Board Effectiveness and Artificial Intelligence Disclosure

A quantitative study analysing the relationship between the effectiveness of the board of directors and disclosures regarding Artificial Intelligence

BUSN79 Degree Project in Accounting and Finance

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Executive summary

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Five key words: Corporate Governance, Board of Directors, Board Effectiveness, Disclosures, Artificial Intelligence

Purpose: The purpose of this study is to investigate how the board effectiveness in Swedish companies listed on OMX Stockholm Large Cap affects disclosures regarding Artificial Intelligence in their Annual and Sustainability reports between the year 2019 to 2022.

Methodology: The study is based on a quantitative method with a deductive approach. Two models are conducted to test the hypotheses of the study; a logistic regression model and a multiple linear regression model.

Theoretical perspectives: The theoretical background of this study is based on Stakeholder, Signalling, Legitimacy and Agency Theories. The expected effect of board effectiveness is analysed through the lenses of those theories to explain the approach towards AI disclosures.

Empirical foundation: The study is based on 121 firms listed on OMX Stockholm Large Cap. The data was collected for the period of four years from 2019 to 2022, giving a final sample of 464 observations.

Conclusions: This study provides empirical evidence for a positive influence of two of the one-dimensional measures of board effectiveness, board independence and board size, on the volume of AI disclosures made by Swedish companies. No support is found for the impact of board effectiveness on the decision to disclose AI-related information as well as board specific skills and the volume of AI disclosures.

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Abstract

As a relatively new phenomenon, Artificial Intelligence (AI) has already proven itself to carry the ability to transform modern-day society. With increased AI use becoming more and more prevalent, both its benefits and potential consequences come to light. Companies wishing to reap the benefits AI can offer also need to consider the possible risks associated with its adoption. Many companies decide to voluntarily disclose information about AI, whether about the use and deployment, the ethical implications or general statements about the phenomenon. The purpose of this study is to investigate the relationship between the effectiveness of the board of directors of Swedish listed firms and AI disclosures. No previous studies have looked at this particular relationship, and this paper is the first to use a comprehensive measure of board effectiveness, the Board Effectiveness Index, in Sweden. Two regression models are conducted on a sample of 121 Swedish companies listed on the OMX Stockholm Large Cap. The results indicate a non-significant relationship between the decision to disclose AI-related information and board effectiveness, however a positive and significant relationship between AI disclosure volume and board size as well as board independence can be established. Board skills show a non-significant relationship with the volume of AI disclosure. The study makes a contribution in the field of corporate governance and corporate disclosure.

Keywords: *Corporate Governance, Board of Directors, Board Effectiveness, Disclosures, Artificial Intelligence*

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1. Introduction

In this section, the background and the problematisation of the topic is presented. This is followed by the purpose of the study leading to the research question.

1.1 Background

Over the years, Artificial Intelligence (AI) has been thought of as an integral part of futuristic societies from science-fiction movies and novels; nowadays it has become a new reality in the modern high-tech societies (Goralski & Tan, 2020). Although there are many definitions of AI, the authors consider one of them especially: "systems that display intelligent behaviour" (European commission, 2019a, p. 1). Putting it simply, the core concept of AI development strives to create machines that can think and act like humans (Goralski & Tan, 2020; Marr, 2018). AI has application in a variety of industries, ranging from education to waste reduction, oil and gas management, healthcare and accounting. As a result, tremendous potential coming from the use of AI can bring benefits in terms of solutions to social and environmental challenges (Ministry of Enterprise and Innovation, 2018). Increasingly, AI displays potential to change the very basic parts of human nature – the way humans live, learn, communicate and work (Goralski & Tan, 2020). According to PriceWaterhouseCoopers, global GDP could increase by up to 14% by 2030 as a direct result of AI, making it one of the largest commercial opportunities in modern times (PwC, 2017). Consequently, AI adoption, integration and ethical dilemmas surrounding it have become a top priority for companies wishing to seize the benefits that this technology could potentially offer. Therefore, the implications of the use of AI must be considered in order for the risks to be handled in a responsible way (Ministry of Enterprise and Innovation, 2018); social and ethical implications AI has on companies and stakeholders should be considered in detail (Bonsón, Lavorato, Lamboglia, & Mancini, 2021).

National differences in the treatment and approach of AI strategies are evident. Sweden adopted a model of 'command and control' meaning that the state plays an important role in protecting its citizens from the risks involved with AI application, as well as tight regulation (Papyshev & Yarime, 2023). Policy instruments involved include academic discipline regarding AI as well as strong ethical principles (Papyshev & Yarime, 2023). Sweden aspires to be a world leader in digital transformation, as countries that successfully harness the benefits coming from AI in a sustainable manner will have significant competitive advantage (Ministry of Enterprise and Innovation, 2018). At the present time, disclosures regarding AI remain voluntary in Sweden, hence due to data availability and Sweden's national approach towards AI being characterised as organised and controlled therefore investigating approaches to AI disclosure was interesting to the authors.

Through creating new, innovative services and completely new business models, AI has the potential to radically disrupt existing markets, making approach to AI a priority for modern companies and their corporate boards (PwC, 2017). European Commission (2018) stresses that increasing human trust in AI-based systems is a prime concern, and one way to do so is for companies to disclose information regarding the use of AI (Bonsón et al. 2021). Disclosures can be thought of as means of communication between companies' board of directors and their stakeholders, particularly investors, so many boards opt to voluntarily supply more information than the law currently requires them to (Pernamasari, 2020). Healy and Palepu (2001) state that boards act on their incentives to voluntarily supply various non-financial and financial information to stakeholders. Previous research has investigated many forms of voluntary disclosure, and the extent of voluntarily supplemented information varies from company to company (Ciaponi & Mandanici, 2015; Pernamasari, 2020). This information includes, but is not limited to, cybersecurity, environmental and social issues and AI. As AI becomes increasingly prominent in everyday life, board of directors need to consider stakeholder interest in this area, especially as stakeholder interests start to be included more often in Codes of Best Practices (Szabó & Sørensen, 2013). Pigé (2002) states that corporate boards are a medium for the exchange of information between management and the company's stakeholders. The effectiveness of a board refers to a board of directors that is able to reach its objectives (Van den Berghe and Baelden, 2005), and is further based on the boards composition and attributes (Smaili, Radu & Khalili, 2022). Given the potential benefits and drawbacks of voluntary disclosure of information and that voluntary disclosures become the boards' responsibility (Ben-Amar & McIlkenny, 2015), a relationship between the effectiveness of boards of directors and AI disclosures could be investigated based on previous research.

1.2 Problematisation

As digitalisation has increased in recent years, the European Union (EU) and other European countries have put more emphasis on AI by introducing regulations and encouraging AI innovations (Bonsón et al. 2021). This has led companies to making disclosures regarding their AI activities, which is also of importance to its stakeholders (Bonsón et al. 2021). Forms of AI use include automated intelligence, assisted intelligence, augmented intelligence and autonomous intelligence (PwC, 2017). As the lines between human and machine tasks are becoming increasingly blurred, issues arise regarding ethical considerations and regulation (PwC, 2017).

Disclosures related to AI are voluntary in Sweden, meaning that Swedish companies can decide if they should disclose AI related information in their Annual and Sustainability Reports and if so, to what extent, which have led companies to disclosing AI-related information in different ways (Bonsón et al. 2021). Previous studies have shown that voluntary disclosures can have benefits for the company. According to Dhaliwal, Li, Tsang and Yang (2011) voluntary non-financial disclosures can lead to a reduction in companies' cost of equity capital. Furthermore, Chijoke-Mgbame, Mgbame, Akintoye and Ohalehi (2019) found positive performance implications for companies making voluntary non-financial disclosures. These findings could give incentives for boards of directors to disclose voluntary non-financial disclosures, such as AI related information, to its stakeholders.

Studies of corporate governance often look at the composition and attributes of the board of directors as determinants of corporate disclosure. Smaili, Radu and Khalili (2022) studied the relationship between board effectiveness and cybersecurity disclosures. The authors found that the decision to disclose voluntary non-financial disclosures is positively affected by the effectiveness of the company boards, and that the amount of voluntary non-financial disclosures is affected by financial expertise within the company and directors' independence. In another study conducted by Ben-Amar and McIlkenny (2015), the authors look at the relationship between voluntary climate change disclosures and the effectiveness of board of directors. The authors found that companies with effective boards are more willing to disclose voluntary non-financial information to its stakeholders. Both of the articles study the relationship between board effectiveness and voluntary non-financial disclosures in Canada (Ben-Amar & McIlkenny, 2015; Smaili, Radu &

Khalili, 2022). This makes it interesting to research if a similar relationship can be found between board effectiveness and voluntary non-financial disclosures, in this case AI disclosures, in Sweden.

According to Swedish guidelines regarding corporate governance, external communication should be characterised by openness and accuracy (Swedish Corporate Governance Board, 2020). This paper will look in more detail into certain board characteristics and their impact on the volume of AI-related disclosure as published by Swedish companies. Board effectiveness as a comprehensive measure of the board's ability to govern efficiently has not been previously examined in Sweden, and, to the best of the authors' knowledge, in an European country. Rather than focus on one-dimensional measures of board effectiveness, such as only looking at board independence, board skills and board specific skills, this paper constructs a Board Effectiveness Index in accordance with Wattanatorn and Padungsaksawasdi (2022). More effective boards disclose more information relating to risk management to signal the company's commitment to reducing such risks (Ben-Amar & McIlkenny, 2015). Furthermore, more effective boards exert more control over management, and therefore should be characterised by higher transparency (Fama, 1980). As a result, the decision to disclose AI information should be influenced by how effective the board is in achieving its objectives. In this paper the authors, supported by previous research, argue that certain board attributes, such as board skills, board independence and board size, will influence the amount of information regarding AI that companies choose to disclose in their Annual and Sustainability Reports. Changes in disclosures are rarely random, but rather reflect governance mechanisms (Healy & Palepu, 2001), highlighting the importance of studying the relationship between corporate governance and disclosures. Adding to this, no research has been conducted regarding the board effectiveness and its impact on voluntary non-financial disclosures in Sweden, more specifically the relationship between board effectiveness and disclosures related to AI in Swedish companies. Therefore, this study aims to fill this research gap and contribute to existing research on AI, corporate governance, board composition and voluntary non-financial disclosures.

1.3 Purpose

The purpose of this study is to investigate how the effectiveness of the board of directors in Swedish companies listed on OMX Stockholm Large Cap affects disclosures regarding Artificial Intelligence in their Annual and Sustainability Reports between the year 2019 to 2022. The purpose leads to the following research question.

Does board effectiveness have an impact on disclosures regarding Artificial Intelligence in companies listed on OMX Stockholm Large Cap?

2. Theoretical background

In this section, definitions of Artificial Intelligence and disclosures are presented, followed by a description of the board oversight role. Then the theoretical frameworks used to further develop the hypotheses of the study are introduced.

2.1 Artificial Intelligence

AI is defined as “systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals” (European commission, 2019a, p. 1). These systems can be integrated with hardware devices, such as self-driving cars or robots with advanced technologies, or be entirely based on software, such as systems for face and speech recognition or voice assistance programs (European commission, 2019a).

Apart from the central role AI will have on companies' future sustainable development, it is important to be aware of the ethical and social implications AI has on companies and its stakeholders (Bonsón et al. 2021). The explainability and development of AI systems in a way for humans to understand them and their actions is important, as this could increase transparency and decrease the risk of errors or biases within the systems, which could further increase the trust humans have in such systems (European Commission, 2018). Disclosing information regarding AI could therefore be a highly effective way for companies to act in line with such needs (Bonsón et al. 2021).

2.2 Disclosures

Disclosures are broadly defined as “the communication of economic information, whether financial or nonfinancial, quantitative or otherwise concerning a company’s financial position and performance” (Owusu-Ansah, 1998, p. 608). Disclosures can be either voluntary or mandatory (Shehata, 2014). Meek, Roberts and Gray (1995) define voluntary disclosures as “free choices on the part of company managements to provide accounting and other information deemed relevant to the decision needs of users of their annual reports.” (p. 555). Mandatory disclosures surround all the information a company provides to stakeholders that serves a purpose of complying with laws and regulations (Shehata, 2014). Lang and Lundholm (1993) argue that annual reports serve as a good representation for companies' disclosure levels.

2.3 Board oversight role

Cullen and Brennan (2017) state that the boards of listed companies are assumed to have complete power over three roles – oversight, monitoring, and control. This idea is corroborated by Jensen and Meckling (1976) who voice that the responsibility of controlling the corporation rests in the hands of the board of directors. The oversight role extends to identifying and managing material risks to the company and considering them in the company's risk management systems; this is thought to be a fiduciary duty of corporate boards (Ben-Amar & McIlkenny, 2015; Desjardins & Willis, 2011). Corporate boards further act as a medium for information exchange between stakeholders and management (Pigé, 2002). It is universally agreed that in order to exercise its monitoring function effectively, board members need both experience and capabilities (Hillman & Dalziel, 2003); therefore it is understood that the attributes of the board will have an impact on the behaviour of the firm (Arayakarnkul, Chatjuthamard & Treepongkaruna, 2022; Chindasombatcharoen, Chatjuthamard, Jiraporn & Treepongkaruna, 2022; Zubeltzu-Jaka, Álvarez-Etxeberria & Ortas, 2020).

The Swedish Corporate Governance Code specifies the requirements for the composition of the board of directors for Swedish listed companies. Consequently, boards are required to fulfil a number of criteria, including that board members should "…exhibit diversity and breadth of qualifications, experience and background" (Swedish Corporate Governance Board, 2020, p. 17). The characteristics and composition of the board serve as means for directing and achieving the company's strategy. Most importantly, the code specifies that any external communication from the company should be reliable and accurate, as well as it should be characterised by openness (Swedish Corporate Governance Board, 2020). Following such guidelines could result in Swedish listed companies disclosing voluntary information about AI to their stakeholders.

2.4 Stakeholder theory

Developed societies have become increasingly concerned with matters such as ethical treatment of workers, sustainability and environmentalism and as a result the Stakeholder Theory has gained in popularity (Freeman, 1984). Since the late 20th century, many academics agree on taking the stakeholder approach to corporate governance (Garcia-Torea, Fernandez-Feijoo & de la Cuesta, 2016; Letza, Sun & Kirkbride, 2004). This is further corroborated by stakeholder interests being increasingly included in Codes of Best Practices (Szabó & Sørensen, 2013). The stakeholder theory acknowledges that besides shareholders, other audiences exhibit an interest in the company's actions and behaviour and might therefore be interested in information regarding such behaviour (Fuente, García-Sánchez & Lozano, 2017). It is important to highlight that taking a stakeholder perspective does not equal promoting stakeholder interests over the ones of shareholders (Garcia-Torea, Fernandez-Feijoo & de la Cuesta, 2016); rather, the breadth of corporate governance is extended by treating shareholders as a type of stakeholder with equal rights (Money & Schepers, 2007). As a direct result of increasing stakeholder pressure, firms are incentivised to disclose more information (Smaili, Radu & Khalili, 2022). Stakeholder theory postulates that the corporate board is responsible for balancing the often conflicting needs of various stakeholders (Pigé, 2002). Fuente, García-Sánchez and Lozano (2017) further state that the board of directors should take actions to maximise the welfare of the audiences that are either directly or indirectly impacted by a company's actions; by doing so the boards would ensure the company's survival in the long term. Based on stakeholder theory, an effective board of directors is expected to reduce information asymmetry between stakeholders and management (Smaili, Radu & Khalili, 2022).

Regarding AI diffusion, the stakeholder theory emphasises the role various stakeholders and audiences have in the process; for instance public-private partnerships, and the joint role of businesses, start-ups, policymakers and academic institutions, amongst others (European Commission, 2021; Leszkiewicz, Hormann & Kraft, 2022). As a result, various groups may have an interest in learning about the company's individual use and attitude towards AI. Building on this, Leszkiewicz, Hormann & Kraft (2022) develop a concept called the "Social value of AI", which brings together the benefits and concerns surrounding AI to various stakeholder groups.

Increased presence of AI disclosures could help firms address the needs of those stakeholders concerned with the increased use and deployment of AI in the company's operations.

2.5 Signalling theory

The cornerstone of signalling theory is to reduce the information asymmetry that could occur between two parties; the signaller and the receiver (Connelly et al. 2011; Spence, 2002). The board of directors are the signallers, as they are insiders of the company who get access to information not available for outsiders (Bonsón et al. 2021). The outsiders of the company are the receivers, in this case the stakeholders, who want to receive the information about the company that only the insiders have access to (Bonsón et al. 2021). The signaller needs to decide if and how they should signal the information, while the receiver has to determine how they should interpret this signal (Connelly et al. 2011). When the board of directors sends the signal, it is assumed to be favourable for them, therefore, companies of high quality could benefit from signalling its advantages to the receivers (An, Davey & Eggleton, 2011). According to Bonsón, Bednárová and Perea (2023) companies have incentives to signal their investments in new technologies, such as AI, to attract new investors. Furthermore, the authors state that companies have incentives to disclose their unobservable characteristics, for instance increased efficiency, sustainability, or value creation that is related to the companies' AI application. Increased transparency through disclosing information regarding the companies' AI activities could lead to increased trustworthiness from the stakeholders towards the companies' processes and products (Bonsón, Bednárová & Perea, 2023).

2.6 Legitimacy theory

Corporate legitimacy is defined as "a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially-constructed system of norms, values, beliefs and definitions" (Suchman, 1995, p. 574). According to Deegan (2022), companies need to legitimise their operations to access resources needed for the continuity of their operations. One of the means to ensure legitimacy strategy is to disclose voluntary and mandatory information about the company's operations (Dumay, Frost & Beck, 2015). A variety of studies support that legitimacy theory provides an explanation for non-financial disclosure. According to Bonsón et al. (2021), legitimacy theory views disclosures as means to reduce the legitimacy gap, by aligning stakeholder expectations and corporate behaviour; furthermore, companies must constantly revise their activities in order for those activities to be socially acceptable.

Suchman (1995) divides organisational legitimacy into three types: cognitive, moral and pragmatic. Cognitive legitimacy is achieved through convincing outsiders that their actions and objectives are desirable and socially accepted (Suchman, 1995). Companies can achieve cognitive legitimacy by disclosing trustworthy and comprehensive information about AI use (Bonsón et al. 2021). Moral legitimacy aims to promote the social welfare aspect of the company's activities, and rests on judgements (Suchman, 1995). In terms of disclosing AI-related information, companies should approach it through ethics; moral legitimacy further requires disclosing information about the possible risks and benefits of AI (Bonsón et al. 2021). Consequently, legitimacy is achieved through susceptibility to trustworthy AI (Bonsón et al. 2021). Finally, pragmatic legitimacy is the exchange of interests between the company and its audience (Suchman, 1995). In line with legitimacy theory, corporate boards should strive to legitimise their actions and objectives, and consequently disclose information about the use and deployment of AI in their operations.

2.7 Agency theory

One theory commonly used in previous research regarding board effectiveness and voluntary disclosures is Agency Theory. According to Jensen and Meckling (1976) the theory is based on the relationship between a principal, who in this study are the shareholders, and an agent, in this case the management. The principal delegates authority to the agent to act and make decisions on behalf of the principal (Jensen & Meckling, 1976). In this relationship, agency costs could occur when there is a lack of written and enforced contracts between the parties and separation of ownership and control, or conflicting interests between the parties (Arayakarnkul, Chatjuthamard & Treepongkaruna, 2022; Fama & Jensen, 1983; Jensen & Meckling, 1976). Given that both the principal and the agent are utility maximisers, there is a possibility that the agent will act against the principal's best interest (Jensen & Meckling, 1976). To reduce the risk of such agency conflicts, the board of directors monitors the management on behalf of the shareholders as they hold the power to control over the management and check that their actions are in line with the shareholders' best interest (Ben-Amar & McIlkenny, 2015; Fama & Jensen, 1983; Hill & Jones, 1992; Jensen & Meckling, 1976). In the study of Ben-Amar and McIlkenny (2015), the authors found that if the board of directors and the shareholders' interests are aligned, their ability to work more effectively when working towards completing their fiduciary duties will increase. Based on this finding, the authors could conclude that effective boards have a positive correlation with the fulfilment of the stakeholders' and investors' need for the firm to disclose voluntary non-financial disclosures (Ben-Amar & McIlkenny, 2015).

2.8 Hypotheses development

2.8.1 Board effectiveness

Van den Berghe and Baelden (2005) refer to an effective board of directors as one that achieves its objectives. In the case of this study, board effectiveness is defined equally. Furthermore, an effective board is presumed to be aware of stakeholder demands regarding AI disclosure, and chooses to disclose such information voluntarily.

In the past, researchers have disputed what factors contribute to board effectiveness. Van der Walt and Ingley (2000) point out certain themes that have emerged from corporate governance literature, including board composition and structure, director selection and performance evaluation criteria. According to John and Senbet (1998), independence, size and composition determine board effectiveness. Patelli and Prencipe (2007) highlight that if the members of the corporate board are the same as the managers of the company, the effectiveness of that board as a control mechanism is slender. Bini et al. (2023) mention that effective corporate boards should actively monitor the consistency of non-financial disclosures to ensure comparability. Lorca, Sánchez-Ballesta and García-Meca (2011) further add other factors such as directors' expertise, split of chairman and CEO roles and the level of director ownership, amongst others. Ben-Amar and McIlkenny (2015) and Smaili, Radu and Khalili (2022) measure board effectiveness using the Board Shareholder Confidence Index (BSCI). The BSCI considers various factors that affect the confidence that shareholders have in the board's ability to fulfil its objectives and duties, and captures the alignment of shareholders' interests with those of the board members (Switzer & Cao, 2011). Such factors include group potential, directors' individual potential and past practices (Ben-Amar & McIlkenny, 2015). However, as the BSCI is based on Canadian companies (Smaili, Radu & Khalili, 2022), the Board Effectiveness Index (Mathew, Ibrahim & Archbold, 2018; Wattantorn & Padungsaksawasdi, 2022) is used in this study as a proxy to measure board effectiveness. More recently, Smaili, Radu and Khalili (2022) argue that shareholders' perception of board effectiveness is built through reading corporate disclosures.

Ben-Amar and McIlkenny (2015) found that more effective boards voluntarily disclose information related to risk due to their commitment to risk management in response to the demands of shareholders. In line with agency theory, higher transparency levels are expected from companies with effective boards as those can exert more control over the actions of management (Fama, 1980). Similarly, due to the growing interest in AI-related technologies, effective boards may be incentivised to legitimise the use and deployment of AI and thus may be willing to disclose AI-related information. Based on legitimacy, stakeholder and agency theories this study develops the following hypothesis.

H1: There is a positive relationship between board effectiveness and the decision to disclose information regarding Artificial Intelligence.

2.8.2 Board independence

Board independence is measured as the proportion of independent directors to the total number of members of the board in most corporate governance literature (Smaili, Radu & Khalili, 2022). Most studies, however, do not specify what is meant by an independent director (Smaili, Radu & Khalili, 2022). Fama and Jensen (1983) highlight the role of independent directors in limiting agency problems that arise as a result of possible collusion with top management.

Jensen and Meckling (1976) use positive agency theory to link corporate governance and the approach towards disclosures as devices used to reduce agency conflicts and protect investors. Furthermore, the board of directors is an important control mechanism for corporate governance, especially due to its monitoring and strategic functions as well as fiduciary obligations to the company's shareholders (García-Meca & Sánchez-Ballesta, 2010). According to Fama and Jensen (1983), the greater the proportion of independent members, the more effective the corporate board will be at monitoring managerial opportunism, and these companies are expected to provide more voluntary disclosures. In line with the signalling theory, Patelli and Prencipe (2007) found that independent board members use voluntary disclosures to signal to the market that they are effective in fulfilling their duties. Simultaneously, companies with reputation of transparency due to the high number of disclosures, have incentives to uphold that reputation by introducing more independent directors (Patelli & Prencipe, 2007). According to stakeholder theory, disclosure should increase due to the presence of independent members of the corporate board, as independent directors are better suited to represent the company's external environment and varying stakeholder demands (Hung, 1998).

Previous empirical studies have emerged with mixed results regarding board independence and the presence of voluntary disclosures. Studies such as those by Patelli and Prencipe (2007) found a positive non-significant association, whereas Brammer and Pavelin (2006) found significant support for the relationship. García-Meca and Sánchez-Ballesta (2010) found that corporations with less concentrated ownership structures and more independent board members are more inclined towards disclosing voluntary information, which is in line with agency costs arguments. Furthermore, the authors found a positive association between voluntary disclosure and board independence, especially for countries with strong investor rights. Smaili, Radu and Khalili (2022) found a positive relationship between board independence and voluntary cybersecurity-related disclosures, and Jizi, Salama, Dixon and Stratling (2014) mention that independent directors can reflect greater transparency. Based on the stakeholder, signalling and agency theories, this study has developed the following hypothesis.

H2: There is a positive relationship between board independence and the volume of disclosures regarding Artificial Intelligence.

2.8.3 Board size

Previous studies from the field of corporate governance state that board size is a crucial factor that determines board effectiveness (Coles, Daniel & Naveen, 2008; Donnelly & Mulcahy, 2008). De Andres and Vallelado (2008) found that larger boards have advantages over smaller boards in terms of efficiency in advising and monitoring management. Furthermore, various authors argue that larger boards bring together more individuals with diverse experiences, which can lead to increased transparency, and, in turn, disclosure (Gandía, 2008; Hidalgo, García-Meca & Martínez, 2011; Naseem, Rehman, Ikram & Malik, 2017). On the contrary, due to a large size, problems stemming from coordination issues between members can lead to the erosion of effectiveness (Coles et al. 2008; Lipton & Lorsch, 1992).

The relationship between board size and disclosure has had mixed results in empirical literature (Smaili, Radu & Khalili, 2022). Some researchers have noted a positive relationship (Jizi, 2017), while others found no significant relationship between board size and disclosure (Prado-Lorenzo & Garcia-Sanchez, 2010). Jizi (2017) found that larger board sizes have a positive relationship with disclosing Environmental Social Governance (ESG) information as a larger number of board members come from diverse backgrounds. In line with the agency theory argument that larger boards result in the increase of monitoring efficiency (De Andres & Vallelado 2008; Emre, 2016) as well as previous research, this paper puts forward the following hypothesis.

H3: There is a positive relationship between board size and the volume of disclosures regarding Artificial Intelligence.

2.8.4 Board specific skills

Erickson, Park, Reising and Shin (2005) found that financial and accounting experience of board members results in greater monitoring efficiency. This is further supported by findings of Elzahar and Hussainey (2012), who found that information asymmetry is reduced more efficiently when board members come from a financial and accounting background; as more information gets disclosed to stakeholders. Board members' skills and experience allow directors to provide alternative opinions on matters concerning the company (Gallego-Álvarez & Pucheta-Martínez, 2022). Bini, Giunta, Miccini and Simoni (2023) also state that companies with high-quality boards will disclose more information. Experienced members of corporate boards ensure that the quality of disclosed information is monitored to reduce information asymmetry, minimise litigation risks and ultimately protect the company's reputation (Lim, Matolcsy & Chow, 2007). Lim, Matolcsy & Chow (2007) further found that characteristics of the board are positively linked to strategic disclosures as well as voluntary disclosure quality.

Michelon and Parbonnetti (2012) stress the importance of non-financial disclosure on the relationship between stakeholders and the company through which legitimacy is established. Consequently, high board quality and effectiveness can be assumed to produce high quality non-financial information which can in turn strengthen stakeholder engagement and establish legitimacy. To the best of the authors' knowledge there is no previous research strictly on the relationship between AI-related disclosures and board specific skills. Based on prior research on non-financial voluntary disclosure as well as legitimacy and signalling theories, this paper presents the following hypothesis.

H4: There is a positive relationship between board specific skills and the volume of disclosures regarding Artificial Intelligence.

3. Methodology

This section presents the methodology of the study, starting with defining the research method, followed by introducing data collection, sample, variables, regression models, processing of data and model assumptions. The section ends with a discussion regarding the reliability and validity of the study.

3.1 Research method

To test the hypotheses of the study, a quantitative method with a deductive approach is used. Using a deductive approach infers starting with one or more theories with a preconceived vision of how something works, and then by using the data, the theories are tested (Sallis, Gripsrud, Olsson & Silkoset, 2021). A quantitative method was chosen as the study aims for a result showing numerical changes in measurable characteristics of the sample that could further be generalised to other resembling situations and give explanations of the predictions as well as the causal relationships (Salkind, 2010).

3.2 Data collection

Similarly to Smaili, Radu and Khalili (2022), a number of steps were followed to collect data on the presence and volume of AI-disclosures for the study's sample. The data was collected manually from Annual and Sustainability Reports for the years 2019 to 2022 released by selected companies on their own websites. The reports that could not be found on the companies' websites were collected from the Retriever Business database. To search for AI-related disclosures in the reports, the following keywords were used: *Artificial Intelligence, AI, Machine learning, Deep learning, Algorithm and Big data.* These keywords were selected as they were used in previous studies examining AI-related disclosures (Bonsón et al. 2021; Bonsón, Bednárová & Perea, 2023) and were therefore chosen for the purpose of this study. To make a quantitative analysis regarding the presence and volume of each company's AI-disclosures, the total words were copied from each Annual and Sustainability Reports and pasted to a Microsoft Word document to calculate the number of words related to AI-disclosures.

Data of all the study's independent and control variables besides industry membership were collected from the Refinitiv Eikon database. The data regarding each company's industry membership were accessed through Retriever Business. In an instance data were missing from the Refinitiv Eikon database, the data were supplemented through manual data collection in companies' Annual and Sustainability Reports as well as Retriever Business. Some independent and control variables were calculated manually. A high amount of Board meeting attendance data were not accessible from Refinitiv Eikon and/or Retriever Business, and were therefore manually calculated from disclosures found in Annual and Sustainability Reports as most companies voluntarily disclose detailed information regarding board meeting attendance. Market-to-Book (MTB) was calculated by dividing market capitalisation by shareholders' equity, both extracted from the Refinitiv Eikon database. Leverage was also calculated manually from total assets and total debt extracted from the Refinitiv Eikon database. Information regarding the percentage of board specific skills was mostly obtained from Refinitiv Eikon database and Retriever Business. Where such information could not be obtained, it was manually computed from information about each board members' educational background and experience, as disclosed in the companies' Annual and Sustainability Reports. A certain degree of judgement was used to determine whether the members' experience could be regarded as specific skills. For the purpose of this paper, industry-specific experience of 10+ years and/or a Master of Business Administration (MBA) were chosen as proxies. After members with such experience were identified, the percent of those was calculated from the total number of board members for a given year. Some data, for instance board independence, could not be sourced from either Eikon Refinitiv or Retriever Business and was therefore manually searched for in the companies' Annual and Sustainability Reports or calculated from meeting attendance information included in the reports.

3.3 Sample

The sample of this study initially consisted of 135 largest companies listed on the Stockholm Stock Exchange, forming the OMX Stockholm Large Cap Index for the year 2023. It should be noted that some of the companies listed in 2019 to 2022, may not have been listed on OMX Stockholm Large cap in 2023. This leads to a risk of survivorship bias in this study, where only the companies that have survived are examined (Brown, Goetzmann, Ibbotson & Ross, 1992). However, as this study is only looking at companies on the Large Cap list, the risk is assumed to be small.

Furthermore, the sample includes longitudinal data from 2019 to 2022, resulting in an initial observation sample of 540. As data for some companies are missing, those observations were excluded from the sample, which gave a final sample of 464 observations from 121 companies (see Appendix A).

Table 1: Summary of observations

Year	**2019**	**2020**	**2021**	**2022**	**Total**
Initial observations	135	135	135	135	540
Observations with missing data	24	21	15	16	76
Final observations	111	114	120	119	464

Table 1 summarises the initial number of observations per year, observations that were excluded due to missing data and final observations.

The industry breakdown of the sample is shown in Table 2 and is as follows: Corporate services (Företagstjänster) take up the largest proportion of the sample with 52.9%, followed by Banking, finance and insurance (Bank, finans & försäkring) at 15.7%. Manufacturing and industrial (Tillverkning & industri) and Real estate activities (Fastighetsverksamhet) account for 9.1% each. The rest of the sample comprises of Law, business and consulting services (Juridik, ekonomi & konsulttjänster) at 4.1%, Data, IT and telecommunications (Data, it & telekommunikation) at 3.3% and Wholesale (Partihandel) at 2.5%. Construction, design and interior design (Bygg-, design- & inredningsverksamhet) accounts for 1.7%. Technical consulting activities (Teknisk konsultverksamhet) and Education, research and development (Utbildning, forskning & utveckling) are the least represented sectors, accounting for 0.8% each. Table 3 below shows industry breakdown per year for the final set of 464 observations.

Table 2: Industry breakdown

Industry	**Number of companies**	**Percentage**
Corporate services	64	52.9
Banking, finance & insurance	19	15.7
Real estate activities	11	9.1
Manufacturing & industrial	11	9.1
Law, business & consulting services	5	4.1
Data, IT & telecommunications	4	3.3
Wholesale	3	2.5
Construction, design & interior design	2	1.7
Education, research & development	1	0.8
Technical consulting services	1	0.8
Total	**121**	**100**

Table 2 shows industry breakdown of the sample.

Table 3: Industry breakdown per year

Industry membership	**2019 (%)**	**2020 (%)**	**2021 (%)**	**2022 (%)**
Corporate services	63 (*56,76*)	63 (*55,26*)	64 (*53,33*)	63 (*52,93*)
Banking, finance & insurance	15 (*13,51*)	16 (*14,04*)	18 (*15,00*)	18 (*15,13*)
Manufacturing & industrial	9 (*8,12*)	11 (*9,65*)	11 (*9,17*)	11 (*9,24*)
Real estate activities	11 (*9,91*)	11 (*9,65*)	11 (*9,17*)	11 (*9,24*)
Data, IT & telecommunications	3 (*2,70*)	3 (*2,63*)	4 (*3,33*)	4 (*3,36*)
Law, business & consulting services	4 (*3,60*)	4 (*3,51*)	5 (*4,17*)	5 (*4,20*)
Wholesale	3 (*2,70*)	3 (*2,63*)	3 (*2,50*)	3 (*2,52*)
Construction, design & interior design	2 (*1,80*)	2 (*1,75*)	2 (*1,67*)	2 (*1,68*)
Technical consulting activities	0 (*0,00*)	0 (*0,00*)	1 (*0,83*)	1 (*0,84*)
Education, research & development	1 (*0,90*)	1 (*0,88*)	1 (*0,83*)	1 (*0,84*)
Total	**111 (*100*)**	**114 (*100*)**	**120 (*100*)**	**119 (*100*)**

Table 3 shows industry breakdown of the sample per year.

3.4 Variables

3.4.1 Dependent variables

Two dependent variables are used for AI-related disclosures in this study. Similar to Ben-Amar and McIlkenny (2015), a binary variable measuring the presence of AI-related disclosures is labelled AI_Discl_Decision, used in Equation 1. The value is 1 if the company discloses AI-related information, and 0 if not. The second dependent variable is the volume of AI-related disclosures, labelled AI_Discl_Vol, used in Equation 2, which consistent with Campbell (2004) is measured by the number of words the companies use to disclose AI-related information in Annual and Sustainability Reports.

3.4.2 Independent variables

3.4.2.1 Board effectiveness

The Board Effectiveness Index (Board_Effectiveness) is a self-constructed proxy for how effective the board is in achieving its objectives, as defined by Van den Berghe and Baelden (2005). Smaili, Radu and Khalili (2022) and Ben-Amar & McIlkenny (2015) in their models use the Board Shareholder Confidence Index (BSCI) developed by the University of Toronto to measure board effectiveness. As this data is only available for Canadian companies, in this study a proxy to measure board effectiveness of Swedish companies had to be computed manually. The Board Effectiveness Index used in this study has been constructed in line with the methodology of Mathew, Ibrahim and Archbold (2018) and Wattantorn and Padungsaksawasdi (2022). The index's composition focuses on the attributes of the board of directors and has the following components: *number of board meetings, board attendance, board specific skills, board size and board independence*. Indicator variables take values depending on whether the variables included in the index are below the sample median, or above or equal to the sample median.

$$Board\ Effectiveness\ Index_{i,t} = I.Board\_Meet_{i,t} + I.Board\_Attend_{i,t} + I.Board\_Skills_{i,t} + I.Board\_Size_{i,t} + I.Board\_IND_{i,t}$$

The first variable, number of board meetings (Board_Meet) refers to the number of documented board meetings in a given year. Board meetings are an important vehicle for suggestion and exchange of information, which in turn can have an impact on performance monitoring of management (Brick & Chidambaran, 2010; Wattantorn & Padungsaksawasdi, 2022). This measure includes both in-person meetings as well as virtual ones. The variable takes a value of 1 when the number of board meetings is greater or equal to the median for the sample, and 0 otherwise.

The second variable, board attendance (Board_Attend) is the average of overall percentage attendance at board meetings as disclosed by companies (Eikon Refinitiv, 2023). Low meeting attendance can be linked to a decline in quality monitoring by the board of directors, which in turn can have a negative impact on objective achievement by the board (Wattantorn & Padungsaksawasdi, 2022). The variable takes a value of 1 where the percentage attendance is greater or equal to the median for the sample, and 0 otherwise.

The third variable, board specific skills (Board_Skills) is defined as “Percentage of board members who have either an industry specific background or a strong financial background” (Eikon Refinitiv, 2023). In accordance with Erickson et. al. (2005), directors’ financial expertise can have a positive impact on board effectiveness through more efficient monitoring. Forbes and Milliken (1999) further argue that to increase the effectiveness of the board, directors should have firm-specific skills and experience. The variable takes the value of 1 if the percentage is greater or equal to the sample median, and 0 otherwise.

The fourth variable is board size (Board_Size). Karim, Vigne, Lucey and Naeem (2022) point out that larger board size can have a positive impact on the board’s monitoring functions. The variable takes a value of 1 if the number of directors is greater or equal to the median for the sample, and 0 if otherwise.

The final variable, board independence (Board_IND), refers to the percentage of independent board members as reported by the company in a given year. In accordance with Fama and Jensen (1983) greater board independence can lead to greater effectiveness in controlling the firm’s management. The variable takes a value of 1 if the percentage of independent directors is greater or equal to the median for the sample and 0 otherwise.

In line with the methodology of Mathew, Ibrahim and Archbold (2018) and Wattantorn and Padungsaksawasdi (2022), the overall measure of board effectiveness, the Board Effectiveness Index, is constructed by combining all above variables and subsequent the scores range from 0 to 5; the index will be used as a proxy to measure board effectiveness (Board_Effectiveness) for the purpose of this study. The data collected was processed in Microsoft Excel where the index was calculated. Table 4 below shows the distribution of scores for the sample of 464 observations for the years 2019 to 2022.

Table 4: Board Effectiveness Index score distribution

Score	0	1	2	3	4	5	Observations
2019	0	25	40	30	15	1	111
2020	2	12	37	36	26	1	114
2021	1	7	34	53	21	4	120
2022	1	15	35	43	24	1	119

Table 4 shows the distribution of the Board Effectiveness Index score by year.

3.4.2.2 Board Size

Board size, in line with Smaili, Radu and Khalili (2022), refers to a number of directors on the board for any given year. In Sweden, the board requirements specify that the board must have at least three members, one of which being a chairman responsible for the firm's commitment to its legal obligations (The Swedish Corporate Governance Board, 2020). Larger board size, in accordance with agency theory, can in general be associated with higher levels of voluntary disclosure (Boateng, Tawiah & Tackie, 2022; Jizi, 2017).

$$Board\ size = number\ of\ directors\ on\ the\ board$$

3.4.2.3 Board Specific Skills

Board specific skills (Board_Skills) is the percentage of board members who have either an industry specific background or a strong financial background (Eikon Refinitiv, 2023). Elzahar and Hussainey (2012) found that boards with members from accounting and financial background are more inclined to reduce information asymmetry through disclosures. Smaili, Radu and Khalili (2022) found that the board's financial expertise has a positive effect on cybersecurity disclosure. Since non-financial disclosures such as cybersecurity and AI disclosures in Sweden are voluntary, a similar result can be expected for the effect of board specific skills on AI-disclosure.

$$Board\ skills = \frac{board\ members\ with\ industry\ specific\ background\ or\ a\ strong\ financial\ background}{total\ number\ of\ board\ members}$$

3.4.2.4 Board Independence

Independent board members are defined as: "Percentage of independent board members as reported by the company" (Eikon Refinitiv, 2023). Board independence is used as an independent variable, and as in accordance with Fama and Jensen (1983) greater board independence can lead to greater board effectiveness in controlling the firm's management. Furthermore, García-Meca and Sánchez-Ballesta (2010) corroborate the premise that board independence has a positive effect on the level of voluntary disclosure.

$$Independent\ board\ members = \frac{independent\ board\ members}{total\ number\ of\ board\ members}$$

3.4.3 Control variables

In this study, control variables have been included to manage the effects of extraneous or third factors that, besides the independent variables, could impact the results of the study (Salkind, 2010). This paper controlled for variables indicated by previous research to be determinants of the presence of voluntary company disclosure. A number of empirical studies show that company-specific factors have an effect on the level of voluntary disclosure (Zamil, Ramakrishnan, Jamal, Hatif & Khatib, 2023). This study controls for the effects of firm size, profitability, leverage, MTB, industry membership, and years.

3.4.3.1 Firm size

Firm size (Firm_Size) is defined through a natural logarithm of the company's total assets for a given year. Logarithmisation of variables is used to rescale the data to decrease outliers (Brooks, 2008). Smaili, Radu and Khalili (2022) postulate that firm size can be an indication of the number of stakeholders, and in turn bigger size should correspond with the number of disclosures due to increased stakeholder pressure. Furthermore, a number of studies show that larger companies disclose a greater amount of non-financial information to stakeholders more often than smaller ones (Bonsón, Bednárová & Perea, 2023; Brammer & Pavelin, 2006). To avoid distortion in the results, logFirm_Size is included as a control variable; and a positive coefficient is expected.

$$Firm\ size = \log(total\ assets)$$

3.4.3.2 Profitability

In line with Liao, Luo and Tang (2015), the variable Profitability (Profitability) is measured as ROA, "Calculated as the Income After Taxes for the fiscal period divided by the Average Total

Assets and is expressed as percentage. Average Total Assets is the average of Total Assets at the beginning and the end of the year.” (Eikon Refinitiv, 2023). Profit-seeking companies may strive to be perceived as socially acceptable and to legitimise their operations and retain resources available to them in the future; may choose to do so through voluntary disclosure (Castelló & Lozano, 2011). As a result, this study controls for the effect of profitability on AI disclosure. A positive coefficient can be expected.

$$ROA = \frac{income\ after\ tax\ for\ fiscal\ period}{average\ total\ assets}$$

3.4.3.3 Leverage

Leverage (Leverage) is the ratio of total debt to total assets. Lopes and Rodrigues (2007) suggest that higher leverage is linked to higher agency costs, which in turn may lead to disclosures being used as means to reduce those costs. To control for the possible implications of leverage on AI disclosure, leverage is included as a control variable. As a result, a positive coefficient for leverage is expected.

$$Leverage = \frac{total\ debt}{total\ assets}$$

3.4.3.4 Market-to-book

Market-to-book ratio (MTB) is calculated by dividing market capitalisation by shareholders’ equity. Brammer and Pavelin (2006) link non-financial reporting with market value of shareholders’ equity as well as the way in which a firm uses its capital. Andrikopoulos and Kriklani (2012) found that a higher MTB ratio will have a positive impact on the amount of voluntary environmental disclosure in Denmark. AI-related disclosures can be thought of what Andrikopoulos and Kriklani (2012) refer to as “non-standardised drivers of value” (p. 61) – the authors hypothesise that companies will disclose such information voluntarily to decrease uncertainties on capitalisations that are not linked to “fundamentals”. As a result, the authors expect a positive coefficient with MTB.

$$MTB = \frac{market\ capitalisation}{shareholders'\, equity}$$

3.4.3.5 Industry membership

Previous research states that the company's industry significantly impacts its disclosure strategy (Meek, Roberts & Gray, 1995; Brammer & Pavelin, 2006; Stanny & Ely, 2008; Ben-Amar & McIlkenny, 2015). Some industries in this study may be prone to work with AI and disclose AI information to a higher extent than others. To control for fixed effects and avoid biases based on the company's industry, industry membership has been included as a control variable. The companies in the sample of the study are from ten different industries, therefore nine dummy variables for each industry have been included using the least square dummy variable (LSDV) approach (Brooks, 2008), where the dummy variables will take the value of 1 if a company is included in that specific industry, and 0 if not. The industry Real estate activities have been randomly selected as a reference variable.

3.4.3.6 Years

Similar to Smaili, Radu and Khalili (2022), this study includes dummy variables for years using the LSDV approach (Brooks, 2008) to control for fixed effects. The research of this study is based on the years 2019 to 2022, therefore three dummy variables have been used with 2019 randomly selected as a reference variable.

Table 5: Summary of the variables used in the study.

Variables	Description
Dependent variables	
AI disclosure decision (AI_Discl_Decision)	Dummy variable = 0 if AI disclosures do not exist, dummy variable = 1 if AI disclosures exist
AI disclosure volume (AI_Discl_Vol)	Number of words in the AI disclosures
Independent variables	
Board effectiveness (Board_Effectiveness)	Board Effectiveness Index (0 to 5)
Board meeting attendance (Board_Attend)	Percentage attendance at board meetings
Number of board meetings (Board_Meet)	Number of board meetings
Board independence (Board_IND)	Percentage of independent board members as reported by the company
Board size (Board_Size)	Total numbers of directors on the board
Board specific skills (Board_Skills)	Percentage of board members who have either an industry specific background or a strong financial background
Control variables	
Firm size (Firm_Size)	Natural logarithm of the firm's total assets
Profitability (Profitability)	Ratio of income after taxes for the fiscal period divided by the average total assets (ROA)
Leverage (Leverage)	Ratio of total debt divided by total assets
Market-to-book (MTB)	Ratio of market capitalization to shareholders equity
Industry membership (Industry)	Industry membership of each company, nine dummy variables for ten industries
Year (Year)	2019 to 2022, three dummy variables for four years

Table 5 shows all the dependent, independent and control variables and their descriptions included in the study.

3.5 Models

In this study, panel data has been used as the data are collected from the companies seen in Appendix A over the years 2019 to 2022. However, some observations for the companies in the final sample were excluded due to them only having Annual and Sustainability reports for some of the years between 2019 to 2022. The reason behind this is, for instance, that some companies listed on OMX Stockholm Large Cap for the year 2023 were established after 2019. Another factor was that the Annual and Sustainability reports for the year 2022 had a delayed publication and were published after the data for this study were collected. As some of the cross-sectional elements have less observations, this study has an unbalanced panel (Brooks, 2008). With an unbalanced panel, there is a risk that bias occurs in case the excluded observations are impacted by endogeneity, this is called selective nonresponse bias (Verbeek & Nijman, 1992). To decrease the risk of biases in the models, the authors looked at the excluded observations to see if there was a distinct pattern, which did not occur as some observations had missing data for one year, and others for more years, and different years. Therefore, a distinct pattern could not be seen. Furthermore, the unbalanced panels use Fixed Effect (FE) estimators, as both of the models include variables that impact the dependent variables cross-sectionally but are constant over time (Brooks, 2008). The fixed effects used in the models are the dummy variables for industry and year. Using the FE estimator decreases the risk of selective nonresponse biases (Verbeek & Nijman, 1992).

3.5.1 Logistic regression model

To test the first hypothesis of this study (H1), a logistic regression model is used. A logistic regression model applies when analysing a correlation between the dependent and independent variables when the dependent variable only has two values (Salkind, 2010). In this model, the AI_Disl_Decision is the dependent and binary variable, which for year *t* and firm *i* takes the value of 1 if a company chooses to disclose AI-related information, and 0 if not. The independent variable is Board_Effectiveness which is the Board Effectiveness Index. The control variables included are Firm_Size, Profitability, Leverage, MTB, and industry membership and years as dummy variables.

Equation 1:

$$AI\_Discl\_Decision_{i,t} = \beta_0 + \beta_1 Board\_Effectiveness_{i,t} + \beta_2 Firm\_Size_{i,t} \\ + \beta_3 Profitability_{i,t} + \beta_4 Leverage_{i,t} + \beta_5 MTB_{i,t} + \beta_{6-14} Industry_{i,t} + \beta_{15-17} Year_{i,t} + \varepsilon_{i,t}$$

3.5.2 Multiple linear regression model

For the other hypotheses of this study (H2, H3 & H4) a multiple linear regression model applies. A multiple linear regression is used to analyse the correlation between the dependent and independent variables while having control over extraneous factors influencing the results by including control variables (Salkind, 2010). Unlike the logistic regression model, the dependent variable is not restricted to having only two values. For year t and firm i, the dependent variable AI_Disl_Vol is the volume of AI disclosure. The independent variables are Board_IND, Board_Size and Board_Skills. The control variables are Firm_Size, Profitability, Leverage and MTB. Industry membership and years are included as dummy control variables.

Equation 2:

$$AI\_Discl\_Vol_{i,t} = \beta_0 + \beta_1 Board\_IND_{i,t} + \beta_2 Board\_Size_{i,t}$$
$$+\beta_3 Board\_Skills_{i,t} + \beta_4 Firm\_Size_{i,t} + \beta_5 Profitability_{i,t} + \beta_6 Leverage_{i,t} + \beta_7 MTB_{i,t}$$
$$+ \beta_{8-16} Industry_{i,t} + \beta_{17-19} Year_{i,t} + \varepsilon_{i,t}$$

3.6 Processing of data

The data used in this study were first sorted and processed in Microsoft Excel. To get the descriptive statistics, run the regressions and conduct the tests the data were transferred to the IBM SPSS Statistics.

3.7 Model assumptions

According to Sallis et al. (2021) the multiple regression model is based on seven assumptions that are important to consider if testing whether the model is robust against deviations from the assumptions. The assumptions are the following:

> (1) The Regression Model Is Linear in the Coefficients, Is Correctly Specified, and Has an Additive Error Term, (2) The Error Term Has a Zero Population Mean, (3) The Independent Variables Are Uncorrelated with the Error Term, (4) Uncorrelated Error Terms (no Serial Correlation), (5) The Residuals Have a Constant Variance (no Heteroscedasticity), (6) The Residuals Are Normally Distributed, (7) No Multicollinearity (Sallis et al. 2021, pp. 203-207).

The first two assumptions (1-2) are presumed to be satisfied as the model is specified, based on theory as well as previous research and have a constant included in this study's equation (Sallis et al. 2021). The rest of the assumptions (3-7) are described in the following sections.

3.7.1 Endogeneity

Endogeneity occurs if one or more independent variables and an error term of an endogenous variable are correlated to each other in a regression model, which violates assumption 3 (Salkind, 2010; Sallis et al. 2021). This could lead to inconsistent and biassed parameter estimates making the inference of the regressions unreliable (Roberts & Whited, 2013). According to previous research, theoretical arguments and empirical evidence have found that board structure is endogenous (Adams, Hermalin & Weisbach, 2010; Hermalin & Weisbach 1988, 1998, & 2003). Adams (2010) explains the joint endogeneity in boards and the problem with it by stating that board composition has an impact on board actions, and that the actions the board members desire to take further affects the board composition. This problem is an example of reversed causality, which is the correlation between the independent variable and the residuals of the regression, and could lead to endogeneity problems (Godfrey, Hoepner, Lin & Poon, 2020). To decrease the risk of endogeneity problems, this study has only included relevant control variables, used in previous literature on similar topics, that lag the dependent variables (Ben-Amar & McIlkenny, 2015). This study is not expecting a reverse causality between the AI disclosures and the independent variables. Reverse causality could possibly take place if this study looked at technological skills, however, this study looks at board specific skills and might be far-reaching to assume that effective board members would be drawn to companies that disclose AI information. Furthermore, reverse causality could be a problem in case this study was only conducted on companies from a technological industry, as board members with technological skills might be interested in AI and drawn to companies that disclose more information regarding AI. It could be relevant in the future to test for reverse causality between the variables if companies' revenue stream was based on AI activity, however, looking at the sample industry breakdown (table 3), this is not the case in this study. As a result, the authors assume no reverse causality between the variables used in the study and AI disclosure. This could be relevant in the future, but as AI is a relatively new phenomenon, it can be speculated that AI disclosure will not impact board effectiveness and composition.

3.7.2 Autocorrelation

According to Sallis et al. (2021) autocorrelation is often a problem in time series analysis, however, this study constitutes panel data as described in section 3.5. The authors further explain that the assumption of no serial correlation (assumption 4) is often satisfied if a sequencing variable is not used in the multiple linear regression. In this study, dummy variables are used for the years to control for the fixed effects (see section 3.4.3.6), that are not considered to be sequencing variables. Therefore, this assumption is presumed to be satisfied.

3.7.3 Heteroscedasticity

Heteroscedasticity refers to the change in the spread of residuals over a range of values; it can be a problem for multiple regression models as it is based on the assumption of homoscedasticity (assumption 5); meaning that the variance of residuals is constant for the population from which the results are drawn (Sallis et al. 2021). When the variance is not constant and heteroscedasticity occurs, the reliability of test results decreases (Breusch & Pagan, 1979). For the multiple linear regression model (H2, H3 & H4), heteroskedasticity tests were conducted. The first tests were the White test and the Breusch-Pagan test. In accordance with these tests, p-value > 0.05 means that heteroscedasticity is not present in the model, and p-value ≤ 0.05 means that a heteroscedasticity problem occurs in the model (Zolna, Dao, Staszewski & Barszcz, 2016; White, 1980). Then a test based on a scatterplot in SPSS was made, which plotts the standardised predicted values against the standardised residuals; if the scatterplot shows a randomly distributed data without distinct patterns no heteroscedasticity problem occurs (Sallis et al. 2021). The reason for conducting three tests was that the Breausch-Pagan test has a higher probability of detecting heteroscedasticity if the variation in the residuals is linear, which may not be established using the White's test (Williams, 2020).

3.7.4 Normal distribution

In distributions of data a problem of outliers can occur, which happens when some observations are not consistent with the rest of the data and can therefore heavily affect the value of the variance of a distribution as well as the mean (Salkind, 2010). This violates assumption 6 (Sallis et al. 2021). To minimise the outliers, the variables that had the most extreme values, AI_Discl_Vol, Board_Meet, Board_Attend, Firm_Size, Profitability, Leverage and MTB, were first winsorized at a percentile of 99% and 1%. However, as many outliers were still present in the data, these variables were then winsorized at a percentile of 97,5% and 2,5%. To test for normality, this study looked at the skewness and kurtosis of the sample data. Skewness refers to the extent the data is skewed in a negative or positive direction, while kurtosis measures the flatness or peakedness of the distribution (Sallis et al. 2021). For a continuous variable to be considered normally distributed, the skewness should have a value of 0 and the kurtosis a value of 3 (Kallner, 2018). Furthermore, a Shapiro-Wilk test was conducted as an additional test of normality. This test looks at the sample data of the study and examines how it fits into a normal distribution, and will show a value between 0 to 1 in the statistic, with value 1 indicating a perfect fit (King & Eckersley, 2019).

3.7.5 Multicollinearity

In regression models, variables can have a high correlation to the dependent variable and to each other; this phenomenon is called multicollinearity and could strongly impact the results (Shrestha, 2020) and hence violate assumption 7 (Sallis et al. 2021). To test for multicollinearity in this study's data, a Variance Inflation Factor (VIF)-test was conducted. VIF measures to what extent the correlated independent variables inflate the estimated regression coefficient, where VIF = 1 means that there is no correlation between the independent variables, VIF between 1 to 5 indicates that a moderate correlation exists, VIF between 5 to 10 shows that multicollinearity occurs, and VIF over 10 indicates high levels of multicollinearity (Shrestha, 2020).

$$VIF = \frac{1}{1 - R^2}$$

3.8 Reliability and validity of the study

To increase the reliability and validity of the study, tools have been used to the highest extent possible to decrease the manual work when gathering the data. Company information has mainly been collected through the Refinitiv Eikon and Retriever Business databases to get reliable data for the study. In some cases the data collected from the databases were compared to information available through the companies' websites and reports. The data that have not been possible to access through these databases have been manually collected from primary sources such as companies' own websites and reports, to increase the validity of the gathered information. Some calculations also needed to be done manually, therefore, the manually gathered and calculated data were double checked before inserting it with the rest of the data to avoid mistakes. Regarding AI-disclosures data, it was manually identified and analysed. This allows for judgements to take place, for instance regarding what is and what is not considered to be information regarding AI according to the authors. As the authors also divided and took half of the companies each when searching for the AI-disclosures, biasness could have impacted the result of the disclosure volume. To increase the reliability and validity of this step the disclosures were carefully read by the authors, and in case of confusion, the authors discussed the disclosures to come up with a mutual agreement. Furthermore, the words of the disclosures were calculated in Microsoft Word to avoid mistakes.

It is important to address the validity and reliability of the Board Effectiveness Index which is included as an independent variable for the purpose of testing H1. As the data for board effectiveness are not available for Swedish companies, the variable had to be computed manually. A number of steps were taken to ensure the reliability of this variable, in order to increase the robustness of the study results. The authors followed the methodology developed by Mathew, Ibrahim and Archbold (2018) and Wattantorn and Padungsaksawasdi (2022). Data for calculating the index were obtained from Eikon Refinitiv and Retriver Business. As mentioned above, if the data were not available through either database, it was manually supplemented and in some instances cross-checked with the companies' Annual and Sustainability Reports. The index was computed in Microsoft Excel and checked by both authors.

4. Results

This section starts with presenting the descriptive statistics and correlation matrix of variables used in the study, followed by a presentation of the results received from testing the model assumptions and the regressions.

4.1 Descriptive statistics and correlations

Table 6: Descriptive statistics

Variable	Mean	Median	Min	Max	St.Dev.	Skewness	Kurtosis
AI_Discl_Decision	0.487	0	0	1	0.500	0.052	-2.006
AI_Discl_Vol	82.419	0	0	690.55	156.122	2.540	6.140
Board_Effectiveness	2.216	3	0	5	1.012	-0.106	-0.436
Board_Attend	96.273	97.675	80	100	4.495	-2.147	4.614
Board_Meet	13.313	12	6	29.425	5.391	1.154	1.125
Board_IND	65.549	66.667	0	100	18.829	-0.114	-0.129
Board_Size	8.537	8	4	18	2.569	0.547	-0.540
Board_Skills	31.411	30	0	100	17.980	0.671	0.773
Firm_Size	10.249	10.266	7.288	13.295	1.447	-0.09	-0.529
Profitability	0.075	0.065	-0.061	0.274	0.064	0.891	1.614
Leverage	0.259	0.253	0.012	5.018	0.140	0.153	-0.695
MTB	4.330	2.847	0.553	20.033	4.278	1.966	3.957
Observations	**464**	**464**	**464**	**464**	**464**	**464**	**464**

Table 6 contains descriptive statistics for variables used in this study. The table displays mean, median, minimum, maximum, standard deviation, skewness and kurtosis for all 464 observations. All variables included in the table use original data, except for Firm_Size where a natural logarithm of total assets is used. The table includes observations between 2019 and 2022. Dependent variables are AI_Discl_Decision and AI_Discl_Vol. Independent variables are Board_Skills, Board_Size, Board_IND and Board_Effectiveness. Control variables are Firm_Size, Profitability, Leverage and MTB.

In table 6, the volume of AI disclosure is on average 82.419, and the dispersion of data has a standard deviation of 156.122. AI_Discl_Vol ranges between 0 and 690.55 words. Median for the sample is 0, suggesting that at least 50% of the sample observations contain no words relating to AI in their Annual and Sustainability reports. The same result can be seen for AI_Discl_Decision that has a median value of 0, indicating that at least 50% of the sample choose to not disclose information regarding AI in the reports. Kurtosis for AI_Discl_Vol is 6.140, indicating that the variable contains some outliers which are expected from this type of data. As seen in table 7 below, over time the volume of AI disclosure decreased between 2019 to 2021 and increased again in 2022. However, the number of companies that disclose AI information steadily increases from 2019 onwards. This may indicate that although more companies in general are willing to disclose AI-related information, they do not feel the necessity to elaborate on the subject from year to year.

Table 7: Summary of AI disclosure

Year	**2019**	**2020**	**2021**	**2022**	**Total**
Observations	111	114	120	119	464
Number of companies disclosing AI information	47	53	62	64	226
Average number of words in AI disclosures	92.01	87.19	80.88	87.71	86.84

Table 7 presents a summary of the disclosures regarding AI as presented in the companies' Annual and Sustainability reports for the years 2019 to 2022. The number of observations for each year are shown, followed by the number of companies disclosing AI related information, and an average number of words of the AI disclosures for all companies together each year.

According to table 6, Board_Skills has a mean of 31.411%, meaning that, on average, 31.411% of board members have board specific skills. The minimum value for Board_Skills is 0%, while the maximum is 100%, indicating that some companies place significance on potential directors' skills more than others. Board_Size has a minimum of 4 and a maximum of 18, with a mean of 8.537. This is in line with the Swedish Corporate Governance Code which specifies that the board of directors should have no fewer than 3 members (Swedish Corporate Governance Board, 2020). Board_IND ranges between 0% and 100%, with a mean of 65.549%. This indicates that the majority of board members are independent with relation to the company's management, which is in accordance with the Swedish Corporate Governance Code (Swedish Corporate Governance Board, 2020). It is also common for Swedish companies for entire boards of directors to be non-executive (Swedish Corporate Governance Board, 2020), which is evident in the median being 66.667%, which indicates that half of the observations have more than 66.667% independent directors. Board_Effectiveness, as described in 3.4.2.1, ranges between 0 and 5, and has a mean of 2.216. The median for the sample is 3, indicating that at least 50% of the sample has values greater than median for 3 of 5 variables included in the Board Effectiveness Index.

Table 8: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) AI_Discl_Decision	1.000											
(2) AI_Disc_Vol	0.541**	1.000										
(3) Board_Meet	-0.032	-0.001	1.000									
(4) Board_Attend	-0.029	-0.009	0.073	1.000								
(5) Board_Skills	0.054	0.047	0.157**	-0.051	1.000							
(6) Board_Size	0.201**	0.199**	-0.203**	-0.094*	-0.108*	1.000						
(7) Board_IND	-0.059	0.045	0.143**	-0.034	0.115*	-0.329**	1.000					
(8) Board_Effectiveness	0.076	0.101*	0.371**	0.181**	0.404**	0.131**	0.369**	1.000				
(9) Firm_Size	0.219**	0.106*	0.150**	0.070	0.080	0.399**	-0.083	0.211**	1.000			
(10) Profitability	-0.164**	0.036	-0.154**	0.025	0.129**	0.114*	0.043	-0.121**	-0.280**	1.000		
(11) Leverage	0.014	-0.138**	0.210**	-0.004	0.033	-0.183**	-0.030	0.014	0.141**	-0.321**	1.000	
(12) MTB	0.014	0.172**	-0.123**	0.015	-0.049	-0.137**	-0.027	-0.079	-0.509**	0.389**	-0.260**	1.000

***p ≤ 0.05 (2-tailed), **p ≤ 0.01 l (2-tailed)**

Table 8 presents the correlation matrix for the variables included in the sample of the study, in accordance with the Pearson correlation.

Table 8 presents the strength of correlation between the variables and two significance levels of 0.01 and 0.05 are indicated as ** and * respectively. The table shows a positive but non-significant correlation between AI_Discl_Decision and Board_Effectiveness which records 7.6%. The correlation matrix shows a positive and significant relationship between Board_Size and AI_Discl_Decision and between Firm_Size with AI_Discl_Decision at 20.1% and 21.9% respectively. This indicates that a larger board size and respectively a larger firm size is positively correlated with the decision to disclose AI related information. Furthermore, AI_Discl_Decision are negatively and significantly correlated to Profitability, at 16.4% at the 0.01 significance level, indicating that higher Profitability is negatively associated with the decision to make AI-disclosures.

The table indicates a positive and significant correlation between AI_Discl_Vol and Board_Size at 19.9%, meaning that a larger board size is positively associated with AI-disclosure volume. The table also indicates a positive and significant relationship between AI_Discl_Vol and Board_Effectiveness at 10,1%. Looking at the correlation between AI_Discl_Vol and the control variables, significant positive values are shown for Firm_Size at 10.6% and MTB at 17.2%, and a negative but significant correlation with Leverage, at -13.8%. This means that larger companies, and respectively companies with higher MTB, to a larger extent, disclose more information regarding AI in their Annual and Sustainability reports. However, companies with higher leverage, are associated with disclosing less AI-information in their reports.

As expected, Board_Effectiveness has a positive and significant correlation with Board_Skills (40.4%), Board_Size (13.1%) and Board_IND (36.9%), at 0.01 significance level. The matrix also shows positive and significant correlation between Board_Effectiveness and Firm_Size, at 21.1% and a negative significant correlation with Profitability at 12.1% respectively.

The matrix displays a positive but non-significant correlation between Board_Skills and the AI_Discl_Vol at 4.7%. The correlation between Board_Skills and the AI_Discl_Decision is also positive and non-significant, at 5.4%.

Expectedly, Board_Meet has a positive significant correlation with Board_Skills (15.7%), Board_IND (14.3%), Board_Effectiveness (37.1%), Firm_Size (15%) and Leverage (21%). However, a negative significant correlation exists with Board_Size (-20.3%) Profitability (-15.4%) and MTB (-12.3%). Board_Attend has a positive significant correlation with Board_Effectiveness (18.1%), as expected. A negative significance at 0.05 level relationship with Board_Size is also present. The positive correlations with Board_Effectivness are in line with the authors' assumptions and the construction of the Board Effectiveness Index.

4.2 Testing model assumptions

4.2.1 Heteroscedasticity

The results of the White test for heteroscedasticity can be seen in Table 9, and show a Chi-Square value of 159.386 and a p-value of 0.114. As the p-value is above 0.05, no heteroscedasticity occurs according to the White Test (see 3.7.3). This result is conflicted with the results of the Breusch-Pagan test (Table 9) that shows a Chi-Square value of 149.278 and a p-value below 0.05. The results of the Breusch-Pagan test indicate that the homoscedasticity assumption for the multiple regression model is violated and a heteroscedasticity problem occurs, which can lead to biassed results of the regression (Salkind, 2010). The Breusch-Pagan test has a higher probability of detecting heteroscedasticity if the variation in the residuals is linear (Williams, 2020). As the results of the White's test indicate homoscedasticity and the results of the Breausch-Pagan test the opposite, it can be concluded that there is a problem of heteroscedasticity, caused by linear variation in the residuals. As both of the tests showed conflicting results, a third test was conducted where the standardised predicted values were plotted against the standardised residuals in a scatterplot using IBM SPSS Statistics. This test showed distinct patterns, and the heteroscedasticity problem was therefore confirmed. To correct for the residual heteroscedasticity problems, robust standard errors were used (Manita, Bruna, Dang & Houanti, 2018) for H2, H3 and H4 as seen in table 12. Robust standard errors can be used to correct for heteroscedasticity problems as it leads to higher requirements of "evidence" against a null hypothesis of homoscedasticity before rejecting it (Brooks, 2008).

Table 9: White and Breusch-Pagan Tests for heteroscedasticity

Test	White	Breusch-Pagan
Chi-Square	159.386	149.278
p-value	0.114	0.000

Table 9 presents the tests conducted for heteroscedasticity in the variables used for the multiple linear regression (H2, H3 & H4). The table shows the Chi-Square value and the p-value for the White test and Breusch-Pagan test. The p-value > 0.05 in the White-test indicates no heteroscedasticity (White, 1980). The p-value ≤ 0.05 in the Breusch-Pagan test indicates heteroscedasticity (Zolna, Dao, Staszewski & Barszcz, 2016).

4.2.2 Normality

To test for normality, this study looked at the kurtosis and skewness values of the variables, and also conducted a Shapiro-Wilk test. As seen in table 6, all the variables have a skewness value around 0 indicating a normal distribution of the variables, except for AI_Discl_Vol and MTB that have the values 2.540 respectively 1.966, which means that a slight positive skewness exists for these variables (Sallis et al. 2021). Regarding the kurtosis values, all the variables have a value between -2.006 and 6.140. Meaning that the variables with a kurtosis value below 3 have a more flat distribution compared to the normal distribution, while the variables with a kurtosis value above 3 are more towards a peaked distribution (Kallner, 2018; Sallis et al. 2021). To test the normality of the variables further, a Shapiro-Wilk test was conducted resulting in all the variables, except for MTB with the value of 0.765, showing a value between 0.9 to 1. This therefore leads to the assumption of the sample data being close to a perfect fit of a normal distribution.

Table 10: The Shapiro-Wilk normality test

Shapiro-Wilk normality test	Statistic
Board_Effectiveness	0.913
Board_IND	0.979
Board_Skills	0.966
Board_Size	0.936
Firm_Size	0.986
Profitability	0.932
Leverage	0.978
MTB	0.765

Table 10 shows the result of the Shapiro-Wilk test conducted for normality in the variables Board_Effectiveness, Board_IND, Board_Skills, Board_Size, Firm_Size, Profitability, Leverage and MTB. If the statistic value is 1 it indicates normality (King & Eckersley, 2019).

4.2.3 Multicollinearity

To test for multicollinearity between the variables, a VIF test was conducted. Table 11 shows that all the dependent and control variables used in each of the regression models have a VIF above 1, but not more than 2.036. This means that a moderate correlation between the variables exists; in other words multicollinearity can be seen as low enough to not have a significant effect on the results of the regressions. For the VIF test, two variables used to compute the Board Effectiveness Index, Board_Meet and Board_Attend, were excluded as they are not directly used in either regressions and only to compute the Board Effectiveness Index, unlike Board_IND, Board_Size and Board_Skills which are used to test H2, H3 and H4.

Table 11: VIF test

Variable	**VIF (H1)**		**VIF (H2, H3, H4)**	
Board_Effectiveness	1.194	1.056	-	-
Board_IND	-	-	1.155	1.258
Board_Skills	-	-	1.055	1.112
Board_Size	-	-	1.484	1.936
Firm_Size	1.416	1.685	1.643	2.036
Profitability	1.520	1.278	1.303	1.551
Leverage	1.571	1.143	1.251	1.642
MTB	1.706	1.517	1.530	1.727
Year (dummy)	Excluded	Included	Excluded	Included
Industry (dummy)	Excluded	Included	Excluded	Included

Table 11 shows results of the VIF test conducted on the variables used in hypothesis 1 and hypotheses 1, 2 and 3. VIF = 1 no multicollinearity, $1 < VIF \leq 5$ moderate multicollinearity, $5 < VIF \leq 10$ multicollinearity, $VIF > 10$ high multicollinearity (Shrestha, 2020).

4.3 Results of the regressions

The results of the regressions are presented in table 12. In the first column, the logistic regression (H1) results are shown, and in the second column, the multiple linear regression (H2, H3 & H4) results can be seen. This study uses a significance level of maximum 5% to be accepted, this is because it is the most commonly accepted level in research (Loftus, 2022). The value of the independent variable coefficients and their significance levels shows if each of the hypotheses of the study is accepted or rejected. The R^2 value shows an explained variance of the regression and takes a value from 0 to 1, where a higher value towards 1 means a higher explained variance (Sallis et al. 2021). For the logistic regression, R^2 nagelkerke is applied. R^2 nagelkerke, also called pseudo-

R^2, is used as a corresponding indicator to the R^2 for linear regression models, to explain the overall strength of a logistic regression model (Hu, Shao & Palta, 2006). The F-value and its significance level shows if the overall model is statistically significant or not (Smaili, Radu & Khalili, 2022). N shows the total number of observations used in each of the regressions.

Table 12: Regression results

Variables	**H1**	**H2, H3 & H4**
Board_Effectiveness	0.044 (*0.108*)	-
Board_IND	-	1.201*** (*0.417*)
Board_Size	-	9.318** (*3.918*)
Board_Skills	-	0.617 (*0.401*)
Firm_Size	0.426*** (*0.094*)	21.113*** (*7.149*)
Profitability	-7.889*** (*2.166*)	-78.858 (*114.711*)
Leverage	-0.605 (*0.887)*	-118.884** (*60.445*)
MTB	0.137*** (*0,034*)	12.728*** (*2.797*)
Constant	-4.812*** (*1.165*)	-309.850*** (*90.936*)
Industry (fixed effect)	Included	Included
Year (fixed effect)	Included	Included
R^2	0.214 (*nagelkerke*)	0.177
F-Value	-	5.018***
N	464	464

***p ≤ 0.1, **p ≤ 0.05, ***p ≤ 0.01**

Table 12 shows the results of the logistic regression (H1) and the multiple linear regression (H2, H3 & H4). The table presents the regression coefficients for Board_Effectiveness, Board_IND, Board_Size, Board_Skills, Firm_Size, Profitability, Leverage and MTB. Furthermore, it shows that the fixed effects for industry and year are included for both the regressions, followed by a presentation of the R^2 value (nagelkerke for H1), the F-value and the total number of observations used in the regressions. In the parentheses, the standard errors are seen for H1, and robust standard errors for H2, H3 and H4.

4.3.1 Hypothesis 1

For the first hypothesis (H1), this study examined if there is a positive correlation between board effectiveness and the decision to disclose information regarding AI. The results of the logistic regression show a positive coefficient with a value of 0.044. The value of the coefficient is however non-significant, therefore, a positive relationship between board effectiveness and the decision to disclose information regarding AI cannot be stated, and H1 is rejected.

The Nagelkerke R^2 has a value of 0.214, indicating a level of variation in the dependent variable AI_Discl_Decision as explained by the independent variable Board Effectiveness of 21.4%. Regarding the control variables, both the coefficients for Firm_Size and MTB are positive and significant on a 1% level. These results show that the higher the firm size and respective MTB, the more likely the companies are to make the decision to disclose information regarding AI. The significant positive relationship between Firm_Size and AI_Discl_Desicion is in line with the results shown in the correlation matrix in table 8. Furthermore, Profitability has a negative coefficient at a 1% significance level, meaning that companies with higher ROA are less prone to take the decision to make AI-disclosures. This is consistent with the correlation matrix table 8 indicating a significant negative relationship between Profitability and AI_Discl_Decision. Leverage is the only control variable that does not have a significant relationship with the dependent variable.

4.3.2 Hypothesis 2, 3 and 4

The second hypothesis of the study (H2) investigates if a positive relationship between board independence and the volume of AI-related disclosures exists. The results of the multiple linear regression for H2 show a positive coefficient for board independence and the number of words regarding AI disclosures with a value of 1.201 at a 1% significance level. This indicates that board independence has a positive effect on the volume of disclosures regarding AI; H2 can therefore be accepted.

The third hypothesis (H3) looks if there is a positive correlation between board size and the volume of AI-related disclosures. The coefficient has a positive value of 9.318 on a 5% significance level. This is further in line with the results of the correlation matrix (table 8) showing a positive and significant coefficient between the two variables. According to the regression results of H3, it can be stated that companies board size positively affects the volume of the disclosures regarding AI, and as this study applies a maximum of 5% significance level, H3 can be accepted.

The fourth hypothesis (H4) examines if a positive relationship between board specific skills and the volume of AI-related disclosures exists. The coefficient between the variables has a positive but non-significant value of 0.617. This result is in line with the correlation matrix (table 8) indicating a positive but non-significant relationship. The results mean that a positive correlation between the board specific skills and the volume of disclosures regarding AI cannot be stated, and H4 is rejected.

The R^2 value for H2, H3, H4 is 0.177 indicating that the variation in the dependent variable, AI_Discl_Vol, is explained by the independent variables in the model at 17.7%. Furthermore, the F-value for this model is 5.018 and significant on a 1% level, indicating the presence of statistical significance in the model. Regarding the control variables, the coefficient for Firm_ Size has the value 21.113 on a 1% significance level, meaning that larger firms disclose more information regarding AI in their Annual and Sustainability Reports, which is consistent with previous research (Bonsón et al. 2021; Brammer and Pavelin, 2006) done on the subject. MTB also shows a positive coefficient with a value of 12.728 significant at a 1% level, which is explained by firms with higher MTB having higher volume of AI related disclosures in their reports. This is further in line with the correlation matrix in table 8 showing a positive and significant relationship between these two variables. Profitability and Leverage both have negative coefficients with the value of -78.858 and -118.884. Only the coefficient for Leverage is significant, and is on a 5% significance level.

5. Discussion and analysis

This section analyses the results received from the regression models based on the theoretical frameworks used in the study and previous research.

5.1 Board effectiveness

The first hypothesis of the study (H1) investigates if board effectiveness has a positive impact on the decision to disclose AI-related information. The results of the logistic regression used to test the H1 show a positive although non-significant coefficient of 0.044, and as a result, H1 is rejected. The model indicates the relationship between board effectiveness and AI disclosure decision to be non-significant.

Despite an increase in the number of firms that disclose AI-related information (Table 7), the results of this study cannot corroborate the notion that board effectiveness has a positive impact on the decision to disclose AI-related information of Swedish companies listed on OMX Stockholm Large Cap. One reason for that could be the relative "newness" of AI and the subsequent lack of guidelines regarding AI reporting making them a voluntary disclosure in the EU at the time this study takes place. As a result, boards may be hesitant to disclose information without baseline guidelines regarding what such information should contain.

Reasons for companies to disclose information could include regulatory pressures and mimetic isomorphism as a direct response to uncertainty. The uncertainty surrounding AI and AI disclosures could pave the way for mimetic isomorphism. DiMaggio and Powell (1983) refer to mimetic isomorphism as the process through which companies imitate each others' behaviour as a response to such uncertainty which leads to the institutionalisation of the practice. The non-significant results of H1 may indicate that mimetic isomorphism in relation to AI disclosures is in its early stages Setyorini and Ishak (2012) state that mimetic isomorphism is burdened with ambiguity, particularly surrounding the objectives and the means to achieve them. As a result, organisations that want to imitate the success of their peers may model their responses on those organisations that they perceive as successful and legitimate (DiMaggio & Powell, 1983).

Consequently, as the approach to AI guidelines gives rise to uncertainty, companies may seek to imitate those organisations that disclose AI information to retain competitive advantage in terms of legitimacy (Deegan, 2009). Various studies suggest the presence of mimetic isomorphism in relation to voluntary non-financial disclosure (Clarkson, Li, Richardson & Vasvari, 2008; Cormier, Magnan & Van Velthoven, 2005). This opens up possibilities for further research, as the practice of disclosing AI information may become institutionalised in time, and the results of similar studies in the future may show results of significance.

An effective board of directors relies on the human capital of its members, particularly on their skills and experience due to their impact on the boards' monitoring efficiency (Erickson et al. 2005). It can be argued that board members with diverse skills and experience may be effective in governing the company whilst having a cautious approach to issues that remain outside the scope of their experience, in this case AI. Furthermore, this paper does not aim to specify the content of the information regarding AI that companies choose to disclose. As a result, the approach and treatment of AI and AI disclosures is individual to each company (Bonsón et al. 2021). For instance, if companies choose to treat the use of AI in their operations as a security risk, then those boards, if effective, will disclose such information to signal commitment to risk management (Ben-Amar & McIlkenny, 2015).

Addressing stakeholder and agency theories, H1 was designed on the assumption that an effective board of directors will disclose AI-related information to satisfy the needs of various groups of stakeholders and mitigate information asymmetry between stakeholders and management. Fama (1980) postulates that effective boards will have higher transparency levels. It is possible that although there is a growing interest in AI, the issue may not be crucial enough for stakeholders to exert pressure on boards of directors to disclose such information at the present time. This follows the lack of institutionalisation surrounding the practice of AI disclosure, giving way for uncertainty and in turn, mimetic isomorphism that may take place in the future to establish legitimacy in the eyes of stakeholders (Cho & Patten, 2007; Martínez-Ferrero & García-Sánchez, 2017).

Regarding signalling theory, although previous studies find evidence that firms see the potential benefits from disclosing information regarding their investment in new technologies such as AI to attract investors (for instance Bonsón, Bednárová & Perea, 2023); the decision to not disclose such information can be treated as a signal in itself. As AI technology is still a new subject, it carries many risks and ethical dilemmas with its adoption (European Commission, 2019b). As a result, effective boards that actively monitor technological trends and stakeholder attitude towards such technologies may opt for a cautious approach to disclosing such information. This is corroborated by Bonsón et al. (2021) who found that 17.5% of companies disclose generic-level information regarding AI, possibly to show that they monitor the current technological development. The decision to only include generic statements may serve as means to divert stakeholder attention away from the companies' activities involving AI (Bonsón et al. 2021).

The need for companies to legitimise their actions to access resources needed for ensuring continuity of operations is crucial (Deegan, 2022). According to Dumay, Frost and Beck (2015), one way to do so is through voluntary disclosure of information. Although a variety of studies support the view that legitimacy theory can explain non-financial disclosure as means to reduce the legitimacy gap (Bonsón et al. 2021), the results of this study show that board effectiveness does not impact the decision to disclose AI information. In line with Suchman (1995), cognitive ability is achieved through convincing outsiders that the company's actions are socially acceptable. Whereas Bonsón et al. (2021) argues that cognitive legitimacy can be achieved by disclosing honest and trustworthy information about AI use, this does not apply to companies who only consider AI adoption. In line with this, effective boards can be expected to withhold information they deem incomplete, for instance about possible AI adoption, and only disclose such information when AI is actually deployed in operations. This could explain the non-significant result of H1, and can be further elaborated by addressing moral and pragmatic legitimacy (Suchman, 1995); boards of companies that again only consider AI adoption in the future may not disclose information about the possible risks and benefits. Another angle to consider is that companies may not feel the need to legitimise their actions through disclosure of AI-related information. Effective boards will be efficient in their disclosure of information relating to risk (Ben-Amar & McIlkenny, 2015), but the result of H1 can suggest that AI may not be treated as risk by boards of directors, and therefore legitimacy gap does not need to be addressed through disclosure.

5.2 Board independence

The second hypothesis of the study (H2) aims to test the relationship between board independence and the volume of AI disclosures. The results show a positive and significant relationship, indicating that board independence has a positive impact on the volume of AI disclosures; H2 can therefore be accepted. The finding is consistent with previous research on voluntary non-financial disclosures (Fama & Jensen, 1983; García-Meca & Sánchez-Ballesta, 2010; Hung, 1998; Jizi, Salama, Dixon & Stratling, 2014; Smaili, Radu & Khalili, 2022). Fama and Jensen (1983) argue that independent directors have incentives to voluntarily disclose information in order to sustain their image as efficient in monitoring the actions of the company. Consequently, it can be argued that independent directors display such monitoring activity not only with regards to company operations, but also external environment - hence may have incentives to disclose AI-related information to show that the company is aware of technological changes. Hung (1998) argues that independent directors should lead to companies disclosing more information as they have more experience in dealing with external environments as well as external stakeholders. Furthermore, García-Meca and Sánchez-Ballesta (2010) found a positive relationship between board independence and voluntary disclosure, particularly in countries that are characterised by strong investor rights. This is in line with stakeholder theory, indicating that investors in such countries can exert pressure on independent directors to disclose more information, and companies in those countries respond to such pressures increasing the amount of words in their disclosures. Sweden has strong investor protection rights (The World Bank, 2019), therefore it could be inferred that Swedish investors are able to exert pressure on independent directors to disclose more AI-related information, confirming significant results of H2. The results therefore indicate support for the stakeholder theory, especially since companies' approach to AI can be significant for various stakeholder groups. Furthermore, Beasley (1996) demonstrates that the proportion of independent board members has a positive relationship with the board's ability to influence decisions regarding disclosure.

In line with agency theory, as mentioned by Jensen and Meckling (1976), corporate disclosures are used as means to reduce agency conflicts. Healy and Palepu (2001) argue that the presence of directors who are independent from management and managers is a solution to agency conflicts. Disclosures regarding AI may therefore serve a purpose of reducing the conflict arising from information asymmetry regarding company's actions and attitudes surrounding AI use and deployment. Similarly, disclosures can also be used by independent directors to show commitment to their duties (Patelli & Prencipe, 2007), which is in line with signalling theory used to develop the hypothesis. Building on that, directors interested in incorporating AI into the company's strategy could use disclosures regarding AI as means to signal to investors their commitment to the issue, resulting in higher volume of those disclosures.

Based on the significant finding of H2, this study contributes to the empirical literature on corporate governance, particularly concerning board attributes, and voluntary non-financial disclosures. As the study is the first to investigate the impact of corporate governance aspects on AI disclosure, a significant relationship between independent board members and the volume of AI disclosures also contributes to research on AI disclosures.

5.3 Board size

The results for the third hypothesis of the study (H3) show a positive and significant relationship between board size and AI-disclosure volume, therefore H3 is accepted. This indicates that larger boards of directors lead to companies disclosing more AI-related information in their Annual and Sustainability Reports. Previous research on the subject of board size and its relationship with voluntary non-financial disclosure has found mixed results. Some researchers found that efficiency problems arising from boards that are too large can cause coordination issues (Coles et al. 2008; Lipton & Lorsch, 1992), whilst other found that larger boards result in higher transparency, and, by extension, more disclosure (Gandía, 2008; Hidalgo, García-Meca & Martínez, 2011; Naseem, Rehman, Ikram & Malik, 2017). H3 was based on the assumption that larger boards have advantages over smaller ones in terms of efficiency in advising and monitoring the management (De Andres & Vallelado, 2008), and that larger boards contain more members with diverse experiences and skills (Hidalgo et. al. 2011; Smaili, Radu & Khalili, 2022; Samaha, Khlif & Hussainey, 2015). This argument is in line with agency theory, where the conflict will be mitigated due to increased efficiency (De Andres & Vallelado, 2008; Emre, 2016). Li, Li, Want and Thatcher (2021) argue that boards with more diverse backgrounds education-wise are better equipped to understand the potential risks and benefits of AI. Therefore, it is assumed that larger boards will be willing to disclose more information regarding AI deployment and use. This corroborates the findings of Jizi (2017) who found that larger boards disclose more ESG information. It can be hypothesised that companies with larger boards tend to imitate each others' disclosure practices in order to appear more legitimate (DiMaggio and Powell, 1983). This study makes a contribution to the existing empirical literature on the subject of corporate governance, specifically board composition, and non-financial voluntary disclosures, notably relating to AI. Since the study is one of the first to look at board composition and the volume of AI disclosure, the study further contributes to research on AI-related matters with relation to corporate governance in Europe.

5.4 Board specific skills

The fourth hypothesis of the study (H4) aimed to test the relationship between board specific skills and the volume of AI disclosure as presented in companies' Annual and Sustainability Reports for the years 2019 to 2022. The results show a positive but non-significant relationship, indicating that a higher percentage of directors with board specific skills does not result in companies disclosing more information relating to AI. H4 is therefore rejected.

The results of this study contradict previous research on other forms of voluntary non-financial disclosure (Lim, Matolcsy & Chow 2007; Smaili, Radu & Khalili, 2022). This could be explained by the relative specificity of AI disclosures which could require particular types of experience and expertise from the directors to be reported in an appropriate manner. As a result, directors that possess board specific skills may lack those relating to the more technological aspect of AI, and therefore limit the volume of AI disclosures. Another possible explanation of this result, is that previous studies that have shown a positive and significant correlation between board specific skills and voluntary non-financial disclosures (Lim, Matolcsy & Chow 2007; Smaili, Radu & Khalili, 2022) have defined board skills in a different way. For instance Smaili, Radu and Khalili (2022) strictly look at board members with accounting and finance expertise and skills, while this study defines board specific skills as having either industry specific or strong financial background.

In line with signalling theory, boards of directors have incentives to supply information to company outsiders (Bonsón et al. 2021). According to Elzahar and Hussainey (2012), directors that come from an accounting and financial background are more willing to reduce information asymmetry using disclosures. It is possible, however, that as this study focuses on board specific skills, such a statement does not hold due to specificity of AI and AI disclosures. Although it can be assumed that board members with specific skills would be willing to disclose AI information (Bonsón, Bednárová and Perea, 2023), uncertainty surrounding AI and its newness may require board members to possess technological instead of financial background to send concrete signals regarding AI to stakeholders, resulting in the volume of such disclosures being limited. According to Li, Li, Wang and Thatcher (2021), directors with R&D experience are more equipped to understand the implications of AI adoption. Building on this, directors with board specific skills may not view disclosing AI information as means to legitimise the company's operations, instead focusing on other forms of financial and non-financial information where they feel as though they have expertise. This may explain the results of H4, as it can be generally assumed that the volume of AI disclosures could depend on the expertise regarding the use and development of the technology. Furthermore, Smaili, Radu and Khalili (2022) postulate that companies have incentives to disclose more information as a response to stakeholder pressure. Directors with board specific skills are expected to be interested in responding to such pressures. The non-significant results of H4 could mean, in line with stakeholder theory, that such pressures are not strong enough to incentivize directors with board-specific skills to disclose more AI-related information.

5.5 Control variables

This study looked at the presence and volume of AI disclosures and controlled for a number of variables that were indicated in previous research to be determinants of voluntary non-financial corporate disclosure. Regarding firm size, our results show a positive and significant result of 21.113 on a 1% significance level for H2, H3 and H4, indicating that larger companies disclose more information regarding AI. This is in line with Bonsón, Bednárová and Perea (2023) who found that larger companies in Western Europe disclose more information regarding algorithmic decision making and Brammer and Pavelin (2006) who note that firm size is positively related to voluntary environmental disclosure in large UK companies. For H1, the results confirm the authors' assumptions that larger firms are more inclined to disclose AI-related information. The positive and significant results are in line with the authors' assumptions defined in section 3.4.3.1.

Similar to previous research on voluntary disclosures and non-financial reporting and firm characteristics (Brammer, Brooks & Pavelin, 2006; Andrikopoulos & Kriklani, 2012), the results of this study further corroborate the notion of higher MTB leading to firms' disclosing more voluntary information to stakeholders. The positive coefficients of 12.728 for H2, H3 and H4 and 0.137 for H1 are both significant at a 1% level and are in line with the authors' assumptions seen in section 3.4.3.4 regarding the impact of MTB on the level of AI-disclosure. The significant relationship between MTB and AI disclosure volume is a result of disclosure being associated with market valuation of the wealth of the company's shareholders (Brammer, Brooks & Pavelin, 2006).

Regarding the decision to disclose AI-related information as outlined in H1, the findings of this paper are consistent with previous research (Brammer & Pavelin, 2006) where no significant relationship between environmental disclosure and leverage was found. Contrary to the authors' assumptions regarding leverage and disclosure volume as outlined in section 3.4.3.3, the results of this study find a negative significant relationship between leverage and AI disclosure volume. The significant negative relationship implies that higher leverage leads to less information regarding AI being disclosed by Swedish companies. This is consistent with Andrikopoulos and Kriklani (2012) who although studied environmental disclosure found that higher leverage leads to companies' disclosures being limited. In accordance with agency theory, higher leverage is expected to result in more voluntary disclosures as means to reduce agency costs (Lopes & Rodrigues, 2007). The non-significant result of this study points out that board members may not view AI disclosures as an effective measure in agency costs reduction, possibly due to specificity of AI disclosures as opposed to for instance environmental or social disclosures.

The results for control variable Profitability contradict worldwide findings as well as the authors' assumptions regarding the impact of a company's financial position on the amount of voluntary non-financial disclosure. In line with Castelló and Lozano (2011), for the purpose of this study a positive coefficient was expected (section 3.4.3.2), as profit-seeking companies strive for social acceptance to legitimise their operations and may do so through voluntary disclosure. This is corroborated by various studies, such as Smaili, Radu and Khalili (2022). The results for H2, H3 and H4 show a negative non-significant relationship between the volume of AI disclosure and the firm's profitability, as measured by ROA. This is partly consistent with some previous research, as many empirical papers found no significance when studying the impact of profitability on voluntary non-financial disclosure (Huafang & Jianguo, 2007; Juhmani, 2013). Consequently, it can be inferred that profitability has no effect on the volume of AI disclosures for Swedish companies listed on the OMX Stockholm Large Cap.

The results for H1 show a negative significant relationship between profitability and the firm’s decision to disclose AI information. Again, this contradicts existing research, as well as the authors’ assumptions. Although some previous studies found similar results, this is generally a minority in research surrounding voluntary non-financial disclosure and profitability. Al-Homaidi, Tabash and Ahmad (2020) studied the relationship between Corporate Social Disclosure (CSD) and profitability in Yemen and found this relationship significant and negative. Duran and Rodrigo (2018) found that non-financial disclosure is negatively impacted by profitability in Latin America. To the best of the authors’ knowledge very few previous studies examined the impact on AI disclosure specifically, especially in Sweden. The specificity of both AI disclosures and Swedish corporate governance could also impact the results, however, more research needs to be conducted to corroborate the results of this study. This unexpected result could be caused by firms treating voluntary non-financial disclosure as means to distract audiences from poor financial performance (Rodrigo & Durant, 2018). Indeed, increased disclosure as means to divert shareholder attention from poor performance has been documented in previous research, for instance by Belhaj and Damak-Ayadi (2013) who found that poorly performing Tunisian firms will undertake more environmental activities and disclose more information about such activities to improve their image in the eyes of stakeholders. Another reason for this relationship worth taking into account is that the sample in this study included years of the COVID-19 pandemic. One could assume that AI-related disclosure had less priority in the eyes of board-members than disclosing information about current affairs, such as the company’s treatment of shareholders and customers during the pandemic. During the pandemic, corporate boards’ priorities shifted towards the continuity of the business as well as resilience of operations (Allen, 2022). Therefore, firms’ profitability figures could have been distorted as a result of the pandemic which had devastating effects on companies’ financial performance in terms of magnitude and scope (Labadze & Sraieb, 2023).

6. Robustness test

In this section, the robustness of the study's models is tested and analysed.

As described in section 3.7.4, some variables used in the regressions were winsorized at the percentile of 2.5% and 97.5% due to extreme outliers resulting in high skewness and kurtosis values. Similar to Zhang, Chong and Jia (2020), the first step of the robustness test was to run the regressions with the initial data before winsorization to see if it would give different results. As seen in Appendix B, the coefficients for Board_Effectiveness, Board_IND, Board_Size and Board_Skills have a positive value with significance for the correlation between the Board_IND and AI_Discl_Vol (H2) and between the Board_Size and AI_Discl_Vol (H3). The same results have been received after the winsorization of the data, as seen in table 12. The second step to check for the robustness of the regression models was to conduct a test analysing how the R^2 value and significance level changes. This test was done by running the regressions with the dependent variable, independent variable and the fixed effects dummy variables for industry and year and then including each control variable one at a time. As seen in Appendix C and D, it is noticeable that the R^2 value increases as the control variables get added. However, the significance level for the dependent variable Board_Effectiveness (H1) increases as the control variables get added. Furthermore, the significance level for Board_Size (H2) increases when the control variables Profitability and MTB are added, while the significance level for Board_Skills (H4) increases when MTB gets added. For Board_IND (H2), the significance level decreases when all the control variables are added in the regression. As the significance level for the majority of the dependent variables in this study (H1, H3 & H4) increases when the control variables are added, it argues against including the control variables in this study's regressions. This was not expected as Smaili, Radu and Khalili's (2022) study that researched the correlation between board effectiveness and cybersecurity disclosures, used the same control variables as this study and did not seem to get the same results when including them. The difference might be based on the fact that this study examines AI disclosures, which could be affected differently than cybersecurity disclosures (Smaili, Radu & Khalili, 2022). However, this study chose to still include the control variables in the regressions based on the arguments that it increases the R^2 value and, as mentioned in section

3.7.1, including relevant control variables used in previous literature on similar topics will lag the dependent variable and therefore decrease the risk of endogeneity problems (Ben-Amar & McIlkenny, 2015). Furthermore, consideration should be paid towards clustering in the data, where errors are independent across data clusters but correlated inside clusters (Cameron & Miller, 2015). For the data used in this study, there is a possibility that clustering of the variables have occurred. However, this study does not implement clustered standard errors to mitigate this potential issue, as this is not possible to be executed in the software program IBM SPSS Statistics used in this study.

7. Conclusion

The first part of this section concludes the study, answers the research question and states the contributions this study makes. This is followed by a discussion regarding future research on the topic.

7.1 Concluding remarks

The aim of this paper was to research how board effectiveness in Swedish listed companies affects disclosures regarding Artificial Intelligence. This led to the research question if board effectiveness has an impact on disclosures regarding Artificial Intelligence in companies listed on OMX Stockholm Large Cap. To conduct this research, 121 number of companies listed on OMX Stockholm Large Cap and their Annual and Sustainability Reports for the years 2019 to 2022 have been analysed. This study found positive and significant relationships for board independence and the volume of disclosures regarding AI, and for board size and the volume of disclosures regarding AI. Positive relationships between board effectiveness and the decision to disclose information regarding AI, and board specific skills and the volume of disclosures regarding AI could also be established, however these were non-significant. These results conclude that board effectiveness as an index measure does not affect disclosures regarding AI in companies listed on OMX Stockholm Large Cap, nor does the part of the index, board specific skills. However, the other one-dimensional measures of board effectiveness, board independence and board size, affects disclosures regarding AI positively. The study has allowed for increased understanding of theoretical frameworks surrounding voluntary non-financial disclosures in the context of AI. Possible application of legitimacy theory, agency theory, signalling theory and stakeholder theory are investigated with regards to a relatively new phenomenon that is AI. The specificity of AI disclosures allows for a new angle to understand director-shareholder relationship and subsequent exchange of information and motivations behind it.

This study makes an empirical contribution from Sweden in the field of corporate governance, regarding board attributes and AI disclosure, notably board independence and board size. Furthermore, practical implications of the results should be considered, notably whether in the future companies will make adjustments in their boards of directors to reflect attitudes towards AI, as communicated through disclosures. The significance such research carries can also have an impact on the regulation of AI disclosures, if such regulation is ever made mandatory. Perhaps, in the near future AI disclosures will become an integral part of non-voluntary disclosure and feature regularly on companies' Annual and Sustainability Reports.

7.2 Future research

The study looked at the relationship between board effectiveness and three of its one-dimensional measures and AI disclosures in Swedish companies listed on the OMX Stockholm Large Cap. Although this study makes several contributions to existing empirical literature on the subject of corporate governance and non-financial voluntary disclosures, some research gaps were identified during the course of the study. As the study was done on only Swedish companies, it could limit the applicability of the results due to differences in corporate governance practices between countries. Any generalisations must therefore be made cautiously and take the country-specific impact into consideration. Furthermore, more concrete results could be drawn if more countries were examined in a similar way. This would also give way for comparisons between countries, as corporate governance guidelines and approaches towards AI of those countries can have an impact on AI disclosures. This issue is particularly raised by Papyshev and Yarime (2023) who compare national attitudes towards AI concluding that EU countries tend to focus on "control" whereas the UK, the US and Ireland prioritise "promotion" through a hands-off approach. Furthermore, only companies listed on OMX Stockholm Large Cap index were included in this study. To enhance the validity of the results and draw general conclusions about Swedish listed companies, future research could also include Mid and Small Cap in the sample.

Considering the regression models used in this study, industries were taken into account as dummy variables to control for fixed effects. Having industry as the independent variable and looking at the industry impact on AI disclosures could be an area of further study, as this could give way for examining whether certain industries are more sensitive to AI. The results of such study could be used in the future by regulators to assess the importance of AI disclosures by industry if such a time comes when AI disclosures become a legal requirement. Furthermore, for the regression models, this study used a couple of control variables, including firm size, profitability, leverage, MTB and dummy variables for years and industry membership. These have been motivated by previous research, however a different set of control variables might account for third factors for specifically AI disclosures differently, which opens up possibilities for further study. This paper looked at the sample of four years, between 2019 and 2022. These years included the COVID-19 pandemic, which could have impacted the variables and thus the results, as briefly discussed in section 5.5. Therefore, similar studies could be done investigating the years after the pandemic to see if different results are obtained. Furthermore, it is important to consider OpenAI's ChatGPT public release at the end of 2022 (Wu, He, Liu, Sun, Liu, Han & Tang, 2023). ChatGPT is a chatting robot with abilities for intelligent storytelling, admitting mistakes and remembering earlier dialogue with users (Wu et al. 2023). The same methodology as used in this study could be applied in the future to include the year 2023 and capture the effect that Chat GPT has on AI, the commonisation of AI in the eyes of the general public and, consequently, on AI disclosures.

Following the line of thought in section 5.1, further studies surrounding the institutionalisation of the practice of disclosing information regarding AI could also give different results, as companies may imitate each others' practices over time. Furthermore, in this study, board specific skills used as the independent variable in the second regression model were defined as board members having strong financial background through having a MBA and/or industry specific background. As the results showed a non-significant correlation between board specific skills and the volume of AI-disclosures, future research on the topic of AI could define board specific skills differently. This could be done by looking at board members with strong technical backgrounds, instead of financial, as it might impact AI disclosures differently and give another result.

Some previous studies have considered the content of AI disclosures (for instance Bonsón, Bednárová & Perea, 2023), however, as AI disclosures are not regulated at the present, the content of such disclosures remains individual to each company (Bonsón et al. 2021). Strength of conclusions from a similar study could be increased if general statements regarding AI, such as the potential of the technology itself, were taken away. This would give way to study those companies who use and deploy AI in their operations, and subsequent disclosures regarding the use.

Addressing statistically significant findings for H2 and H3 makes it important to consider the concept of substantive significance. Substantive significance refers to the practicality of the result and its theoretical implications (Priest, 2005). Priest (2005) stresses its importance in social science research, recommending supplementing statistical findings with a combination of descriptive statistics, confidence intervals, effects size measures and replication. One way to consider substantive significance is through a meta-analysis, similar to Khlif and Souissi (2010) who looked at determinants of corporate disclosure. Future studies on the topic and their empirical contributions could therefore be strengthened by utilising such techniques. It is only when such measures are taken that the goals of social research are met (Priest, 2005).

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9. Appendices

Appendix A

1. AAK
2. AddLife
3. Addnode Group
4. Addtech
5. AFRY
6. Alfa Laval
7. Arjo
8. Assa Abloy
9. AstraZeneca
10. Atlas Copco
11. Atrium Ljungberg
12. Autoliv SDB
13. Avanza Bank
14. Axfood
15. Balder
16. Beijer
17. Bilia
18. Billerud
19. BioArctic
20. Biotage
21. Boliden
22. Boozt
23. Bravida Holding
24. Bufab
25. Bure Equity
26. Castellum
27. Catena
28. Cint Group
29. Corem Property Group
30. Creades
31. Diös Fastigheter
32. Dometic Group
33. Electrolux
34. Electrolux Professional
35. Elekta
36. Embracer Group
37. Epiroc
38. EQT
39. Ericsson
40. Essity
41. Evolution
42. Fabege
43. Fenix Outdoor
44. Fortnox
45. Getinge
46. H&M
47. Handelsbanken
48. Hemnet Group
49. Hexagon
50. Hexatronic Group
51. Hexpol
52. HMS Networks
53. Holmen
54. Hufvudstaden
55. Husqvarna
56. Industrivärden
57. Indutrade
58. Instalco
59. International Petroleum Corp.
60. Intrum
61. Investor
62. JM
63. Kindred Group SDB
64. Kinnevik
65. Lagercrantz Group
66. Latour
67. Lifco
68. Lindab International
69. Loomis
70. Lundberg
71. Medicover
72. Mips
73. MTG
74. Munters Group AB
75. Mycronic
76. NCAB Group
77. NCC
78. New Wave
79. Nibe Industrier
80. Nolato
81. Nordnet
82. NP3 Fastigheter
83. Nyfosa
84. Orrön Energy
85. OX2
86. Pandox
87. Peab
88. Platzer Fastigheter Holding
89. Ratos
90. SAAB
91. Sagax
92. Sandvik
93. SBB Norden
94. SCA
95. Sdiptech
96. SEB
97. Sectra
98. Securitas
99. Sinch
100. Skanska
101. SKF
102. SSAB
103. Stillfront Group
104. Storskogen
105. Sweco
106. Swedbank
107. Swedish Orphan Biovitrum
108. Systemair
109. Tele2
110. Telia Company
111. Thule Group
112. Trelleborg
113. Troax Group
114. Viaplay Group
115. Vitec Software Group
116. Vitrolife
117. Volati
118. Volvo
119. Volvo Car
120. Wallenstam
121. Wihlborgs Fastigheter

Appendix A shows a list of Swedish companies listed on OMX Stockholm Large Cap used in the sample of the study.

Appendix B

Variables	**H1**	**H2, H3 & H4**
Board_Effectiveness	0.099 (*0.106*)	-
Board_IND	-	1.282*** (*0.478*)
Board_Size	-	12.858*** (*4.112*)
Board_Skills	-	0.570 (*0.466*)
Firm_Size	0.159 (*0.381*)	43.102 (*30.776*)
Profitability	20.044 (*37.163*)	-2981.638 (*3000.357*)
Leverage	0.471 (*0.467*)	-28.911 (*33.187*)
MTB	0.071*** (*0.023*)	10.660*** (*1.704*)
Constant	-4.927*** (*0.955*)	-273.986*** (*79.893*)
Industry (fixed effect)	Included	Included
Year (fixed effect)	Included	Included
R^2	0.166 (*nagelkerke*)	0.153
F-Value	-	4.237***
N	464	464

***p ≤ 0.1, **p ≤ 0.05, ***p ≤ 0.01**

Appendix B shows the results of the logistic regression (H1) and the multiple linear regression (H2, H3 & H4) before winsorization of the variables AI_Discl_Vol, Board_Meet, Board_Attend, Firm_Size, Profitability, Leverage and MTB at a percentile of 2.5% and 97.5% were conducted.

Appendix C

AI_Discl_Decision (H1)	**1**	**2**	**3**	**4**	**5**
Board_Effectiveness	0.172* (*0.100*)	0.063 (*0.105*)	0.036 (*0.106*)	0.043 (*0.106*)	0.044 (*0.108*)
Firm_Size		0.309*** (*0.078*)	0.255*** (*0.081*)	0.254*** (*0.081*)	0.426*** (*0.094*)
Profitability			-4.455** (*1.806*)	-4.901*** (*1.878*)	-7.889*** (*2.166*)
Leverage				-0.765 (*0.881*)	-0.605 (*0.887*)
MTB					0.137*** (*0.034*)
Constant	-1.206*** (*0.420*)	-4.253*** (*0.885*)	-3.330*** (*0.959*)	-2.959*** (*1.049*)	-4.812*** (*1.165*)
Industry (fixed effect)	Included	Included	Included	Included	Included
Year (fixed effect)	Included	Included	Included	Included	Included
$\boldsymbol{R^2}$ *(nagelkerke)*	0,109	0.151	0.167	0.169	0.214
F-Value	-	-	-	-	-
N	464	464	464	464	464

***p ≤ 0.1, **p ≤ 0.05, ***p ≤ 0.01**

Appendix C shows the results of a robustness test for the logistic regression (H1). In this test, AI_Discl_Decision, Board_Effectiveness and the fixed effects dummy variables for industry and year are initially included in the regression. Then each of the control variables are added one at a time.

Appendix D

AI_Discl_Vol (H2, H3 & H4)	**1**	**2**	**3**	**4**	**5**
Board_IND	0.978** (*0.419*)	0.973** (*0.421*)	0.987** (*0.420*)	0.961** (*0.419*)	1.201*** (*0.405*)
Board_Size	10.948*** (*3.239*)	10.734*** (*3.719*)	10.986*** (*3.713*)	9.384** (*3.790*)	9.318** (*3.641*)
Board_Skills	0.694* (*0.404*)	0.686* (*0.409*)	0.765* (*0.411*)	0.723* (*0.410*)	0.617 (*0.394*)
Firm_Size		0.721 (*6.130*)	3.487 (*6.311*)	4.942 (*6.334*)	21.113*** (*6.627*)
Profitability			219.487* (*123.826*)	137.395	-78.858 (*130.002*)
Leverage				-126.485** (*64.234*)	-118.884* (*61.731*)
MTB					12.728*** (*2.065*)
Constant	-132.896*** (*48.743*)	-138.554** (*68.515*)	-188.552** (*73.943*)	-126.785 (*80.103*)	-309.850*** (*82.498*)
Industry (fixed effect)	Included	Included	Included	Included	Included
Year (fixed effect)	Included	Included	Included	Included	Included
R^2	0.092	0.092	0.099	0.106	0.177
F-Value	3.032***	2.837***	2.868***	2.942***	5.018***
N	464	464	464	464	464

$^*p \leq 0.1$, $^{**}p \leq 0.05$, $^{***}p \leq 0.01$

Appendix D shows the results of a robustness test for the multiple linear regression (H2, H3 & H4). In this test, AI_Discl_Vol, Board_IND, Board_Size, Board_Skills and the fixed effects dummy variables for industry and year are included in the regression. Then each of the control variables are added one at a time.