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# *Introduction*

The rapid digital transformation of the business environment has profoundly reshaped the role of auditing and financial reporting. One of the most relevant developments in the internal audit and financial control is the progressive adoption of artificial intelligence (AI). In fact, audit was traditionally dependent on exclusively human judgement and professional expertise. However, nowadays audit tends to be increasingly supported by AI tools able to analyze a large volume of data, detect anomalies, and improve decision-making efficiency (Fedyk et al., 2022; Issa et al., 2016). Thus, one of the most emerging questions within this changed audit reality is: does AI adoption in audit functions improve accounting quality?

Accounting quality (AQ) is a multidimensional concept which reflects how faithfully financial statements represent a firm's economic performance and position. A high-quality accounting system should provide reliable and relevant information in order to permit investors to make economic decisions with complete information and awareness. Moreover, a good accounting system should enhance capital market transparency, and support both managerial accountability and regulatory compliance (Dechow et al., 2010; Moeller, 2010). Prior research has identified different AQ drivers both quantitative like accruals level, financial restatements, timely loss recognition and qualitative like internal control systems, governance mechanisms, and auditors' skills and expertise (Carolina et al., 2020; Dechow et al., 2010; *International Accounting Standards and Accounting Quality - BARTH - 2008 - Journal of Accounting Research - Wiley Online Library*, 2008; Khan et al., 2025). However, although there is an increasing attention over the AI's role in auditing, there is no clear evidence on whether AI actually improves accounting quality especially if we consider the European context. In fact, most of the studies performed in this field refer to data of companies located in United States or Asia (Al-Okaily, 2024; Fedyk et al., 2022).

In Italy, where the corporate landscape is characterized by concentrated ownership structures, family-led companies, and a bank-centered financial system, the integration of AI into audit functions remain at an early stage. As a matter of fact, according to a report of the European Commission (*Digital Economy and Society Index (DESI) 2022 | Shaping Europe's Digital Future*, 2022) Italy seems to have one of the slowest AI adoption rate in Europe. This because Italy has an historically shown skepticism toward technology adoption and it is a country which tends to favor traditional methods across business practices. This makes Italy an unexplored context especially regarding the theme analyzed in this thesis: AI adoption can concretely enhance accounting quality or human judgement still prevails as primary determinants of a reliable financial reporting?

The aim of this thesis is to address this gap by empirically testing the relationship between AI intensity adoption in audit functions and accounting quality considering a sample of 145 Italian listed firms. In particular, this work provides a novel measure of AI intensity adoption by gathering data from personal LinkedIn profiles of the internal auditors of the sample companies. The data collection is performed through a Python scripts and Google SerpApi queries. Then this variable is combined with traditional financial indicators collected from Refinitiv database in order to build a cross-sectional regression model. The dependent variable (accounting quality) is proxied by the level of accruals. In addition, since the sample is characterized by many various firms working in different sectors, industry fixed effects are introduced to capture this sectoral heterogeneity. Finally, an interaction term between AI adoption and firm size – represented by the natural logarithm of total assets – (AI x Size) is introduced to test whether larger companies benefit more from AI tools by reducing the accruals level and thus improving the accounting quality.

The remainder of the thesis proceeds as follows. The first chapter discusses the related literature regarding the accounting quality definition and measures and its relationship with AI and human judgement and then presents the research question and hypothesis analyzed. Afterward, the second chapter introduces the comprehensive resume dataset, discusses the construction of the AI adoption ratio, the interaction term (AI x Size), the dependent variable (accounting quality) and the other control variables considered in the model. Chapter three discusses the empirical results concerning the relationship between AI adoption, accounting quality and firm size and how they interact together and also the impact on accruals level of the other control variables. Finally, the last chapter (chapter four) discusses the limitations, the contributions and the possible future developments of this study.

# 1. Literature Review

## 1.1. Accounting Quality: Meaning and Measures

Accounting quality or AQ is referred to as how well financial statements reflect a firm's economic performance and financial position in actual terms. Quality accounting provides for the availability of financial information that is reliable and relevant to help make economic decisions and enhance capital market transparency. Accounting quality also supports managerial accountability by serving as foundation for performance evaluation and regulatory compliance.

To understand the multidimensional nature of AQ, this literature review organizes the main drivers into two broad categories: quantitative drivers, which are commonly derived from observable financial data, and qualitative drivers, which refer to internal organizational features and human-centered judgements.

### 1.1.1. Quantitative Drivers of Accounting Quality

There are different measurable indicators to evaluate accounting quality. Barth et al. (2008) (*International Accounting Standards and Accounting Quality - BARTH - 2008 - Journal of Accounting Research - Wiley Online Library*, 2008) categorize these into three principal dimensions: earnings management, timely loss recognition, and value relevance. Their work provides detailed methods for capturing the extent of manipulation or transparency in financial reporting practices:

- Earnings management: measured using earnings smoothing metrics (e.g., variance of changes in net income scaled to total assets; the mean ratio of the variability of the change in net income to the variability of the change in operating cash flows; correlation between accruals and cash flows – e.g., net income minus operating cash flow divided by total assets ) and management towards earnings targets (e.g., clustering of small positive net income observations). These are estimated using regression-based residuals with controls for firm-specific and market-related characteristics. Higher earnings management generally implies lower accounting quality, as financial statements may not faithfully represent the firms' actual economic performance.

- Timely loss recognition: assessed by analyzing the sensitivity of reported earnings to large negative shocks. High-quality reporting systems are expected to recognize losses more promptly, indicated by a large and positive coefficient on large negative earnings indicator.
- Value relevance: evaluated by the strength of the statistical relationship between accounting numbers and capital market outcomes (e.g., adjusted $R^2$ from a regression of stock price on net income and equity book value or from regressions of net income per share on annual stock return). High $R^2$ means the accounting information better reflects firm value.

Although Barth et al. (2008) focus on these three primary categories, other indicators are frequently used in audit and fraud research. One such widely recognized metric is financial restatements. In fact, other researchers argue that restatements are observable outcomes of low-quality earnings and signal material weaknesses in accrual estimation, internal controls, or deliberate misreporting (Dechow et al., 2010). This study defines restatements as a proxy for an earnings misstatement. However, the restatements which interest the SEC[1] investigation are the ones that are intentional and material. (Dechow et al., 2010). Another work (Burns & Kedia, 2006) claims that one of the determinants of this intentional manipulation of earnings is managerial compensations. In fact, they found a positive association between the sensitivity of the CEO's option portfolio to stock price and the likelihood of restatements. (Efendi et al., 2007) have instead discovered that the probability of restatements increases when the CEO has considerable holdings of in-the-money stock options. Moreover, the same research has highlighted that restatements are more likely present in companies where the CEO takes part to the board of directors or belongs to the founding family.

However, there are some other studies which neglect these correlations found between restatements and the managerial compensation (*Chief Executive Officer Equity Incentives and Accounting Irregularities - ARMSTRONG - 2010 - Journal of Accounting Research - Wiley Online Library*, 2010) and between the further and the independence of the board of directors (Agrawal & Chadha, 2005).

Such mixed and weak evidence of restatements' determinants demonstrates that they are not a trustworthy driver of intentional misstatements which is a specific dimension of earnings quality and which is associated by many researchers to restatements. In fact, as (Dechow et al., 2010) have noticed this mixture of results it might be determined by the fact that the restatement sample combines intentional and unintentional misstatements.

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[1] Security and Exchange Commission.

### *1.1.2. Qualitative Drivers of Accounting Quality*

Another study (Hennes et al., 2008) focus and deepen the research about restatements distinguishing them in restatements due to errors and those due to irregularities. This distinction is helpful in order to better understand the relationship between accounting quality and financial restatements from another point of view which is less technical. As a matter of fact, the author here explains that restatements are related not only to technical aspects such as misapplication of standards or internal control weaknesses but can be also linked to ethical and governance dimensions of the reporting process. For example, irregularities may be caused by elements which cannot be captured by purely quantitative performance indicators as they are connected to human's values and behavior like managerial integrity, lack of an unbiased and objective judgment, or other weaknesses in the supervision system.

Recent literature further expands the discussion on AQ drivers, particularly in relation to the internal resources of an organization. More specifically a study on internal audit consulting services, identifies several critical drivers – management support, organizational status, organizational culture, data analytics (DA), continuous audit, and internal auditor skills and competencies – that significantly influence the quality of strategic and risk management services offered by internal auditors (Khan et al., 2025). Using the Resource-Based View (RBV) theory[2], the authors argue that these elements represent internal capabilities which enhance the quality of internal audit consulting services. In fact, all the hypotheses stated in this paper assume a positive relationship between these internal resources and the quality of internal audit. The empirical analysis of this research – based on survey data from Bangladesh listed companies – confirms that most of these drivers positively affect internally audit quality, with the exception of auditor independence, which was not found to have a statistically significant impact. For example, DA helps to identify irregularities in business transactions promptly, continuous auditing enables risk-based planning, anomaly and non-compliance detection, and real-time analysis.

[2] According to this theory, a company's competitive advantage depends on its internal resources (Barney, 1991).

### *1.2. Other Accounting Quality Drivers: Internal Control and Accounting Information System*

Accounting information system (AIS) is defined by (G. H. Bodnar and W. S. Hopwood, 2013) as a set of people and resources designed to produce information from data processing of financial and other data. AIS quality can be measured from different perspectives. (Carolina et al., 2020) uses three dimensions to evaluate it: integration, flexibility, and usability. However, the most important thing to have a good quality system is a system which is able to achieve goals, in particular organizational goals (DeLone & McLean, 2003). Different studies have claimed that the success of the AIS is positively influenced by a good internal control system – the process designed by boards of directors, management and other personnel to purpose effectiveness and efficiency of operations, reliability of financial reporting and compliance with applicable law and regulation (Moeller, 2010). (Fitriati & Susanto, 2005) have demonstrated that an AIS is integrated, flexible, easy to use and easy to access when it is supported by a good quality internal control. In addition, the work of (Carolina et al., 2020) – already mentioned above – has emphasized how an efficient internal control system is needed to prevent mistakes that can give a negative impact on the AIS process and output.

Then, it has also been studied the relationship between AIS and accounting information. According to (Fitriati et al., 2020) the effective application of AIS produces quality accounting information that is relevant, accurate, timely and complete. Also (MEIRYANI et al., 2020) define the quality of accounting information system as an organizational strength to achieve the quality of accounting information.

Finally, based on all these studies on AIS and accounting information quality (Carolina et al., 2020) have deepen the analysis and found an additional relationship between AIS, accounting information quality and internal control. In fact, they've started by studying the correlation between internal control and AIS quality. By following the footsteps done by (Fardinal, 2013) and other researchers, they showed that internal control positively influences the AIS quality. In addition, they continued the work of prior researches (Fitriati et al., 2020; MEIRYANI et al., 2020) to demonstrate how AIS quality positively influence accounting information quality. They concluded by proving that internal control not only influences the AIS system quality, but it also positively impacts the accounting information quality. Therefore, it is clear the fundamental role that internal control has in order to reach accounting quality.

## *1.3. AI and Accounting Quality*

### *1.3.1. AI and Financial Restatements*

To better understand the relationship between AI and accounting quality (AQ), we examine how AI adoption influences one key AQ driver previously discussed: financial restatements. Restatements are widely recognized in literature as a robust proxy for low audit and accounting quality, as they signal material errors or omissions in previously issued financial reports (DeFond & Zhang, 2014; Rajgopal et al., 2021).

A recent study by (Fedyk et al., 2022) investigates whether artificial intelligence is improving the audit process by analyzing a large sample of 36 major US public accounting firms – including both Big 4 (Deloitte, EY, KPMG and PwC) and non-Big 4 firms. Using a novel dataset based on employee resume data from Cognism Inc.[3], the study constructs a regression model to assess how the proportion of AI-skilled workers employed at audit firms over the prior three years impact the likelihood of financial restatements.

Their results are significant and compelling: a one-standard-deviation increase in AI human capital is associated with a 5% reduction in the likelihood of financial restatements, a 1.4% decrease in material restatements, a 1.9% decrease in restatements related to accruals or revenues recognition, and a 0.3% drop in SEC investigation related to restatements.

To ensure the validity of the results, the authors control for several variables known to affect audit quality, including firm size, profitability (ROA), leverage, Big 4 affiliation, market activity (e.g., market-to-book ratio), and litigation exposure, along with industry and year fixed effects.

The study provides additional insights on where AI's impact is most significant. Specifically, the effect of AI is stronger in the later years of the sample (2014-2017), reflecting the increasing sophistication and maturity of AI tools. Furthermore, AI seems more beneficial when auditing older firms – which possess richer historical datasets – and new clients, where auditors lack prior engagement knowledge. Finally, AI resulted to have a greater impact in the retail sector, characterized by a high volume of repetitive transactions and thus can benefit from anomaly detection algorithms.

These findings provide a strong empirical support for the claim that AI can enhance audit quality by reducing errors and increasing reliability in financial disclosures.

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[3] A commercial database provider that collects professional profiles and resume data.

### *1.3.2. AI and Earnings Management*

Another critical quantitative driver of accounting quality is earnings management. Earnings management refers to the strategic manipulation of financial reporting to meet targets or smooth earnings. Companies may engage in accrual-based (AEM [4]) or real-activity based (REM [5]) manipulation to meet benchmarks or influence perceptions. This happens because the main objective of firms is to maximize shareholders' value. Firm's interest is to report positive earnings, positive earnings growth and meet analysts' forecasts in order to acquire capital. However, it is unlikely that companies can meet these expectations all the time, though they are unwilling to suffer stock price decreases. For this reason, firms might manage earnings in order to meet shareholders' expectations and to hold equity.

Recently, some research has been conducted to analyze the relationship between the exploitation of AI in audit practice in order to reduce earnings management and enhance transparency.

A study performed by (Kadhim & Al Ani, 2023) investigates how AI can mitigate these discretionary interventions in earnings figures. Their research, focusing on Iraq firms, demonstrates that AI tools support real-time data analysis, cross-checking of anomalies, and integration with advanced predictive systems. This permits the improvement of the transparency of earnings reports by reducing the discretionary power of managers over accruals.

Another research (Balushi, 2021) provides a more comprehensive analysis of how AI-powered Big Data Analytics (BDA) improves the quality of internal audit functions (IAF), which in turn limits earnings management. As a matter of fact, the work identifies a negative relationship between IAF quality and earnings management. This confirms what we've already mentioned before: a high level of earnings management decrease the accounting quality. (Balushi, 2021) has then expanded the analysis by showing that this negative correlation between IAF quality and earnings management is more pronounced for firms which use big data analytics and AI for IAFs purposes than those that do not. This means that firms with higher audit function quality and strong AI integration are less likely to engage in earnings manipulation. Moreover, (Balushi, 2021) argues that auditors should be trained in order to control these tools and used them to be helped in their work. This will allow them to disclose fraud and anomalies, diminish earnings management and maintain objectivity in their judgement.

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[4] Accrual Earnings Management (AEM) happens when managers use judgements in financial reporting to alter accrual.
[5] Real Earnings Management (REM) comprehends deviating from normal business practices to manipulate reported income. The cash flow from operations will be affected.

### *1.3.3. AI and Qualitative Drivers*

As we've seen AI tools can help auditors in their work and improve accounting quality – based on the literature previously analyzed. However, these considerations emerge when dealing with quantitative drivers of accounting quality, but we haven't considered yet the relationship between AI and the qualitative driver of AQ.

A recent study has brought attention to the vulnerabilities and limitations  associated with AI systems such as violations of human rights, lack of accountability, lack of transparency, lack of explainability, biases, and data privacy risks (Li & Goel, 2024). Moreover, these tools may be more exposed to cyber-attack.

For this reason, there is an open discussion about AI auditing and governance. An idea proposed within the (Li & Goel, 2024)'s work is to conduct an effective and efficient audit of AI systems in order to guarantee AI lawfulness, ethics, and technical robustness which is currently an understudied field. As a matter of fact, any audits for AI systems have been implemented yet and thus no precise qualitative drivers has been identified.

### *1.3.4. The relationship between AI, Internal Control System and Accounting Information Quality*

Few research has been done around this theme. However, a very recent study has analyzed the relationships between the AI adoption intensity and internal control system and accounting information quality. In fact, the work of (Monteiro et al., 2023) has found that companies with a large amount of data and complex production data can benefit from the AI adoption which will help them to transform these complex data into actionable and insightful information. The sample was made up of 381 Portuguese companies and the data were gathered through online surveys.

The AI adoption intensity was measured based on the number of business activities where AI has been implemented and how AI implementation has impacted the business processes.

The accounting information system quality was estimated based on the scale built by (Soudani, 2012). The employees had to answers to questions like: does the data storage contributes to the integrity of the financial reporting process, and does it reflect accurately and fairly the company asset? Data processing actually improves the quality of financial reports and it speeds up the process to generate them and overcome human weaknesses in data processing?

Finally, the internal control system quality is defined by (Phornlaphatrachakorn, 2019) as a set of process which can guide an organization to achieve effectiveness and efficiency of operations, provide assurance regarding the reliability of financial reporting and adhere to applicable laws and regulations. Within (Monteiro et al., 2023)'s work this variable was adapted from (Phornlaphatrachakorn, 2019) by creating a measurement scale of five Likert scale points. Some of the dimensions considered to measure its quality were: the contributions of this variable to the improvements of company's operational efficiency and effectiveness and to the achievement of firms' business targets, goals and objectives; the ability of the internal control system to prepare financial and non-financial information with quality, etc.

According to the results of this study, it seems that the intensity of AI adoption contributes positively to the internal control system quality but has no direct relationship with the accounting reporting system quality. Instead, AI influences the accounting information system quality through internal controls. In fact, AI positively affects internal controls quality with a beta equal to 0.32 ($p < 0.001$). Whereas internal control quality has a positive impact on accounting information system quality (AIS) with a beta equal to 0.61 ($p < 0.001$). This brings to a positive indirect effect of AI on AIS quality (circa equal to $0.20 = 0.32*0.61$). Overall, the model explains about 39% of AIS quality's variance.

### *1.3.5. The relationship between AI and the Firm's Size*

Another important factor which influences companies to adopt AI in their accounting systems is the size of data to manage. As a matter of facts, different studies have demonstrated the positive impact of AI on the internal accounting systems for firms with a large amount of data to handle.

The research already mentioned of (Monteiro et al., 2023) has shown that the intensity of AI adoption has a strong connection with the manufacturing industry. This happens because industries which have to deal with a large amount of data and complex production data benefit a lot from AI adoption. In fact, from European Commissions' results (*Digital Economy and Society Index (DESI) 2022 | Shaping Europe's Digital Future*, 2022) it has emerged that the uptake of AI technologies is much higher in large enterprises compared to SMEs. In 2021 the share of large undertakings adopting AI was three times higher than those of SMEs (29% versus 7%).

Moreover, the sectors with a higher AI adoption rate tend to be the ones which comprehends repetitive activities which need to be recorded in an automated and fast way. This includes sectors like retail, manufacturing, electricity, gas, steam, air conditioning and water supply, etc.

Another work (Bin-Nashwan et al., 2025) has emphasized the vital role that big data governance plays in strengthening the positive relationships between AI adoption and the accuracy of financial reporting. Furthermore, also the association between the AI adoption and audit efficiency positively benefit from big data governance. This because governance frameworks strengthen the dependability and reliability of AI-driven analytics and reporting results by enabling solid foundations for data quality, compliance with regulatory standards, and risk management practices. However, companies which have implemented an internal and developed system of big data governance tend to be of bigger size. This because they have to manage a large amount of data and thus, they have to carry out a mature data governance system to maintain a good quality internal control and to handle this big amount of information efficiently. Furthermore, this is required by regulation which imposes to firms which achieve some specific sizes to be subject to stricter controls by competent Authorities (*Delegated Directive - EU - 2023/2775 - EN - EUR-Lex*, 2023; *Directive - 2014/56 - EN - EUR-Lex*, 2014; *Regulation - 537/2014 - EN - EUR-Lex*, 2014).

### *1.4. Human Judgement and Accounting Quality*

Although AI has progressively gained importance as accounting tool, it is still not independent from human judgment. In fact, as specified in (Li & Goel, 2024)'s research a human responsibility chain is necessary across the entire AI lifecycle in order to explain and justify the algorithmically supported decisions. In addition, when it comes to a more ethical and complex valuation, AI is not able to replace the human's work, which it is essential to guide and give precise instructions to AI audit tools. Thus, currently AI is just an instrument to facilitate and accelerate the auditors' work.

In another study, it is mentioned that accounting quality is influenced by auditor's characteristics such as tenure, independence, and expertise (DeFond & Zhang, 2014). Moreover, human judgement continues to have a crucial role in accounting in order to assess whether none of these red flags are present:

- Consistent conservative accounting policy;
- A tax income stream that is derived from recurring, rather than one time, transactions related to the basic business;
- Sales that quickly convert to cash after being recorded;
- Earnings not inflated by unrealized inflation or currency;
- Earnings trends that are stable and predictable;
- Fair value accounting application is prudent and reasonable;
- The level of accounting accruals is reasonable.

Another study (Fedyk et al., 2022) explains that nowadays firms are investing a lot in AI to automate human analysis tasks. This might affect inexperienced auditors, and not the ones with more experience and accumulated institutional capital. However, the accounting profession is one of the most at risk of being replaced by AI (Frey & Osborne, 2017) due to the nature of this job characterized by tasks which comprehend actions like decision-making, prediction, and anomaly identification that can be performed by AI.

Also a more recent research (Khan et al., 2025), emphasizes that auditors' skills and competencies have a positive correlation with the quality of audit consulting services. In particular, their analytical skills allow them to analyze complex issues, pinpoint underlying causes, and find out effective solutions.

Therefore, also human judgement remains a critical factor which improves accounting quality. However, there are no clear quantitative and qualitative ways to measure its impact on AQ.

## *1.5. Research Gap*

Based on the literature review, it's clear that accounting quality (AQ) is both influenced by various quantitative – e.g., earnings management, value relevance timely loss recognition, and financial restatements, etc. – and qualitative drivers – e.g., ethical judgement, auditor's capabilities, and governance-related aspects, etc. Other influencing factors include the quality of the internal control system as well as the accounting information system.

Different studies have shown that artificial intelligence (AI) can enhance AQ. For instance, (Fedyk et al., 2022) demonstrate that an increase in AI audit workers implies a statistically significant reduction in financial restatements, especially in retail environments which are particularly suited to reap the benefits from AI due to the presence of small repeated transactions – e.g., high transaction volumes, rapidly growing e-commerce sector, and need for predictions regarding inventory impairment. Furthermore, most of the processes of the manufacturing sector are suited to be automated through AI tools for the same reasons, as we've seen before (Monteiro et al., 2023).

Moreover, (Kadhim & Al Ani, 2023) and (Balushi, 2021) stated that AI improves transparency thus permitting the reduction of accrual-based or real activity management. Therefore, it has been demonstrated that AI can increase audit efficiency and quality by lessen human error and strengthen control over earnings management.

However, all these contributions focus on quantitative effect of AI on AQ considering a database of American or international firm samples. Whereas there hasn't been yet analyzed the impact of AI adoption on accounting quality by considering a sample of Italian firms. In fact, it seems that poor research around this theme has been done in Italy. This can be due to the lack of data regarding the AI tools adopted by Italian companies within their internal audit functions as well as the difficulty to trace them.

Moreover, none of the works done until now have analyzed predictive relationships between AI and AQ using regression models developed in SPSS. In fact, most of the prior studies have employed firm-level data aggregated at an international level using database like Cognism Inc. or relied on surveys and interviews. However, none of them has utilized data extrapolated directly from the financial statements of the firms included in the sample.

Finally, all the studies mentioned in the literature review investigate a variety of accounting quality proxies – such as material restatements, revenue accruals, SEC investigation – but none of those papers assess the relationship between accruals – and thus the accounting quality –, the intensity of

AI adoption by internal auditors – operationalized as the ratio of AI-specialized auditors to total auditors at the firm level – and the firm size – represented by the natural logarithm of total assets.

### *1.6. Research Question and Hypothesis*

Given these gaps, this thesis aims to answer the following research question:

"Does the adoption of artificial intelligence improve accounting quality in the context of Italian listed companies with the increase of the size?"

To explore this question, I've developed a cross-sectional regression model using data from a sample of all Italian companies listed in 2024.

Accounting quality has been measured through the level of accruals, calculated as (net income – operating cash flow) divided by total assets. The AI intensity adoption is captured through a ratio defined as the number of auditors with AI skills divided by the total number of auditors within each firm.

To account for heterogeneity across the various industries, I've generated some dummy variables to control for industry fixed effects by gathering the companies' sample into nine clusters of different sectors.

Then I've also taken into account some other control variables like firm size (log of total assets), profitability (ROA), and leverage.

Moreover, an interaction term between AI adoption ratio and the firm size (*AI x Size*) was included in order to explore whether the effect of AI adoption on accounting quality differs depending on company scale – as we've already seen in the literature review.

Thus, the hypothesis tested was: "AI adoption improves accounting quality with the increase of firm size".

This approach permits to empirically evaluate whether AI adoption has a positive and significant impact on AQ – taking firm size into account – in comparison to firms which rely on traditional audit methods based on human judgement.

# 2. Methodology and Data

## 2.1. Research Design and Objective

The approach to measuring AI adoption leverages data taken directly from financial statements of the firms considered in the sample: all the Italian listed company in 2024. The study is performed through a quantitative, cross-sectional regression analysis which aims to understand whether AI adoption in auditing activities has a statistically significant impact on Accounting Quality (AQ) in the context of Italian companies, with data of December 2024. The purpose of this work is to empirically investigate whether companies with higher size tend to benefit more from AI adoption as they have a higher AQ, measured by a lower level of accruals, in comparison to firms which rely on traditional auditing techniques.

Due to the novelty and the data limitation in this field – particularly in Italian context – this work contributes to:

- Construct a unique and manually collected dataset by gathering data from Refinitiv from the financial statements of each company considered in the sample;
- Create a variable to measure the AI adoption by collecting data from the LinkedIn profiles of the employees of each firm and searching how many of the total internal auditors are AI-skilled workers;
- Create an interaction term *AI x Size* to measure how the effect of AI intensity adoption changes by the size and understand whether with the increase of the size, the AI adoption in audit functions improves the AQ;
- Perform a linear regression in SPSS to assess the relationship between the independent variable (*AI*), the interaction term (*AI x Size*) and the dependent variable (AQ – represented by the *level of accruals*) – controlling for firm characteristics.

I begin by describing the data and then detail the construction of the regression model with the related measures.

## *2.2. Sample and Data Collection*

To evaluate whether AI adoption can increase accounting quality (AQ), I've gathered data from Refinitiv focusing on the last available year (2024) of all the Italian listed companies.

I've selected the companies considering the following criteria:

- Availability of financial statements in 2024;
- Use of the euro as standardized currency to ensure comparability;
- Positioning of the headquarters in Italy as the scope of this study is to analyze only the impact of AI on AQ considering only the Italian listed undertakings.

The sample of the listed firms is composed by 145 companies. For each company within the sample, I've collected from Refinitiv the following information: net income, cash flow from operating activities, total assets, ROA, total debt, and the industry sector. Then, to calculate the accruals I've used the following formula[6]:

$$Accruals = \frac{(Net\ Income - Cash\ \text{Flow from Operating Activities})}{Total\ Assets}$$

Finally, in order to consider the adoption of AI I've created a variable "AI intensity adoption". The variable is a ratio composed by the number of AI-skilled auditors and total auditors of each company.

The data regarding the employee of each company were collected by launching a Python script. The ratio was built based on data retrieved from LinkedIn profiles of the employees of each firm. This was possible thanks to Google Search API (SerpApi) which has permitted to avoid the manual data collection – by visiting each single LinkedIn profile to find the data – and to ensure that only public indexed information was used.

[6] This is a proxy for earnings management – one of the critical drivers of accounting quality – widely used in the accounting and audit literature (Dechow et al., 2010). It reflects the portion of earnings not supported by actual operating cash flow, so the accruals. The higher it is this number the lower is the quality of earnings, and thus AQ. This measure is scaled by the total assets in order to avoid confounding effects due to the different firm size (Fedyk et al., 2022).

Thus, for each firm $i$, the AI adoption proxy is defined as:

$$AI\ Intensity_i = \frac{\#\ (\text{profiles matching "AI audit" for } i)}{\#\ (profiles\ matching\ \text{"}audit\text{"}\ for\ i)}$$

Therefore, the numerator is composed by the number of employees who have written in their LinkedIn profile “AI audit” in connection with the firm they work for; whereas the denominator counts the number of employees distinguishing by each firm within the sample who have written just “audit” in their profile.

In order to reduce noise from company pages and posts, I’ve constrained results to people profiles via site: linkedin.com/in.

For each firm, two queries were issued: one to find the AI audit employees and one for the audit employees in general.

The API returns a total results count for each query for the numerator and the denominator.

Data, as already mentioned, were collected with a short Python program which utilizes the SerpApi Google through the personal key and gather the total results field for each query. The SerpApi key was inserted in a configuration file (“config.json”) recalled through the Python script. To ensure stability and reproducibility, there were created:

- Input list: a CSV file with one column “Company” where were listed all the companies considered in the sample;
- Outputs: the script writes “output.csv” with the following columns with the gathered data: “Company”, “AI_auditors_count”, “Auditors_total_count”, “AI_Adoption_Index”.

Thus, the Python script searches data for each company present in the input list (“companies.csv”) and writes down the results for each query in the file named “output.csv”.

In conclusion, the AI Adoption ratio was adjusted in order avoid misleading results: sometimes AI auditors were more than the general auditors, which is impossible since logically if an employee is an AI-skilled auditor, he/she is automatically an auditor, and this has to be counted within the denominator. For this reason, I’ve created and used an adjusted ratio composed like this:

$$Adjusted\ Ratio = \frac{AI\ auditors\ count}{(Auditors\ total\ count + AI\ auditors\ count)}$$

Therefore, an important assumption of this model is that when an employee has written on his/her LinkedIn profile that he/she is an AI auditor of a specific firm, then this means that he/she adopts AI when he/she performs his/her auditor job within the company considered.

Last thing to notice is that I've considered the last available financial data (2024) because LinkedIn doesn't permit to filter for the year, thus the data retrieved through the Python script and Google SerpApi refer to the most recent data (2024-2025). For this reason, to maintain coherence between the data used in the model I've chosen to consider only the year 2024 performing a cross-sectional analysis.

The Python script is shared in the *Appendix* as well as the financial data of the sample companies (respectively *table 4* and *image 2*).

## *2.3. Regression Model*

The statistical analysis involved conducting a multiple linear regression on the data gathered from the financial statements and LinkedIn profiles to assess the influence of the independent variable on the dependent variable. The multiple linear regression model is a statistical model which allows to estimate the relationship between the quantitative dependent variable (*level of accruals*) and two or more independent variables. In the case of the analysis performed in this thesis, I've worked with one independent variable, an interaction term and some control variables. The independent variable considered is the *AI intensity adoption* and the interaction term is composed by the *AI intensity adoption* multiplied by the *size* – represented by the natural logarithm of total assets of each firm considered in the sample. Therefore, this model is based on the following equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 W_2 + \beta_3 X_1 W_2 + \beta_4 W_3 + \ldots + \beta_n W_{n-1} + \varepsilon$$

where Y is the dependent variable, also referred as "response variable", X is the independent variable, also referred to "predictor", $\beta_0$ is the intercept, whereas the Ws represent the control variables. The term $X_1W_2$ represents the interaction term between the independent variable – *AI intensity adoption* ($X_1$) – and the control variable – *size* ($W_2$). Each $\beta$ stands for the slope coefficient and the $\varepsilon$ is the error term.

The resulting data has then been reported in tables for further analysis to assess whether the hypothesis was supported or not. To test this, I chose a significant level of 5% so the confidence level is equal to 95%. Therefore, to have a statistically significant results there should be a p-value that is less than 5%. In this case the hypothesis tested wouldn't be rejected, and this would mean that AI adoption by auditors improves the accounting quality (lower level of accruals).

### *2.3.1. The Dependent Variable – Level of Accruals*

The dependent variable Y is determined by the difference between the net income and the cash flow from operating activities divided by total assets. The data were taken from the last financial statements available, thus the one of the 31st of December 2024. However, there are some exceptions regarding some data especially for the firms which publish financial statements in March, April and June 2024. These exceptions regard the following companies: Danieli, Juventus Football Club, Piquadro, Sesa, and Società Sportiva Lazio.

This variable measures the level of accruals (net income – operating cash flow) scaled by the total assets, in order to avoid confounding effects due to the different size of the enterprises considered in the sample. Lower values indicate a low level of accruals, and thus a high accounting quality, whereas higher values show a high level of accruals, and so a low accounting quality.

### *2.3.2. The Independent Variable and the Interaction Term – AI and AI x Size*

The independent variable assesses the effectiveness of the AI adoption on accounting quality – represented by the level of accruals. In the model it is a ratio created through a Python script and Google SerpApi to gather data directly from LinkedIn profiles of the employees of each undertaking considered in the sample.

However, as we've seen the AI adoption is mostly influenced by the firm size and has a higher effect on accounting quality with the increase of the size. For this reason, I've decided to consider also this aspect in the model and so I've created in SPSS the following interaction term: *AI x Size*.

The interaction term is composed by the following variables:

- $AI\ Intensity_i = \frac{\#(AI\ audit\ profiles)_i}{\#(audit\ profiles)_i}$
- $Size_i = \log(Total\ Assets_i)$

In order to avoid multicollinearity problems with the variables included in the interaction term, I've centered the variables at their mean (G, 2011). Thus, the modified variables appear like this:

- $AI_i^c = AI\ Intensity_i - mean(AI\ Intensity)$
- $Size_i^c = Size_i - mean(Size)$
- $(AI \times Size)_i = AI_i^c \times Size_i^c$

It is important to notice that centering does not change the model fit, but it only shifts the zero point so that:

- The coefficient of $AI_i^c$ is the average effect of the AI intensity adoption on accounting quality (Y = *the accruals level*) when the size is at its sample mean;
- The coefficient of $Size_i^c$ is the average effect of the size on accounting quality (Y = *the accruals level*) when the AI adoption is at its sample mean;
- The coefficient of $(AI \times Size)_i$ captures how the effect of AI adoption on accounting quality (Y = *the accruals level*) changes with the size.

### *2.3.3. The Control Variables*

Control variables were used to consider exogenous factors that might influence variation in the dependent variable. The variables included in the model – in order to control for firm characteristics that can affect the effect of AI on AQ – were the following:

- The natural logarithm of total assets (*Size*) – larger firms are subject to more scrutiny and thus tend to have better governance and higher AQ (Dechow et al., 2010). This variable – as we've already seen – was centered in order to avoid multicollinearity problems with the interaction term and the independent variable;
- Net income scaled by average total assets (*ROA*) – more profitable firms might be less incentivized to manipulate earnings, whereas growing firms or loss-making companies tend to manage earnings to encounter market expectations;

- Total debt scaled by total assets (*Leverage*) – financial pressure may increase earnings management and reduce AQ (Balushi, 2021);
- Some dummy variables were included in order to control for the industry effects. I've clustered the different undertakings into 9 sectorial groups:
  - Financials which comprehends firms working in the following sectors: Banking Services; Insurance; Investment Banking & Investment Services
  - Industrials which comprehends firms working in the following sectors: Machinery, Tools, Heavy Vehicles, Trains & Ships; Construction & Engineering; Transport Infrastructure; Freight & Logistics Services; Passenger Transportation Services; Aerospace & Defense; Professional & Commercial Services; Office Equipment
  - Utilities which comprehends firms working in the following sectors: Electric Utilities & IPPs; Multiline Utilities; Natural Gas Utilities
  - Resources which comprehends firms working in the following sectors: Oil & Gas; Oil & Gas Related Equipment and Services; Construction Materials; Chemicals; Containers & Packaging
  - Technology which comprehends firms working in the following sectors: Software & IT Services; Integrated Hardware & Software; Computers, Phones & Household Electronics; Electronic Equipment & Parts
  - Consumer Goods which comprehends firms working in the following sectors: Automobiles & Auto Parts; Textiles & Apparel; Leisure Products; Household Goods; Specialty Retailers; Hotels & Entertainment Services; Food & Tobacco; Beverages; Food & Drug Retailing
  - Healthcare which comprehends firms working in the following sectors: Healthcare Equipment & Supplies; Healthcare Providers & Services; Pharmaceuticals
  - Communication and Media which comprehends firms working in the following sectors: Telecommunications Services; Media & Publishing
  - Real Estate which comprehends firms working in the following sectors: Residential & Commercial REITs; Real Estate Operations

  Within the regression model the dummy variable for the financials sectors was excluded to permit to maintain the intercept and to prevent multicollinearity problems with the dummies.

# 3. Results

In this chapter, there will be discussed the results of the regression model performed in SPSS after commenting the descriptive statistics of the variables considered in the model.

## 3.1. Descriptive Statistics

Table 1 reports a summary of statistics of the variables considered in the model across the 145 Italian firms considered in the sample.

The mean of the dependent variable (*level of accruals)* is negative and equal to -3.50%. This makes totally sense since the level of accruals should be negative as to have a good accounting quality the cash flow from operating activities (CFO) should be higher than the net income. In fact, a higher CFO and a lower net income means a low level of accruals, and thus a high accounting quality. The standard deviation of the level of accruals resulted equal to 9.96%. It is a quite high number, and it indicates that the data points are spread out over a wider range of values. In fact, the data set is composed by companies totally different one from each other's both for size and industry reasons. So, this can partially explain the high dispersion between the data points.

Looking at the independent variable (the *AI intensity adoption*, *AI_c*), the mean is logically equal to 0, as a mean centered measured has an average of 0 by construction, whereas the standard deviation is equal to 32.03. The values range from -24.57 to 75.41. This means that within the sample there are many firms with AI-skilled auditors, but there are also some other companies which seem to not have them. This might be due to the heterogeneity of the sample composed by many undertakings from different industries and with various dimensions. Thus, the need to automate the audit functions may be subjective and depending on these factors.

The control variable log of total assets (*log_TA_c*) – also mean-centered – has a standard deviation of 1.06 and it varies from -3.68 to a maximum of 2.67. This confirms the huge variation between the firms' size considered in the sample.

The interaction term (*AI x Size*) has a negative mean equal to -6.14 and a standard deviation equal to 33.23. The minimum value is -178.62 and the maximum is 143.62 and this shows that AI intensity adoption varies a lot according to the size of the company. Since the sample is composed by different and very heterogeneous Italian firms, this variation is even more emphasized here where size differs a lot across the companies, and thus also the AI intensity adoption which we will see that is fairly influenced by the size – as stated in the literature.

Among the financial controls, the *ROA*'s average is equal to 1.48% but it appears to have a high dispersion with a standard deviation of 11.66%. The range varies from -106.03% – indicating the presence of some extreme negative outliers for companies with a negative profitability – to a maximum of 20.50% – for highly profitable firms. Also, the *leverage* seems to have this big variation across the sample firms. In fact, the standard deviation is equal to 181.02%, whereas the mean is equal to 42.08% and a maximum above 2000%. This suggests that there are many outliers within the sample with highly leveraged firms – typical capital structure in the Italian context (Russo, 2016).

Finally, the industry dummy variables display the sectoral distribution of the undertakings within the sample. The biggest shares of companies belong to the industrial and consumer goods sectors (both equal to 23%), followed by the financials' sector equal to 15%. Whereas smaller shares appertain to the following industries: technology (9%), utilities (8%), communication and media (8%), resources (6%), healthcare (4%), and real estate (3%).

Overall, the descriptive statistics emphasize a high variance across the firm sample in accruals, AI intensity adoption, and financial characteristics due to the different size and industry to which they appertain. This further justifies the inclusion within the regression model of firm size controls and industry fixed effects.

*Table 1 – Descriptive Statistics*

| Variable | Mean | St Dev | Min | Max |
|---|---|---|---|---|
| Accruals | -3.50% | 9.96% | -41.23% | 82.93% |
| AI_c | 0.0 | 32.03 | -24.57 | 75.41 |
| log_TA_c | 0.0 | 1.06 | -3.68 | 2.67 |
| AI x Size | -6.14 | 33.23 | -178.62 | 143.62 |
| ROA | 1.48% | 11.66% | -106.03% | 20.50% |
| Leverage | 42.08% | 181.02% | 0.00% | 2197.56% |
| Dummy Financials | 0.15 | 0.360 | 0 | 1 |
| Dummy Industrials | 0.23 | 0.425 | 0 | 1 |
| Dummy Utilities | 0.08 | 0.276 | 0 | 1 |
| Dummy Resources | 0.06 | 0.229 | 0 | 1 |
| Dummy Technology | 0.09 | 0.287 | 0 | 1 |
| Dummy Consumer Goods | 0.23 | 0.421 | 0 | 1 |
| Dummy Healthcare | 0.04 | 0.200 | 0 | 1 |
| Dummy Communication and Media | 0.08 | 0.276 | 0 | 1 |
| Dummy Real Estate | 0.03 | 0.183 | 0 | 1 |

### *3.2. OLS Regression Results*

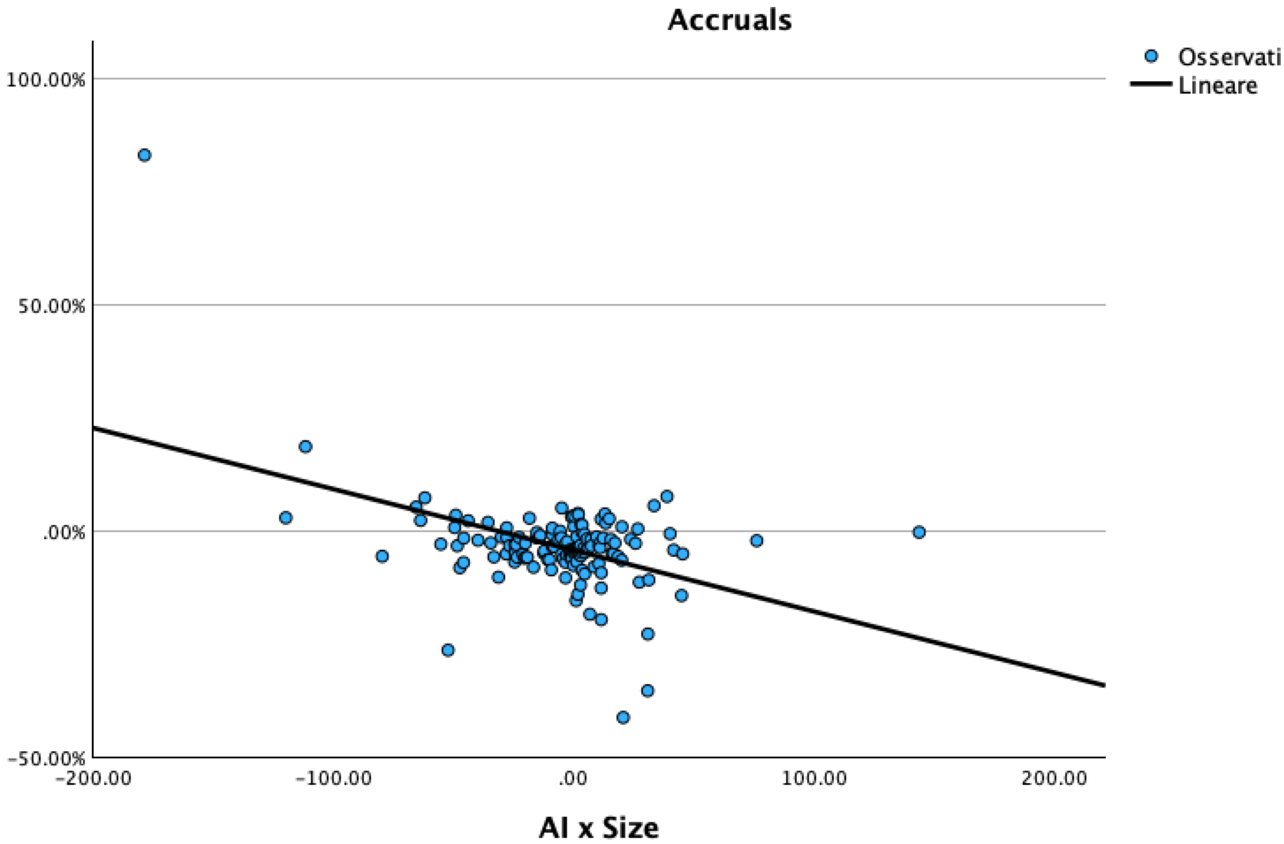
Table 2 shows the results of the analyses conducted. Model 1 is the baseline model including only the control variables. Model 2 adds the independent variable (*AI intensity adoption*). This is the full multiple linear regression model for the study, and it shows that AI adoption with the increase of firm size has a significant negative effect on the increase in the level of accruals, as the coefficient of the interaction term (*AI adoption x Size*) is negative and significant ($\beta = -0.033$, $p < 0.05$). This means that the *AI adoption x Size* decreases the level of accruals and so increases the accounting quality. Thus, the hypothesis is supported, and it is not rejected.

Both models are highly significant ($p < 0.001$), with a strong explanatory power. The value of the R-squared is equal to 0.717 for the baseline model, whereas it grows in the full model (model 2) up to 0.726, suggesting a modest improvement in the model fit with the inclusion of the independent variable (*AI intensity adoption*). Therefore, the adoption of AI in audit functions enhances the explanatory power of the model in explaining the accruals pace, beyond the traditional financial and industry-level determinants. In fact, an R-squared equal to 0.726 signifies that more than a half of the observed variations in the dependent variable are well explained by the independent variable, the control variables and the interaction term. So, there is a correlation between the AI intensity adoption, the size and the level of accruals. Afterward, it can be also seen that the p-value of the F-test ($< 0.001^{b}$) is lower than the considered significant level of 5%. Therefore, there is more than 99% of probability that the independent and control variables and the interaction term are very good in explaining the dependent variable (Y). Thus, the overall model is statistically significant.

Then, considering more in detail the relationship between each explanatory variable with the dependent variable, it can be observed that:

- The mean-centered *AI intensity adoption* (*AI_c*) is not statistically significant on its own ($p >$ 10%), demonstrating that this variable does not exert a direct and uniform impact on accruals across the Italian firms considered. However, the interaction term *AI x Size* is negative and significant at the 5% level ($\beta = -0.033$, $p < 0.05$) – as already mentioned. This result highlights the fact that as it can be intuitively deducted from the literature review the effect of the AI adoption is contingent on the firm's size: in bigger companies, the AI adoption is associated with lower accruals level (higher accounting quality), while in smaller firms this effect is weaker. In particular, the negative beta of the interaction term means that for each one-unit increase in firm size (*log_TA_c*), the marginal effect of AI intensity adoption on accruals level decreases by 0.033 points, ceteris paribus. Therefore, in bigger firms the presence of AI auditors is associated with a stronger reduction in accruals and thus with a higher accounting quality. *Figures 1* shows clearly this relationship between the interaction term (*AI x Size*) and the dependent variable (*level of accruals*).

*Figures 1 – Relationship between AI x Size and accruals' level plotted in SPSS*




- The *natural logarithm of total assets* (*log_TA_c*) is also statistically insignificant on its own ($p > 10\%$) in both models and it becomes significant combined with the AI intensity adoption as we've already seen.
- The *ROA* is highly statistically significant at a level of less than 1% and positive in both models ($\beta = 0.503$, $p < 0.001$ in Model 1; $\beta = 0.478$, $p < 0.001$ in Model 2). This because generally it is expected a positive association between ROA and abnormal accruals. In fact, firms with growing profitability levels tend to manipulate earnings in order to support the earnings' growth and satisfy the market expectations (*Internal Audit Quality and Financial Reporting Quality: The Joint Importance of Independence and Competence - ABBOTT - 2016 - Journal of Accounting Research - Wiley Online Library*, 2016).

- The *leverage* is also highly statistically significant and it positive influences the level of accruals in both models ($\beta = 0.065$, $p < 0.001$ in Model 1; $\beta = 0.061$, $p < 0.001$ in Model 2). This is not surprising as *leverage* tends to be associated with a more abnormal accruals to allow non-violation of debt covenants to meet debt-covenant restrictions (Ater & Hansen, 2020; Press & Weintrop, 1990).
- Regarding the *industry fixed effects*, the results display that most of the coefficient of the industry dummy variables are negative and significant. This means that the sectors like industrials, utilities, resources, technology, consumer goods, healthcare, communication and media are associated with systematically lower accruals level relative to the omitted reference category (the financials dummy). The only exception is the real estate industry which is not significant. This makes sense as the real estate sector tends to be similar to the reference group concerning the accruals pace. In fact, the real estate business is quite akin to the financials' one: they both rely on asset-intensive balance sheet; in both sectors revenue recognition tends to be linked to long term contracts and market cycles; they are both subject to heavy regulation; they both exploit high leverage and external financing.

Overall, the results suggest that AI adoption alone does not have an impact on accounting quality. Instead, it has a significant effect on AQ when combined with the firm size, with larger firms appearing to better leverage from AI tools in audit in order to reduce accruals level and improve the AQ. Traditional determinants like profitability (*ROA*) and *leverage* remain strong and significant drivers of accruals' variation, whereas the industry fixed effects confirm that sectoral heterogeneity is an important factor to control for.

*Table 2 – OLS Regression with Level of Accruals as dependent variable. * stands for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$*

| | **Model 1 (Baseline Model)** | **Std. Error** | **Model 2** | **Std. Error** |
|---|---|---|---|---|
| Number of observations | 145 | | 145 | |
| R-squared | 0.717 | | 0.726 | |
| AI_c (X) | | | 0.005 | 0.016 |
| log_TA_c | -0.151 | 0.581 | -0.030 | 0.588 |
| AI x Size | | | -0.033** | 0.016 |
| ROA | 0.503*** | 0.068 | 0.478*** | 0.070 |
| Leverage | 0.065*** | 0.004 | 0.061*** | 0.005 |
| Dummy Industrials | -6.363*** | 1.672 | -5.610*** | 1.693 |
| Dummy Utilities | -8.674*** | 2.003 | -8.275*** | 2.037 |
| Dummy Resources | -8.965*** | 2.316 | -8.576*** | 2.330 |
| Dummy Technology | -7.678*** | 2.272 | -6.863*** | 2.281 |
| Dummy Consumer Goods | -8.063*** | 1.720 | -7.351*** | 1.738 |
| Dummy Healthcare | -8.936*** | 2.648 | -8.165*** | 2.651 |
| Dummy Communication and Media | -10.630*** | 2.190 | -10.406*** | 2.178 |
| Dummy Real Estate | 0.574 | 3.063 | 1.629 | 3.081 |

Dependent variable: Level of accruals (Y)

### *3.3. Multicollinearity Analysis*

In table 3 there can be observed the Variance Inflation Factor (VIF) indexes to check for multicollinearity. Multicollinearity is present when the independent or/and the control variables are correlated. In case of the model test it seems that there are not multicollinearity issues as all the VIF values are below 10, and in fact most are lower than 3. This means that each variable is gouging a different effect, thus there are not any redundant variables. Therefore, all the explanatory variables used in the model help in explaining in one direction which is the relation with the dependent variable (*level of accruals*).

However, the only variables that tend to be a bit correlated to each other are the *ROA* (3.206) and the *leverage* (3.310) since they have the highest VIF values, but they still remain within the acceptable range. Thus, no multicollinearity problems are present also in this case.

The independent variable – *AI adoption intensity* (*AI_c*) – the control variable *Size* (*log_TA_c*) and the interaction term (*AI x Size*) also have a very low VIF, respectively equal to 1.213, 1.888 and 1.378. This confirms that mean-centering has successfully reduced the potential multicollinearity problems between the *AI intensity adoption*, the *Size* and the interaction term. Similarly, the industry dummy variables show low VIF values which ranges from 1.3 to 2.6. Also, this demonstrates that including the fixed effects within the model doesn't create multicollinearity issues.

Therefore, the VIF test highlights that the model is stable since multicollinearity does not bias the estimation, and the regression coefficients can be reliably interpreted.

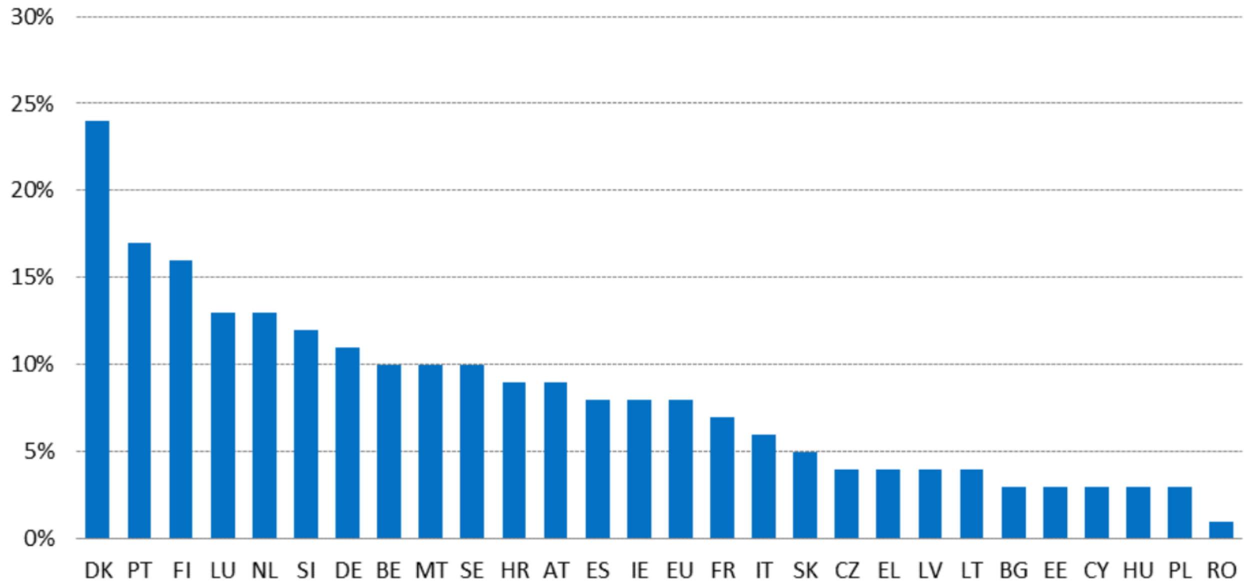
*Table 3 – VIF Test for Collinearity*

| Variable | VIF |
|---|---|
| AI_c | 1.213 |
| log_TA_c | 1.888 |
| AI x Size | 1.378 |
| ROA | 3.206 |
| Leverage | 3.310 |
| Dummy Industrials | 2.503 |
| Dummy Utilities | 1.532 |
| Dummy Resources | 1.376 |
| Dummy Technology | 2.065 |
| Dummy Consumer Goods | 2.583 |
| Dummy Healthcare | 1.356 |
| Dummy Communication and Media | 1.751 |
| Dummy Real Estate | 1.537 |

# 4. Discussion

AI adoption within the audit functions is a theme which is still under evaluation in many different countries, and much research has been conducted especially in America in order to find out whether it improves auditors' works both in efficiency and in effectiveness. However, no clear results have come to light, in particular in the Italian context no study has been performed to understand whether AI enhance the accounting quality and thus the audit's work. In fact, in Italy the integration of AI tools within different business functions is slower and delayed by some skepticism. Therefore, more traditional methods still prevail over the most automated ones. As a matter of fact, Italy is one of the country with the lowest adoption rate according to the Digital Economy and Society Index (DESI) report of the European Commission (*Digital Economy and Society Index (DESI) 2022 | Shaping Europe's Digital Future*, 2022) – *image 1*, below.

*Image 1 – Enterprises using an AI technology (% of enterprises), 2021*




Source: Eurostat, European Union survey on ICT usage and e-commerce in enterprises.

However, the study discussed in this thesis has permitted to find relevant outcomes for future research and developments. In fact, an important aspect which has emerged from the results is that while the AI adoption on its own does not directly improve accounting quality, its interaction with firm size highlights an important contingency: bigger companies take most advantage from AI tools in order to reduce the accruals level and enhance the financial reporting's reliability. At the same time, traditional factors like profitability – represented by ROA – and leverage remain relevant drivers of accruals' variation, emphasizing the still central role of the human judgement within the audit practice in the Italian context.

### *4.1. Limitations and Possible Developments*

This thesis provides an innovative attempt to empirically measure the relationship between the AI adoption in audit functions and accounting quality (AQ) among the Italian listed companies. Nevertheless, there are some limitations which must be acknowledged.

Firstly, there are some methodological limitations that should be considered. The proxy for the AI intensity adoption was built based on publicly available LinkedIn data, filtered through Google SerpApi queries. Although this approach allows for transparency and reproducibility, it should be noticed that final results can have some biases. This happens because LinkedIn profiles are self-reported and may not be consistently updated across firms, bringing to potential under or over estimation of the AI-skilled auditors. Moreover, also the denominator (total auditors) was estimated through keyword-based research, thus also in this case there might be some omitted data, and the final count might not reflect the exact number of audit employees within each firm. Therefore, further research can complement this by retrieving data through internal surveys, proprietary dataset like Cognism Inc., etc.

Secondly, temporal limitations might have influenced the final outcomes. In fact, the study analyzes the financial data of a sample of 145 Italian listed companies considering only one year: the 2024. Thus, the research is a cross-sectional analysis based on data of the last available financial year. This because the data relative to the AI adoption rate are the more recent one (2024-2025) since LinkedIn does not permit to filter for the year. For this reason, in order to maintain coherence across the sample data, I've chosen to select the most recent data which date back to 2024. Undoubtedly, a dataset comprehending a cluster of years (e.g., from 2020 to 2024) would have brought to a more dynamic analysis and it would have permitted a deeper investigation regarding how AI adoption evolves alongside regulatory changes, technology development, and firm growth.

Thirdly, there are some model limitations that should be noticed.  In fact, despite the inclusion of standard controls such as firm size, ROA, leverage, and industry fixed effects, there can be some unobservable factors that may still bias the results. For instance, corporate governance quality, board independence, or external audit characteristics (Big 4 versus non-Big 4) may also influence the accruals level (Dechow et al., 2010). Moreover, also human judgement remains a critical qualitative determinant of AQ which is difficult to operationalize quantitatively (Khan et al., 2025; Li & Goel, 2024).

Lastly, the sample is composed by only Italian listed firms, which operates under specific institutional, regulatory, and cultural settings. In particular, Italy is famous for its concentrated ownership structure, high family involvement – most of Italian companies are SMEs and are led and founded by a family – and a relatively bank-centered financial system (Enriques & Volpin, 2007). These features may limit the relationship between AI adoption and accounting quality in comparison to more market-oriented systems such as US and UK. Thus, expanding the study to other European countries might bring to a broader generalizability.

In conclusion, based on these limitations, many developments are possible for future research. First, expanding the dataset longitudinally may capture the AI's impact on AQ across time, regulatory cycles and also different countries. Second, refining the AI proxy through primary data gathered through internal surveys or with firms' collaboration might reduce undesirable biases. Third, adding to the model more accounting quality proxies (e.g., financial restatements, value relevance, timely loss recognition) and control variables would allow the triangulation of results (Dechow et al., 2010; *International Accounting Standards and Accounting Quality - BARTH - 2008 - Journal of Accounting Research - Wiley Online Library*, 2008). Finally, creating a human judgement proxy can enable a direct comparison with the AI adoption in audit functions and this might permit to understand whether AI improves accounting quality relative to human judgement.

## *4.2. Implications of the Study for Academia*

From an academic point of view, this thesis contributes to connect two relative dissociated streams of literature: accounting quality and artificial intelligence adoption in audit. While prior studies have focuses on AI adoption in audit functions in international contexts like Jordan, America and Portugal (Al-Okaily, 2024; Fedyk et al., 2022; Monteiro et al., 2023), little research has been performed in Italy. By operationalizing AI intensity adoption through an original data collection method, this study provides an empirical foundation for further academic research.

The outcomes show that AI adoption alone does not directly improve accounting quality. Instead, its benefits arise when combined with firm size, as it has been found that with the increase of the company size, the AI adoption enhances the accounting quality – effect captured by the negative coefficient of the interaction term (*AI x Size*). This confirms the theoretical expectations: bigger undertakings have to deal with more complex datasets and strong and mature internal controls and corporate governance, allowing them to extract greater value from AI audit tools (Bin-Nashwan et al., 2025; Monteiro et al., 2023). Whereas this effect is weaker or absent for smaller firms.

These findings encourage academics to reflect over this contingency between AI adoption and firm size. Moreover, there are some factors not considered which might influence the final results and that can be tested in future research. This comprehends moderators like board independence, internationalization level, digital maturity. In addition, another factor that can be inserted as control variable in the analysis is a proxy of the level of governance which we've seen that influences a lot the quality of the financial reports.

Finally, this study informs the broader literature on human judgement versus AI in accounting quality. In fact, despite the technological advances, the positive coefficient of ROA and leverage indicate that traditional financial drivers still remain stronger determinants of accruals. This suggest that human judgement and firm-level incentives continue to be crucial in determining the accruals level and thus the accounting quality, with AI acting as a complementary rather than a substitutive factor, especially in the Italian context.

### *4.3. Implications for Auditors*

For practitioners, the findings provide several relevant insights.

First, auditors should recognize that AI cannot be utilized as a standalone tool to improve accounting quality. In fact, its effectiveness depends on firm's size: larger firms tend to benefit most from AI as their audit functions have to deal with big dataset, repetitive transactions, and complex reporting structures where AI can quickly and efficiently identify anomalies and reduce earnings management. On the other hand, smaller firms might not feel the necessity to exploit AI audit tools as they do not have to handle a big amount of complex data, in most cases.

Second, as we've already mentioned several times, this study confirms that human judgement continues to have a central role in accounting. In fact, we've seen that accruals remain strongly influenced by profitability (ROA) and leverage incentives as they've both resulted significant variables in the statistical model in determining the accruals level. This acknowledges what has already been stated by (DeFond & Zhang, 2014) who claim that auditor's characteristics such as tenure, independence, and expertise have a big influence on accounting quality. In particular, it is important that auditors maintain a critical skepticism and professional expertise in areas like valuation, impairment testing, and complex revenue recognition. Therefore, AI should be considered as an additional and complementary tool to the human work, enhancing efficiency and detection capacity, but not replacing the professional responsibility.

Third, auditors should take into account that there is an evident sectoral heterogeneity. As a matter of fact, we've tested that most of the dummies resulted significant variables in the model. This suggests that the impact of AI tools differs according to the sector. This because in data intensive sectors like technology, consumer goods, the AI adoption might have a clearer impact on accruals level, whereas in asset-intensive industries like real estate, financials this effect may be weaker. This further confirms what other authors have claimed: firms which have to handle a large number of repetitive activities tend to have a higher AI adoption rate since they benefit more from these automated tools (Fedyk et al., 2022; Monteiro et al., 2023).

Finally, the study makes auditors aware about the fact that AI can become an important audit tool in order to achieve a competitive advantage by investing in AI skills. Training auditors in AI tools and recruiting AI-skilled workers can be considered as justified investments for this purpose. However, companies must balance these technological investments with continue emphasis on auditor independence, ethical standards, and professional judgement (Li & Goel, 2024).

### *4.4. Implications for Policymakers*

The results of the analysis might be useful also for regulators and policymakers.

First, the conditional effect of AI adoption – stronger in larger firms – can bring to a potential gap between big and small firms in terms of accounting quality. Policymakers should recognize whether small and medium sized enterprises (SMEs) need some support – such as subsidies, tax incentives, or shared AI platforms – to guarantee also to these undertakings the benefits of technological adoption and avoid the concentration of this advantage in the hands of the large corporations. This is a very important consideration especially within the Italian context where most of the firms are SMEs (Burinskienė & Nalivaikė, 2024).

Second, since, as we've seen, profitability (ROA) and leverage continue to be strong determinants of accruals level, this may limit AI tools in their role of reducing earnings management. For this reason, regulators should facilitate AI's role by continuing to promote transparency, auditor independence, and robust corporate governance mechanisms (Dechow et al., 2010; Li & Goel, 2024).

Third, policymakers should encourage the ethical and responsible integration of AI in audit functions. This because as (Li & Goel, 2024) have already noticed, AI usage in auditing may have some limitations and vulnerabilities which need to be considered. These vulnerabilities can result in human rights violations, cyberattacks (Guembe et al., 2022), and increased discrimination of minority groups – especially when the affected people do not have the possibility to interrogate and contest decisions driven by an algorithm (Crisan et al., 2022).

Finally, this thesis emphasizes the importance of data accessibility for research and policymaking. The challenges encountered to collect data and find a measure for AI intensity adoption in Italy evidences broader issues in transparency. Nowadays, where AI and digital tools are becoming increasingly relevant, regulators should require firms to disclose information about their advanced technologies in internal audit and financial reporting. This would not only intensify market transparency but also facilitate academic research and inform policymakers of possible regulatory developments.

# *Conclusion*

This thesis aims to investigate whether the adoption of artificial intelligence within audit functions improves accounting quality in Italian listed firms. A unique dataset has been constructed by integrating financial statements data from Refinitiv with auditor information gathered from LinkedIn profiles. The originality lies in the introduction of the AI intensity adoption ratio: AI-skilled auditors over the total auditors.

The regression analysis provided several key findings. First, AI adoption on its own does not seem to improve accounting quality. The direct effect of AI intensity adoption on accruals resulted statistically insignificant, suggesting that AI tools, when isolated, might not have a meaningful impact in order to reduce earnings management or improve transparency. However, when combined with firm size, AI adoption has a significant and negative interaction effect: larger companies which have adopted AI audit tools show lower accruals, thus they have a higher accounting quality. This result confirms what has been demonstrated by prior literature: bigger firms, due to their greater data intensity, stronger governance, and more mature internal control systems, leverage more from AI technologies in audit.

Second, traditional AQ determinants remain highly influential. In fact, profitability (ROA) and leverage have shown a significant and positive effects on accruals level, recognizing the relevant role that firm-level incentives and financial pressures continue to have in influencing the earnings management behaviors. Thus, despite technological advances, human judgement and economic incentives are still important drivers of the accounting outcomes. Moreover, the significance of the industry dummies has proved that sectoral heterogeneity impacts the accruals level, with industry like utilities, technology, and customer goods displaying lower accruals compared to the financials' sector.

These results indicate that AI should not be considered as a substitute for human auditors but rather as a complementary tool whose effectiveness depends on organizational characteristics – mostly firm size. In general, the Italian context seems to have a lower AI adoption rate in business practices due to cultural skepticism toward technological integration, but it also appears a promising field especially for larger, more data-intensive undertakings.

From a theoretical point of view, this study expands the literature on accounting quality by integrating the AI adoption as a determinant and introducing a new way to operationalize this variable. From a practical standpoint, it suggests that auditors and policymakers should consider AI as a complementary tool which decreases accruals level, but only when supported by adequate governance and data infrastructure. Regulators may also reflect on the possibility to promote disclosure requirements on AI adoption in auditing in order to guarantee more transparency and comparability across firms.

Finally, this work recognizes its limitations – such as reliance on cross-sectional data, potential biases in AI ratio based on self- reported data on LinkedIn profiles, and Italian specific context – but also emphasizes future possible developments for academics including longitudinal studies, cross-country comparisons, and the integration of additional accounting quality proxies and other control variables like corporate governance level and digital maturity.

## *Appendix*

*Table 4 – Financial Data of the Italian Listed Firms considered in the sample*[7]

| Company | log_Total Assets | Accruals | Leverage | ROA | AI Intensity |
|---|---|---|---|---|---|
| A2A | 4.30 | -2.99% | 36.55% | 4.61% | 0.00% |
| Acea | 4.09 | -10.39% | 46.24% | 3.10% | 20.16% |
| Acinque | 3.03 | -18.43% | 24.91% | 2.01% | 0.00% |
| Aedes | 0.83 | 2.66% | 1.77% | -19.30% | 18.62% |
| Aeffe | 2.60 | 3.05% | 44.01% | 4.54% | 25.69% |
| Aeroporto Guglielmo Marconi di Bologna | 2.56 | -6.89% | 8.92% | 7.01% | 57.95% |
| Alerion Clean Power | 3.23 | 3.83% | 65.84% | 6.16% | 0.00% |
| Alkemy | 2.05 | -22.80% | 24.03% | -12.20% | 0.00% |
| Amplifon | 3.60 | -7.66% | 43.51% | 3.79% | 24.01% |
| ANIMA Holding | 3.43 | -2.02% | 8.01% | 8.97% | 77.68% |
| Ariston Group | 3.55 | -8.71% | 25.71% | 0.06% | 37.70% |
| Arnoldo Mondadori Editore | 3.06 | -5.55% | 22.44% | 5.75% | 12.46% |
| Ascopiave | 3.16 | -4.79% | 29.30% | 2.50% | 0.00% |
| Askoll | 1.48 | -14.31% | 44.72% | -23.83% | 0.00% |
| Assicurazioni Generali | 5.73 | -2.19% | 6.97% | 0.80% | 55.82% |
| Autostrade Meridionali | 1.45 | 1.69% | 0.00% | 0.77% | 17.39% |
| Avio | 3.04 | -4.96% | 1.06% | 0.59% | 72.95% |
| Azimut Holding | 4.01 | 7.56% | 0.27% | 5.86% | 78.92% |
| B&C Speakers | 1.94 | 5.54% | 20.08% | 20.50% | 0.00% |
| Banca Generali | 4.23 | -1.47% | 7.71% | 2.67% | 0.03% |
| Banca Ifis | 4.14 | 2.55% | 38.77% | 1.17% | 37.97% |
| Banca Mediolanum | 4.94 | -0.08% | 8.34% | 1.37% | 21.07% |
| Banca Monte dei Paschi di Siena | 5.09 | 2.21% | 17.68% | 1.59% | 0.01% |
| Banca Popolare di Sondrio | 4.75 | 1.86% | 19.92% | 1.01% | 0.00% |
| Banco BPM | 5.30 | 3.44% | 15.39% | 0.96% | 0.00% |
| Banco di Desio e della Brianza | 4.27 | 3.71% | 28.07% | 0.66% | 37.86% |
| BasicNet | 2.67 | -5.11% | 34.65% | 5.44% | 69.46% |
| Bastogi | 2.48 | 0.86% | 43.49% | 2.22% | 0.00% |
| Beewize | 0.90 | 2.86% | 92.15% | -21.79% | 74.66% |
| Bialetti Industrie | 2.19 | -11.36% | 84.44% | -0.62% | 0.00% |
| Biesse | 2.91 | -1.35% | 25.30% | 0.51% | 0.05% |
| BPER Banca | 5.15 | 2.77% | 17.43% | 1.02% | 14.58% |
| Brembo | 3.67 | -3.45% | 26.74% | 6.05% | 0.02% |
| Brioschi Sviluppo Immobiliare | 2.34 | -1.87% | 35.10% | -0.41% | 0.00% |
| Brunello Cucinelli | 3.24 | -3.98% | 55.20% | 8.23% | 0.00% |
| Buzzi Unicem | 3.94 | -0.87% | 6.94% | 11.56% | 10.53% |

[7] Source: Refinitiv (*LSEG Data & Analytics* | *Financial Technology & Data*, 2025).

| Company | log_Total Assets | Accruals | Leverage | ROA | AI Intensity |
|---|---|---|---|---|---|
| Cairo Communication | 3.26 | -4.13% | 11.70% | 3.88% | 0.00% |
| Caltagirone | 3.68 | -8.63% | 7.33% | 5.76% | 0.00% |
| Caltagirone Editore | 2.80 | -1.61% | 4.17% | 1.40% | 0.00% |
| Carel Industries | 2.93 | -3.07% | 17.93% | 7.14% | 89.94% |
| Cembre | 2.43 | -1.31% | 4.23% | 16.37% | 23.21% |
| Cementir Holding | 3.44 | -5.16% | 7.19% | 8.13% | 18.70% |
| CIR - Compagnie Industriali Riunite | 3.44 | -6.96% | 41.06% | 1.89% | 0.00% |
| Class Editori | 2.22 | 0.41% | 27.39% | -2.22% | 0.00% |
| Comer | 3.05 | -3.84% | 14.30% | 5.80% | 0.01% |
| Credito Emiliano | 4.83 | 3.55% | 17.99% | 0.91% | 25.75% |
| CSP International Fashion Group | 1.98 | -5.64% | 14.15% | -0.37% | 84.91% |
| Danieli | 3.87 | -1.21% | 7.81% | 3.39% | 0.02% |
| Datalogic | 2.86 | -2.82% | 12.52% | 2.07% | 0.00% |
| Davide Campari-Milano | 3.93 | -4.87% | 33.76% | 2.54% | 49.64% |
| De Nora | 3.15 | -1.92% | 11.19% | 6.05% | 69.22% |
| De'Longhi | 3.64 | -3.49% | 14.93% | 7.98% | 0.00% |
| Diasorin | 3.52 | -5.16% | 30.69% | 5.74% | 16.79% |
| DoValue | 3.16 | -5.12% | 53.58% | 1.13% | 21.73% |
| Edison | 4.12 | -2.77% | 7.68% | 2.87% | 0.06% |
| El.En. | 2.87 | -3.41% | 6.31% | 8.61% | 0.00% |
| Elica | 2.60 | -2.69% | 24.26% | 2.32% | 0.00% |
| Emak | 2.85 | -3.76% | 39.01% | 0.93% | 0.00% |
| ENAV | 3.38 | -6.41% | 24.85% | 5.34% | 13.47% |
| Enel | 5.27 | -3.32% | 37.98% | 4.30% | 0.00% |
| Eni | 5.17 | -7.03% | 25.07% | 1.91% | 0.01% |
| EPrice | -<br>0.39 | 82.93% | 2197.56% | -106.03% | 73.05% |
| ERG | 3.80 | -4.45% | 48.84% | 3.29% | 0.01% |
| Esprinet | 3.31 | 0.93% | 12.97% | 1.12% | 20.63% |
| Eurogroup Laminations | 3.12 | -0.77% | 35.24% | 2.93% | 0.00% |
| Eurotech | 2.05 | -35.32% | 23.88% | -27.09% | 0.05% |
| Expert.ai | 2.02 | -10.87% | 17.56% | -13.61% | 0.15% |
| Fabbrica Italiana Lapis ed Affini (FILA) | 3.07 | -0.31% | 30.27% | 6.82% | 9.76% |
| Ferrari N.V. | 3.98 | -4.26% | 35.55% | 17.39% | 85.60% |
| Fiera Milano | 2.82 | -5.79% | 52.16% | 2.71% | 66.67% |
| Fincantieri | 3.98 | -4.31% | 22.69% | 0.30% | 22.28% |
| FinecoBank | 4.54 | 1.43% | 5.81% | 1.92% | 26.90% |
| Gambero Rosso | 1.57 | -6.52% | 40.76% | -5.28% | 13.07% |
| Garofalo Health Care | 2.93 | -1.56% | 26.99% | 2.65% | 66.76% |
| Geox | 2.84 | -12.66% | 48.49% | -0.71% | 0.05% |
| Gruppo Ferretti | 3.22 | 5.02% | 1.98% | 5.40% | 90.29% |
| Gruppo FNM | 3.37 | -5.31% | 47.41% | 2.67% | 56.05% |

| Company | log_Total Assets | Accruals | Leverage | ROA | AI Intensity |
|---|---|---|---|---|---|
| GVS | 2.97 | -6.85% | 34.98% | 3.49% | 21.11% |
| Hera | 4.18 | -2.38% | 36.26% | 3.56% | 21.41% |
| I Grandi Viaggi | 2.02 | -8.05% | 4.61% | 3.26% | 37.72% |
| ICOP | 2.50 | -2.96% | 18.63% | 7.03% | 94.01% |
| IGD SIIQ | 3.27 | -4.13% | 43.78% | -1.54% | 0.00% |
| Illimity | 3.92 | -0.37% | 28.73% | -0.77% | 0.00% |
| IMMSI | 3.36 | -4.76% | 48.21% | 1.29% | 93.73% |
| Interpump Group | 3.53 | -3.83% | 23.64% | 6.89% | 41.94% |
| Intesa Sanpaolo | 5.97 | 5.23% | 19.47% | 0.91% | 0.00% |
| Inwit | 3.98 | -4.31% | 48.84% | 3.76% | 21.85% |
| Iren | 4.09 | -5.85% | 41.00% | 2.54% | 0.02% |
| Italgas | 4.08 | -5.18% | 60.02% | 4.39% | 18.10% |
| Italmobiliare | 3.38 | 3.12% | 20.35% | 4.61% | 12.58% |
| Itway | 1.67 | -0.66% | 13.55% | 1.08% | 0.00% |
| Iveco Group | 4.29 | -4.91% | 32.44% | 2.84% | 0.00% |
| Juventus Football Club | 2.83 | -19.63% | 41.13% | -26.34% | 0.20% |
| Leonardo | 4.53 | -1.39% | 13.96% | 3.60% | 0.02% |
| Lucisano Media Group | 2.05 | -26.37% | 33.90% | 2.27% | 66.67% |
| LVenture Group | 1.82 | 18.58% | 11.85% | 14.18% | 99.96% |
| Maire | 3.87 | -1.09% | 8.44% | 3.09% | 0.01% |
| MARR | 3.08 | -1.82% | 37.46% | 3.56% | 0.02% |
| Mediobanca | 5.00 | 0.57% | 44.32% | 1.39% | 19.28% |
| Moltiply Group | 2.97 | -4.77% | 35.98% | 4.64% | 99.98% |
| Moncler | 3.74 | -6.36% | 17.39% | 12.19% | 0.00% |
| Monrif | 2.24 | -3.25% | 58.25% | 0.13% | 22.07% |
| NewPrinces | 3.37 | -4.64% | 54.08% | 10.11% | 36.80% |
| Nexi | 4.39 | -3.31% | 14.34% | 0.75% | 0.02% |
| Olidata | 1.95 | -15.42% | 13.07% | 1.09% | 23.90% |
| Orsero | 2.84 | -3.37% | 29.00% | 4.08% | 8.74% |
| OVS | 3.45 | -9.28% | 44.52% | 1.82% | 98.79% |
| Piaggio | 3.28 | -4.17% | 36.14% | 3.58% | 20.73% |
| Pininfarina | 1.96 | -9.54% | 18.87% | -7.06% | 21.26% |
| Piquadro | 2.26 | -2.78% | 31.14% | 5.66% | 0.00% |
| Pirelli | 4.14 | -6.06% | 28.55% | 3.68% | 0.01% |
| Poste Italiane | 5.44 | -0.33% | 32.03% | 0.73% | 91.53% |
| Prysmian | 4.26 | -5.83% | 29.75% | 4.75% | 0.01% |
| Rai Way | 2.66 | -8.16% | 30.54% | 19.29% | 99.54% |
| RCS MediaGroup | 3.03 | -4.23% | 17.49% | 6.01% | 26.49% |
| Recordati | 3.71 | -2.99% | 48.39% | 8.92% | 15.90% |
| Reply | 3.42 | -5.26% | 7.17% | 8.54% | 0.01% |
| Risanamento | 2.18 | -11.98% | 1.81% | -28.15% | 22.12% |
| Sabaf | 2.55 | -5.68% | 27.11% | 2.22% | 0.00% |

| Company | log_Total Assets | Accruals | Leverage | ROA | AI Intensity |
|---|---|---|---|---|---|
| Safilo Group | 2.93 | -6.40% | 15.45% | 2.57% | 51.91% |
| Saipem | 4.16 | -5.20% | 20.77% | 2.23% | 0.00% |
| Salvatore Ferragamo | 3.23 | -14.03% | 46.43% | -3.87% | 0.00% |
| Seri Industrial | 2.88 | 0.65% | 23.73% | 4.27% | 91.70% |
| Sesa | 3.33 | -3.83% | 19.93% | 4.11% | 97.14% |
| Snam | 4.55 | -1.55% | 51.30% | 3.63% | 20.43% |
| Società Sportiva Lazio | 2.47 | 7.27% | 18.22% | 13.80% | 99.10% |
| Softlab | 1.41 | -5.79% | 7.94% | -0.49% | 42.19% |
| SOGEFI | 2.88 | 1.23% | 16.44% | 1.89% | 16.45% |
| Sol | 3.33 | -6.15% | 32.50% | 7.60% | 0.03% |
| Stellantis | 5.32 | 0.71% | 17.93% | 2.69% | 0.01% |
| Tamburi Investment Partners | 3.29 | 3.28% | 23.39% | 1.91% | 16.72% |
| Technogym | 2.96 | -7.97% | 12.24% | 10.35% | 0.03% |
| Terna | 4.43 | -1.50% | 50.57% | 4.16% | 0.01% |
| Tesmec | 2.63 | -5.02% | 47.65% | 0.05% | 0.00% |
| Tessellis | 2.46 | -41.23% | 35.73% | -19.50% | 0.00% |
| TIM | 4.58 | -10.25% | 40.56% | 0.17% | 0.01% |
| Tinexta | 3.07 | -3.93% | 26.32% | 2.27% | 0.00% |
| Toscana Aeroporti | 2.47 | -2.69% | 30.74% | 5.67% | 66.43% |
| Trevi | 2.88 | -7.26% | 41.55% | 0.75% | 0.03% |
| TXT e-solutions | 2.65 | -1.63% | 37.87% | 4.24% | 95.53% |
| UniCredit | 5.89 | 2.28% | 23.29% | 1.25% | 0.01% |
| Unipol | 4.92 | -2.10% | 6.65% | 1.37% | 0.00% |
| Valsoia | 2.11 | -1.90% | 5.87% | 6.58% | 11.63% |
| Webuild | 4.26 | -5.11% | 16.11% | 1.16% | 71.54% |
| Zignago Vetro | 2.88 | -6.21% | 33.67% | 6.59% | 35.45% |

*Image 2 – Python script*

```python
# ai_audit_ratio_search.py

import pandas as pd, requests, json, time
from pathlib import Path

BASE_URL = "https://serpapi.com/search.json"

def load_api_key():
    cfg = json.loads(Path("config.json").read_text())
    return cfg["SERP_API_KEY"]

def serp_total_results(query, api_key):
    r = requests.get(BASE_URL, params={"engine":"google","q":query,"api_key":api_key})
    return r.json().get("search_information",{}).get("total_results",0)

def run(companies_csv="companies.csv", out_csv="output.csv"):
    api_key = load_api_key()
    firms = pd.read_csv(companies_csv)["Company"].dropna().tolist()
    rows = []
    for c in firms:
        q_ai = f'"{c}" site:linkedin.com/in "AI audit"'
        q_audit = f'"{c}" site:linkedin.com/in audit'
        ai = serp_total_results(q_ai, api_key)
        audit = serp_total_results(q_audit, api_key)
        ratio = ai/audit if audit>0 else None
        rows.append({"Company":c,"AI_auditors_count":ai,"Auditors_total_count":audit,"AI_Adoption_Index":ratio})
    pd.DataFrame(rows).to_csv(out_csv,index=False)
```

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