, customer targeting, marketing content	Core
	AI in decision-making	AI offers insights, teams decide independently	Supports decisions
	AI in products and services	Not embedded yet	No integration
	AI autonomy level	AI acts purely as a suggestion tool	Manual use
	Perceived impact of AI	Improved collaboration and transparency, collectivistic leadership stronger	Significant
Company C	AI in internal workflows	AI processes documents, marketing automation, and fraud prevention	Regular
	AI in decision-making	AI influences final decisions in sales and marketing investment	Reoccurring use
	AI in products and services	Some automation embedded in software	Limited use
	AI autonomy level	Employees have full autonomy, optional employee AI assistance	Assistive
	Perceived impact of AI	Easier collaboration within the team	Moderate
Company D	AI in internal workflows	AI used by all employees for text creation, SDR tool testing	Supportive
	AI in decision-making	Inspires decision-making, helps to brainstorm, humans make final decision	Supports decisions
	AI in products and services	Plan to embed into customer websites in 2025	No integration

	AI autonomy level	AI suggests, humans decide, low level supportive tool	Manual
	Perceived impact of AI	Sales efficiency improved, teams slightly more independent	Moderate
Company E	AI in internal workflows	AI deeply embedded, product design, marketing, customer support	Core
	AI in decision-making	Often used in decision making but not fully automated	Reoccurring use
	AI in products and services	AI is embedded into the product extensively, key component	Essential part
	AI autonomy level	All employees retain autonomy, AI is an assistant	Assistive
	Perceived impact of AI	Increased efficiency, AI brings in more innovation	Transformative
Company F	AI in internal workflows	AI used in marketing campaign assistance	Supportive
	AI in decision-making	AI provides insights, final decisions made by the team	Supports decisions
	AI in products and services	AI incorporated into customer support on a low level	Limited use
	AI autonomy level	AI only offers guidance if needed, employees retain autonomy	Manual use
	Perceived impact of AI	Data-informed decision making, improved collaboration within teams	Moderate

Note: Interview category labels correspond to the structured grouping of the 26 questions outlined in Appendix 3

APPENDIX 2

Organizational Leadership Capability questionnaire

Dear Respondent,

The purpose of this questionnaire is to assess organizational leadership, specifically the collective leadership capabilities within your organization. Completing the questionnaire is anonymous and takes approximately 10 minutes. The raw data collected through this survey will be fully accessible only to the employees of your company. When publishing processed survey results, your possible preference to keep the company's name confidential will be strictly respected.

Thank you for your cooperation!

Please indicate your gender

Male Female Other/prefer not to specify

Please indicate your age
up to 30 years 31-50 years over 50 years

Please indicate your highest education
Secondary education Bachelor's degree Master's degree or higher

Please indicate the length of your work experience in the IT field
1-5 years 5-10 years more than 10 years

Alignment and cohesion

1. We have a common understanding and knowledge of operational plans and programs (business strategy)
Do not agree at all 1 2 3 4 5 6 7 Completely agree

2. We have set both main purpose and interim objectives
Do not agree at all 1 2 3 4 5 6 7 Completely agree

3. My personal objectives align with the company's long-term objectives
Do not agree at all 1 2 3 4 5 6 7 Completely agree

4. I am actively involved in setting our objectives and putting them into practice
Do not agree at all 1 2 3 4 5 6 7 Completely agree

Informal communication

1. We socialize with our co-workers after business hours
Do not agree at all 1 2 3 4 5 6 7 Completely agree

2. Our organization arranges gatherings that are not work related*
Do not agree at all 1 2 3 4 5 6 7 Completely agree

3. Our organization arranges work related gatherings*
Do not agree at all 1 2 3 4 5 6 7 Completely agree

4. Our organization has spaces (rest areas) where we gather to interact with colleagues
Do not agree at all 1 2 3 4 5 6 7 Completely agree

Extent of centralization

1. At work, everyone is treated as equals
Do not agree at all 1 2 3 4 5 6 7 Completely agree

2. All employees have sufficient freedom in their work
Do not agree at all 1 2 3 4 5 6 7 Completely agree

3. We make important decisions using the process of common discussion*
Do not agree at all 1 2 3 4 5 6 7 Completely agree

4. Decisions are based primarily on experience and competence, not on job positions*

Do not agree at all 1 2 3 4 5 6 7 Completely agree

Control-feedback system

1. I consider our control methods to be fair
Do not agree at all 1 2 3 4 5 6 7 Completely agree

2. Good results are noticed
Do not agree at all 1 2 3 4 5 6 7 Completely agree

3. Good results are sufficiently recognized
Do not agree at all 1 2 3 4 5 6 7 Completely agree

4. In our organization employees and employers discuss together the expectations of employees
Do not agree at all 1 2 3 4 5 6 7 Completely agree

Organizational performance

1. Our organization uses the full potential and abilities of its workers
Do not agree at all 1 2 3 4 5 6 7 Completely agree

2. Our organization offers good developmental opportunities
Do not agree at all 1 2 3 4 5 6 7 Completely agree

3. Our organization is forward-looking
Do not agree at all 1 2 3 4 5 6 7 Completely agree

4. Our organization deals with increasing work performances
Do not agree at all 1 2 3 4 5 6 7 Completely agree

5. Our organization is successful
Do not agree at all 1 2 3 4 5 6 7 Completely agree

6. Our organization successfully withstands competition in the future
Do not agree at all 1 2 3 4 5 6 7 Completely agree

APPENDIX 3

Interview questions and categories

AI in internal Workflows (7 questions)

1. Can you describe how AI is currently used within your organization?
2. Which AI tools, software, or technologies does your company currently use?
3. How long has your company been using AI?
4. How does AI support your sales and marketing activities?

   a. Does it assist with customer segmentation, lead generation or personalized marketing?
   b. Are AI-driven chatbots or virtual assistants used for customer support?
   c. How does AI contribute to forecasting sales or customer behavior?

AI in Decision-Making (6 questions)

5. To what extent do employees in commercial teams rely on AI tools for decision-making?
6. How does AI impact decision-making within your teams?
   a. Does AI provide recommendations and do teams follow these?
   b. Do employees have autonomy, or does AI dictate their workflow?
7. Do you believe AI affects leadership styles in your organization?
8. Has AI led to any shifts in power dynamics within your organization?

AI in Products and Services (4 questions)

9. How does AI influence product or service development in your organization?
   a. Is AI used in automating processes, predictive analytics or product recommendations?
   b. Are AI-driven solutions embedded in your company’s products?
10. What future plans do your company have for expanding AI use?

AI Autonomy Level (4 questions)

11. Who drives AI adoption in your organization?
12. Has AI changed the way your teams collaborate or innovate? If so, how?
13. What challenges have you encountered in integrating AI into your product development processes?
14. How dependent is your company on AI for core business processes? (supportive tool, essential tool?)

Perceived Impact of AI (5 questions)

15. Have you observed any improvements in efficiency or performance due to AI use in sales and marketing?
16. Are there any challenges or limitations in using AI within sales and marketing?
17. Would you say AI fosters a more collectivistic or individualistic leadership model?
18. How frequently do employees engage with AI tools in their daily work?

19. How advanced would you rate your company's AI usage compared to industry peers?

Resümee

Tehisaru ja kollektivistliku eestvedamise omavaheline seos

Tänapäeva tiheda konkurentsi ja kasvava konkurentsiga ärimaastik nõuab ettevõtetelt uute ja efektiivsemate organisatoorsete juhtimisstiilide kasutuselevõttu. Kollektivistlik eestvedamine on organisatoorse eestvedamise praktika kus rõhk on pandud just jagatud otsustele, meeskondlikule koostööle ning ühistele eesmärkidele (Yammarino et al. 2012). Tehnoloogiavaldkonnas on viimastel aastatel on üha enam tähelepanu pööratud uuele tehnoloogiale – tehisaru (AI). Paljude autorite arvates on tehisarul potensiaali muuta ettevõttesisest koostööd, strateegilist juhtimist ja otstusvõimet. Käesoleva uurimustöö eesmärk on uurida kas kollektivistlikul eestvedamisel ja tehisarul on omavaheline seos.

Uurimustöö fookuses on kuus Eesti IT valdkonna ettevõtet keda uuriti läbi kombineeritud metoodika. Valitud ettevõtete töötajad vastasid organisatoorse eestvedamise võimekuse küsimustikule ning teiseks intervjureeriti iga ettevõtte kommertsosakonnast kahte juhti. Intervjuu eesmärk oli saada arusaam antud ettevõtete tehisaru kasutusest, mis eesmärgil neid tööriistu kasutatakse ning kas tehisaru on kaasatud ka ettevõtte otsustusprotsessidesse. Töö käigus analüüsiti iga ettevõtte küsimustu ja intervjuu vastuseid eraldi. Uuringu tulemused näitasid mõõdukat, kuid järjepidevat negatiivset seost AI intensiivsuse ja kollektivistliku juhtimise vahel. Kõige kõrgema AI intensiivsusega ettevõte (ettevõte E) saavutas kõige madalamad tulemused kollektivistliku juhtimise mõõdistikul. Vastupidiselt sellele näitas ettevõte F, kus on mõõdukam AI kasutus, kõrgemaid kollektivistliku juhtimise näitajaid. Ettevõtted kes kasutavad oma igapäevaülesannetes intensiivselt tehisaru ja kelle otsustusprotsessidesse on see tööriist suuresti põimitud, olid küsimustiku vastuste põhjal pigem individualistlike juhtimistunnustega. Ettevõtted kes kasutavad tehisaru toetava tööriistana ning otseselt ei lähtu tehisaru ettepanekutest olid küsimustike vastuste põhjal kõrgete kollektivistlike eestvedamistunnustega.

Kuigi uurimistöö vastas autori esitatud küsimustele on sellel siiski mitmeid piiranguid, mis tulenevad piiratud valimist ning Eesti IT valdkonna ettevõtetele keskendumisest ning valimi suurusest (n=6). Tulevased uuringut peaksid uuringu valimit laiendama ning keskenduma nii suuremale geograafilisele piirkonnale kui ka rohkematele tööstusharudele.

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