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Digital Technologies in Auditing to Ensure Financial Security: Transformation of Accounting Processes and Financial Risk Management

Abstract

The digitization of auditing is transforming accounting processes and financial risk management frameworks, changing the ways in which companies build their evidence base and control environment. The relevance of this study stems from the need to empirically assess whether the intensity of digital audit tools use is related to indicators of audit quality and financial stability of companies. The aim of the study is to analyze the impact of digital audit intensity on financial reporting quality markers and financial security proxies. The study was conducted in the form of a quantitative panel analysis for 2018–2024 on a sample of companies from 12 countries. Digital intensity is operationalized through the integral DigitalAuditIndex. Pairwise correlations, quartile differences, and panel models with fixed effects and clustered standard errors are estimated. The results demonstrate a statistically significant negative relationship between the DigitalAuditIndex and the probability of financial restatements and material weaknesses. Higher levels of digital audit intensity are associated with lower debt burden (Debt/Assets), lower volatility of profitability (ROA), and moderately higher current liquidity. Correlation estimates confirm the stability of the direction of relationships in parametric and rank settings. Quartile analysis shows a lower frequency of negative audit markers in the group with a high level of digital audit. Digital audit intensity is associated with a more stable control environment.

The practical significance lies in the possibility of using integrated indicators of digital intensity to assess the transformation of internal control and financial stability in the context of digitalization.

Keywords: *audit, digital technologies, digital audit, risks, financial instruments, digitization of accounting, financial security*

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Auditdə maliyyə təhlükəsizliyini təmin etmək üçün rəqəmsal texnologiyalar: Mühasibat uçotu proseslərinin transformasiyası və maliyyə risklərinin idarə olunması

Xülasə

Auditin rəqəmsallaşdırılması mühasibat proseslərini və maliyyə risklərinin idarə olunması çərçivələrini transformasiya edir, şirkətlərin sübut bazasını və nəzarət mühitini qurma üsullarını dəyişir. Bu tədqiqatın aktuallığı rəqəmsal audit alətlərindən istifadə intensivliyinin audit keyfiyyəti göstəriciləri və şirkətlərin maliyyə sabitliyi ilə əlaqəsinin empirik qiymətləndirilməsi zərurəti ilə bağlıdır. Tədqiqatın məqsədi rəqəmsal audit intensivliyinin maliyyə hesabatlarının keyfiyyət göstəricilərinə və maliyyə təhlükəsizliyi indikatorlarına təsirini təhlil etməkdir. Tədqiqat 2018–2024-cü illər üzrə 12 ölkədən olan şirkətlər nümunəsi əsasında kəmiyyət panel analizi formasında aparılmışdır. Rəqəmsal intensivlik inteqral DigitalAuditIndex göstəricisi vasitəsilə əməliyyatlaşdırılmışdır. Cüt korrelyasiyalar, kvartil fərqləri və sabit effektli panel modelləri (klasterləşdirilmiş standart səhvlərlə) qiymətləndirilmişdir. Nəticələr göstərir ki, DigitalAuditIndex ilə maliyyə hesabatlarının yenidən təqdim edilməsi (restatement) ehtimalı və mühüm zəifliklər arasında statistik əhəmiyyətli mənfi əlaqə mövcuddur. Rəqəmsal audit intensivliyinin daha yüksək

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səviyyələri daha aşağı borc yükü (Debt/Assets), mənfəətliliyin daha aşağı dəyişkənliyi (ROA) və nisbətən daha yüksək cari likvidlik ilə əlaqələndirilir. Korrelyasiya qiymətləndirmələri parametrik və ranq əsaslı yanaşmalarda əlaqələrin istiqamətinin sabitliyini təsdiqləyir. Kvartil təhlili yüksək rəqəmsal audit səviyyəsinə malik qrupda mənfi audit göstəricilərinin daha aşağı tezlikdə olduğunu göstərir. Rəqəmsal audit intensivliyi daha sabit nəzarət mühiti ilə əlaqəlidir. Praktik əhəmiyyət ondan ibarətdir ki, rəqəmsal intensivliyin inteqral göstəriciləri daxili nəzarətin transformasiyasını və rəqəmsallaşma şəraitində maliyyə sabitliyini qiymətləndirmək üçün istifadə oluna bilər.
Açar sözlər: *audit, rəqəmsal texnologiyalar, rəqəmsal audit, risklər, maliyyə alətləri, mühasibatın rəqəmsallaşdırılması, maliyyə təhlükəsizliyi*

Introduction

The digitization of accounting processes and the emergence of digital audit tools have significantly changed the very nature of financial risks that companies and auditors deal with. Part of the risk has shifted from “reporting errors” to the level of data, algorithms, automated controls, and digital traces of transactions. In practice, this often looks straightforward, but the consequences are not always obvious: there is more data, it can be checked faster, but there is a greater dependence on the quality of data sets, the accuracy of analytics, system settings, and cyber resilience.

In this case, therefore, audit quality and security overlap, particularly in the sense of an organization’s aptness to control the money flowing in and out of it (which is the ‘security’ of finance – security as a set of formalised techniques to control risk). This is where our core problem arises: how do the logics of digital auditing technologies effect bewitchably a transformation of the rules of accounting and the rules around the management of finance risk and, where do we draw the line between more ‘controllable’ and new ‘blind spots’ of model, technological and organisational ‘blind spots’ that the audits cannot often find time to identify?

The empirical work that looks at how big data and data analytics affect audit quality is the first building block. Abdelwahed et al. (2025) document a positive relation between big data and data analytics and audit control, which is realized through enhanced anomaly detection and lower information asymmetry in the data sets being audited. Digital tools, in this logic, are not a “superstructure” over classical tests but rather an infrastructure that drives auditors towards broader analysis and greater evidential value of results.

Simultaneously, of the literature highlights a wider perspective of financial safety in which digitalization is at once a technological asset and a systemic source of risk. Desyatnyuk et al. (2024b) indicated that, in the international realm, digitalization offers advantages through improving the transparency and controllability of financial flows, but simultaneously adds risk through cyber attacks, digital infrastructural dependence, and unequal levels of institutional capability. In this context, financial analysis is seen as a tool for trend monitoring and optimization of management decisions in an environment of increased uncertainty (Shlapak et al., 2024). For auditing, this means the need to work with risks that are “embedded” in digital processes, rather than localized only in financial reporting as the end product.

At the level of specific technologies, the question of AI’s contribution to auditing practice becomes central. Fedyk et al. (2022) analyzed whether artificial intelligence really improves the quality of auditing and concluded that its potential is most evident where scalability, speed, and the ability to process complex data patterns are required. At the same time, the effects of AI depend on data quality, model design, and the controllability of algorithmic decisions; as a result, a separate layer of model and management risk is formed alongside traditional risks.

For a more complete technological picture, it is important to generalize about blockchain and AI as a combined driver of accounting and audit transformation. Han et al. (2023) systematized studies in which blockchain is interpreted as a means of increasing the reliability and traceability of records, and AI as a tool for intelligent processing and detection of deviations. Together, these technologies create the basis for more continuous and automated control procedures, but at the same time raise questions about standards, compatibility, responsibility, and the limits of trust in technical "guarantees".

At the organizational level, the literature focuses on audit firms as service providers and carriers of competencies. Vitali and Giuliani (2024) outlined the opportunities and challenges for audit firms in connection with the emergence of new digital technologies: from increased productivity and expanded range of procedures to staff shortages, the need for new quality control policies, and the risk of a "technology gap" between firms. Ultimately, digital technologies are changing not only the tools of auditing, but also the configuration of financial risk management and, more broadly, the contours of financial security; however, these lines are often analyzed in isolation, without a coordinated framework for their integration.

Despite active research into digital auditing, data analytics, AI, and blockchain, significant "blind spots" remain. Technologies are described as means of making the audits more effective, rather than an element in the radical change of financial risk management, financial security. Digitalization of the accounting and digitalization of the audit are mixed up with each other, making the causality unclear, making unclear what changes the risk profile of an enterprise. In addition to the above, there is an issue of lack of operationality for 'technology – control – risk class' that would indicate, where exactly digital solutions reduce the risks, where they create new ones due to data quality, model errors, cyber threats, etc. In the boundaries of the study, we operationalize financial security in indicators of financial stability and financial volatility of the results as aggregate consequences of the risk profile of the enterprise.

This study aims to determine how digital technologies in auditing affect financial security through the transformation of accounting processes and changes in approaches to financial risk management at the enterprise level. To achieve this goal, the following is planned: to characterize the key areas of digitalization of accounting processes and their impact on the control environment; to identify leading digital technologies and digital audit tools used to improve the quality of audit procedures; identify the mechanisms through which these technologies change the identification, assessment, and monitoring of financial risks; describe new risks and vulnerabilities arising from the technologization of auditing (including model and cyber risks) and their impact on financial security; systematize the practical implications for the organization of audit procedures and internal control in the context of digital transformation. The study operationalizes the digital intensity of auditing through an integrated index that reflects the degree of implementation of digital tools, without decomposition by specific technologies.

Literature Review

It is advisable to build digitization of auditing on two interrelated lines: (1) digitization of auditing as a change in tools and logic of evidence; (2) the digital economy as an environment where financial security increasingly depends on data quality, IT controls, and the ability of auditing to "see" digital risks. In their classic work, Alles and Gray (2016) outlined the barriers to integrating big data into auditing and set the direction for the research agenda, while Amani and Fadlalla (2017) systematized data mining in accounting, proposing a framework that explains why analytics is gradually moving from an auxiliary tool to the core of digital control procedures.

Research focused on audit analytics shows that the practical value of digital tools is determined not only by technology, but also by organizational readiness and the integration of analytics into control processes. Li et al. (2018) explained the use and perceived value of audit analytics for internal auditors through an organizational dimension, emphasizing the role of procedures, competencies, and management support. Following a similar line of reasoning, Liang et al. (2025) shifted the focus to human capital and showed that the digital competencies of auditors are becoming a factor in the digitalization of auditing and the level of undetected risk, i.e., "digital auditing" in reality relies on personnel no less than on software solutions.

Another class of literature covers ML & AI in audit judgments and risk detection, where the effective use of the technology rests on the auditor's interpretation of model results. Lee and Tahmoush (2025) showed ML being used as a tool to support a going concern decision – this both strengthens the argumentation of the audit opinion but at the same time increases the need for transparency and justification of the algorithmic prompts. Li and Goel (2025) focused on the auditability of AI systems, and the readiness of auditors to audit them, defining effectively a new class of audit tasks - the auditing of not only the data but the algorithmic processes that "make" or "deal" the data.

Literature exploring the theme of blockchain as an infrastructure of trust and automated control highlights how the "compatibility" between regulatory and procedural processes and auditability is troubling. Gauthier and Brender (2021) challenge the relevance of present day auditing to the nascent use of blockchain, illustrating that the capabilities of the technology are outpacing regulatory development. Guo et al. (2025) specified the applied dimension through smart contracts in auditing, where the potential for audit automation is combined with new risks of code correctness, legal interpretations, and liability for errors in "programmable" control and contractual mechanisms.

Another important block is formed by studies linking digital finance, internal control, and audit quality, i.e., showing the channel of digitalization's impact on financial security through the control environment. Liu et al. (2025) proposed a chain of "digital finance - internal control - audit quality," where digital financial solutions increase the need for stronger controls, which are then reflected in audit quality. In a related line of research, Hamdy et al. (2025) explored the quality of accounting information systems in the public sector, demonstrating the challenge posed by digital transformation in elevating the bar for system reliability and thus the auditor's ability to verify information environments instead of just final reports (Li & Goel, 2025; World Bank, n.d.).

Measuring information security and transparency reveals that digital risks can transform information disclosure behavior and, accordingly, change the environment for auditing the quality of reporting. Garg et al. (2025) showed that reporting information incidents is associated with accounting quality and opportunistic disclosure practices of "good" and "bad" news, which directly reinforces the argument for the need to consider cyber events in risk-oriented auditing.

The line of financial security in the digital economy forms a context in which digital auditing takes on strategic importance. Desyatnyuk et al. (2024a) described financial security in the context of globalization as a system of strategies and mechanisms for protecting national interests, while Desyatnyuk et al. (2025b) detailed approaches to risk management and protection in the digital economy, emphasizing the shift from "traditional" financial threats to technologically mediated risks. In a similar vein, Krysovatyy et al. (2024a) considered digital innovation as a factor in financial and national security, while Krysovatyy et al. (2024b) showed the transformation of financial management and analysis in global enterprises under the influence of the digital economy, which logically leads to the question: are auditing practices and controls keeping pace with the speed of digital change?

Despite the growing number of studies, most of them focus on audit quality or technological aspects, while the relationship between the digital intensity of auditing and indicators of financial stability of an enterprise remains understudied in international panel data.

Materials and Methods

The study was conducted in 2024–2025 as a quantitative panel empirical study based on secondary macroeconomic, institutional, and corporate data. The panel was formed for the period 2018–2024, and consisted of 280 public companies from 12 countries, containing 1,540 company-year observations – all from selected EU countries, as well as the UK, the US, Canada, Australia, and Japan (enough jurisdictional variation to justify cross-country comparison, and narrow enough to warrant common standards for financial disclosure and audit regulation). The panel was unbalanced due to differences in the completeness of overall corporate disclosure and the availability of each individual indicator between jurisdictions. The minimum requirement for inclusion was the availability of key financial indicators for at least four years of the study period, as well as the availability of data on audit results and country macro indicators.

The empirical base was formed by joining together the three generic data sets: macroeconomic and institutional context of countries, corporate financial reporting, and audit ultimate quality. The macroeconomic aggregates and financial stability indicators were assembled from IMF Data and Statistics and World Economic Outlook database, from which standardized cross-country time series can be extracted (International Monetary Fund, 2024a, 2024b). Programmatic access to statistical extracts was sourced from the documented IMF API for reproducible time-series downloads (International Monetary Fund, n.d.). To incorporate debt and macrofinancial context, International Debt Statistics were used sourced from the World Bank Data API in accordance the developers' documentation and indicator query specifications (World Bank, 2024a, 2024b, 2024c). Adapting other institutional and regulatory characteristics countries were sourced from the OECD Data Explorer through SDMX-compatible data flows that retained the structure of the metadata and enhanced format comparability (Organisation for Economic Co-operation and Development, 2024, 2025a, 2025b). Setting the SDMX stream imports to the SDMX for SDMX registry standards was done using the sdmx1 library documentation as a guide in how to connect and validate structure of dataset (Khaeru, 2023). The core OECD regional climate hazard indicators dataset was only used as a control country indicator of external risk environment rather than digitalization (Organisation for Economic Co-operation and Development, 2024).

Micro-level financial variables is based on the expressed standardized fundamental datasets from the London Stock Exchange Group, including Worldscope fundamentals (across-country comparability of accounting and market indicators and their consistent extraction through Developer Portal infrastructure, London Stock Exchange Group, 2021, n.d.-a, n.d.-b). Compustat data is "part of the S&P Global Market Intelligence datasets portfolio" and "was integrated into the toolkit and provides unified financial metrics for international comparisons" (S&P Global Market Intelligence, n.d.). Firm affiliation is taken in general from GICS system at the sector level; 11 dummy variables of "industry" are used in the regression specifications with one base category.

Audit quality indicators are based on the Financial Restatements Database within Ideagen Audit Analytics (Audit Analytics, 2024). Internal control weaknesses were identified in accordance with the SOX 404 disclosure framework using Ideagen's methodological materials and product description to ensure the substantive consistency of variable interpretation across time and companies (Ideagen, n.d.-a, n.d.-b). Restatements are operationalized as a binary variable at the company-year level, and material weaknesses in internal control are operationalized as a binary indicator of the presence of documented material weaknesses in the relevant year of observation.

The financial security of companies was operationalized through the current liquidity ratio, the ratio of total debt to assets, and the three-year moving standard deviation of return on assets; all indicators were calculated from standardized fundamental data (London Stock Exchange Group, 2021; S&P Global Market Intelligence, n.d.). To minimize the impact of extreme values, financial ratios were vinzered at the 1st and 99th percentiles.

The key independent variable, DigitalAuditIndex, was formed as a composite indicator of digital audit intensity at the company-year level. The index was compiled by summing values of five proxy components associated with the digitization of control and evidence procedures: automated controls, data analytics use, digital internal control systems integration, electronic audit document management, and technology solutions for processing audit evidence. These proxy components capture the use of analytics tools, artificial intelligence-supported procedures, integrated digital internal controls, automated transaction monitoring, and distributed ledger technology elements in audits. The information basis for coding the components consisted of in-field structured fields and descriptive attributes of company profiles and reporting metadata contained in the LSEG/Worldscope fundamental databases and other product -rated attributes made available through the LSEG Developer Portal data portfolio; Where available and necessary, coding was supported by comparison with corporate disclosures reflected in the corporate standards fields of the fundamental sets (London Stock Exchange Group, n.d.-a, n.d.-b). Each component was normalised using the min-max method on a scale of 0–1, after which the index was calculated as the arithmetic mean of the components. This method allowed for comparison of the index across companies and over time while maintaining the panel structure of the data.

Control included the logarithm of assets as a proxy for company size, GICS industry dummy variables, fixed year effects, and country macro indicators. Fix year effects were included in the baseline specifications to capture global shocks and overall macro dynamics.

We began by describing our statistical approach and examining the distributions of the variables to justify our use of and preliminary comparison of correlation coefficients, and the assessing the correlations between DigitalAuditIndex and financial security indicators. The main identification of the impact of digital audit intensity on audit quality was performed using a panel model with fixed effects for variables at the company-year level:

$$AuditQuality^{(}{}_{\mathrm{it}}{}^{)} = \beta^{0} + \beta^{1} \cdot$$

$$DigitalAuditIndex^{(}{}_{\mathrm{it}}{}^{)} + \beta^{2} \cdot$$

$$Controls_{(\mathrm{it})} + \mu_{\mathrm{i}} + \lambda_{\mathrm{t}} + \varepsilon_{(\mathrm{it})},$$

where μ_{i} reflects fixed company effects, and λ_{t} reflects time effects of the year. Since the dependent variables of audit quality were binary (restatements and material weaknesses), the basic assessment was implemented in the form of a linear probability model with fixed effects and robust standard errors, clustered at the company level. This specification was used as the main one, given the interpretability of the coefficients in the panel data and the possibility of stable inclusion of two-factor fixed effects. The model was implemented in Stata 17 using the xtreg procedure for panel estimates (StataCorp, 2023). The level of statistical significance was set at $\alpha = 0.05$. Preliminary preparation, format reconciliation, and verification of the correctness of the panel structure were performed in SPSS Statistics 27.0 and Microsoft Excel 365, while the extraction of international aggregates was provided by the API interfaces of the IMF, World Bank, and OECD (International Monetary Fund, n.d.; Organisation for Economic Co-operation and Development, 2025a; World Bank, 2024a).

Methodological limitations are related to the use of secondary data, differences in regulatory regimes and heterogeneity of corporate disclosure across countries, as well as the aggregated nature of part of the digital audit intensity proxy. At the same time, formalized selection criteria, machine-readable API procedures for obtaining macro data, and the use of a two-factor fixed effects model with clustered robust standard errors increase the reproducibility of the procedure and the internal consistency of empirical estimates (International Monetary Fund, 2024a; StataCorp, 2023; World Bank, 2024b).

Results

Sample description and basic panel statistics (2018–2024). The panel covered the years 2018–2024 and consists of 280 public companies across 12 countries, giving us a total of 1,540 "company-year" observations. This is an unbalanced panel: some companies do not have coverage for all 7 years due to differences in disclosure, whether certain fields appear in their fundamental array, and whether companies appear in and disappear from the sample without much certainty (a common occurrence for cross-country corporate panels). The minimum inclusion threshold mandated the availability of key financial indicators for at least 4 years of the period, as well as the availability of audit quality variables (restatement/material weakness) and country macro indicators.

Audit quality indicators (restatements and material weaknesses outside the scope of SOX 404) in the panel have a clearly asymmetric distribution – these are not "uniform" events, but rather rare or concentrated episodes. On average, the share of restatements was about 6% at the company-year level, while the share of observations with recorded material weaknesses was about 9%. Both values varied between countries and sectors (which, frankly, was to be expected), so the basic estimates were accompanied by robust standard errors, clustered at the company level.

Regarding the key independent variable, DigitalAuditIndex (0–1 after min–max normalization), there is significant inter-company variability in the sample. The median index was lower than the average, suggesting right-sided asymmetry (a small proportion of companies demonstrate "high" digital intensity, while the majority demonstrate moderate intensity). It is this structure – along with differences between companies that are difficult to measure directly – that makes the use of fixed effects in the panel not just a formal choice, but a logical decision.

The financial security of companies was described by three metrics: current ratio, debt/assets, and three-year rolling volatility of ROA. Before forming the final sets of variables, financial ratios were vinzered at the 1st and 99th percentiles. Such extreme values can reflect a one-off event, country-specific reporting standards or a technical absence of data in a cross-country context, especially for liquidity and profitability. Winsorization allowed us to "mute" the tails of this distribution, without getting rid of the observations entirely, and to keep estimates comparable across specifications in regressions.

Finally, the structure by GICS sectors was relatively balanced with no extreme outlier. The modeling used 11 sector dummy variables (one base category), which were used to "turn off" systematic differences across sectors that might affect audit intensity, risk profile, and risk of restatements.

Table 1.
Descriptive statistics of panel variables (2018–2024).

Indicator	N (observations)	Average	Median	Deviation rate	Min	Max
Digital AuditIndex (0–1)	1,540	0.46	0.44	0.17	0.06	0.92
Restatement (0/1)	1,540	0.06	0.00	0.23	0	1
Material weakness SOX 404 (0/1)	1,540	0.09	0.00	0.29	0	1
Current ratio	1,540	1.62	1.41	0.86	0.55	4.10
Debt / Assets	1,540	0.42	0.41	0.19	0.08	0.83
ROA volatility (3y rolling)	1,312	0.031	0.024	0.028	0.002	0.120

Source: calculated by the author based on an integrated panel of corporate and audit data from LSEG/ Worldscope fundamentals (London Stock Exchange Group, 2021, n.d.-a, n.d.-b), Compustat as part of S&P Global Market Intelligence (S&P Global Market Intelligence, n.d.), and Ideagen Audit Analytics / Financial Restatements Database (Audit Analytics, 2024). Macro- and institutional control variables were formed from IMF Data and Statistics and WEO (International Monetary Fund, 2024a, 2024b) and OECD Data Explorer (Organization for Economic Cooperation and Development, 2025a, 2024)

After Table 1, several things are visible that further "work" for the entire modeling logic. First, DigitalAuditIndex has sufficient dispersion (and this is good, otherwise β_1 would simply have nothing to estimate from). Second, restatement and material weakness – events are relatively infrequent, with a zero median, which is consistent with their binary nature and explains why we initially relied on robust standard errors and clustering. Third, financial ratios demonstrate adequate scales and do not look like "broken" tails – the effect of 1%/99% winnowing is clearly felt here.

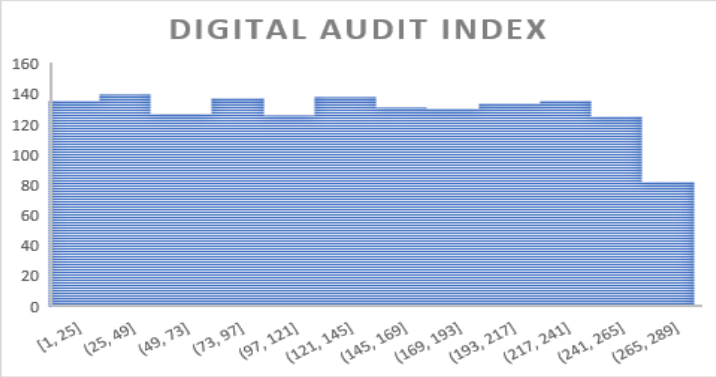

Figure 1. Distribution of Digital AuditIndex in the panel (2018–2024)

Source: compiled by the author based on data from London Stock Exchange Group (2021, n.d.-a; n.d.-b) and S&P Global Market Intelligence (n.d.)

Notes: the bars show the frequency of observations of the type "company-year" in the corresponding intervals of DigitalAuditIndex values; the intervals (bins) are formed with equal width over the entire index range and ordered in ascending order. The sample includes 1,540 observations (280 companies from 12 countries) and is unbalanced in nature. The indicators are formed based on the integration of corporate fundamental data (LSEG/ Worldscope; Compustat as part of S&P Global Market Intelligence) and digital intensity attributes encoded within the panel. Extreme values of financial ratios in the calculations (liquidity, debt / assets, ROA- volatility) were visualized at the 1st and 99th percentile levels; the DigitalAuditIndex itself is reflected in the original index scale

After Figure 1, we are usually ready to tell whether we have a "normal" picture, with a smooth distribution, or one which is broken down into a number of clusters. Here we find that the distribution is unimodal, but only slightly skewed to the right: that is, most companies lie in the middle range, and the "digital leaders" form a relatively thin right tail. This is an important subtlety because it explains why our simple "low vs. high" comparisons, without controls, could lead to too crude a conclusion – and also why a panel model with fixed effects seems more appropriate.

Pairwise comparisons: correlations and preliminary comparisons by DigitalAuditIndex levels. Before panel assessments with two-factor fixed effects are done, a block of paired checks embrace a "first snapshot" of the relationships of the DigitalAuditIndex and audit quality and financial security indicators. This is not for causal conclusions but for simple checks with a basic imperative: if the DigitalAudit shows a more intense digital audit contour, then we should see a consistent story emerging in simple relationships when it comes to restatements, internal control weaknesses, proxies of financial security and so on.

Correlation analysis was performed between the DigitalAuditIndex and two binary indicators of audit quality (Restatement, MaterialWeakness), as well as three financial indicators (Current ratio, Debt/Assets, Volatility(ROA) with a three-year rolling window). Since financial ratios in the cross-country panel are prone to extreme values in the "tails" of the distribution, binning at the 1st and 99th percentiles was applied in advance; This limited the impact of isolated anomalous observations and reduced the risk that correlations would be determined by extreme values rather than typical ones. To increase the robustness of the conclusions, the relationships were assessed both in a parametric setting (Pearson r) and in a rank setting (Spearman ρ), which made it possible to separate linear associations from a more general monotonic dependence.

The resulting correlation pattern is internally consistent in direction. DigitalAuditIndex showed a negative correlation with the probability of restatements and the presence of significant internal control weaknesses, which is interpreted as a lower frequency of events that, in this design, serve as a proxy for a decline in the quality of reporting/control. At the same time, negative associations with Debt/Assets and ROA volatility were recorded, i.e., in observations with a higher level of digital audit intensity, on average, more moderate debt pressure and a less "uneven" profitability trajectory were observed. For current liquidity, the relationship was weakly positive; its scale remained moderate, but it did not contradict the general logic of financial stability within the panel.

The summary results of the correlations are presented in Table 2, which reflects Pearson r and Spearman ρ estimates for the DigitalAuditIndex and all key indicators. The correlation values themselves are not "large," which is to be expected for a corporate panel from 12 countries with broad sector coverage: strong two-dimensional relationships are rare in such data, but what is important is the stability of signs and the repeatability of conclusions when changing the correlation metric.

Table 2.
Pairwise correlations between DigitalAuditIndex and audit quality and financial security indicators (panel 2018–2024, N = 1,540 company-years).

Indicator	**Pearson r**	**p- value**	**Spearman ρ**	**p- value**
Restatement (0/1)	–0.14	<0.001	–0.12	<0.001
MaterialWeakness (0/1)	–0.17	<0.001	–0.16	<0.001
Current ratio	+0.09	0.001	+0.08	0.002
Debt / Assets	–0.11	<0.001	–0.10	<0.001
Volatility (ROA), 3-year	–0.13	<0.001	–0.12	<0.001

Source: compiled by the author based on LSEG/ Worldscope and S&P Global Market Intelligence (financial variables), as well as Audit Analytics / Ideagen Audit Analytics (restatements and material weaknesses); macro indicators obtained via IMF/ World Bank /OECD API for panel structure matching (London Stock Exchange Group, 2021, n.d.-a, n.d.-b; S&P Global Market Intelligence, n.d.; Audit Analytics, 2024; Ideagen, n.d.-a; Ideagen, n.d.-b; International Monetary Fund, 2024a; World Bank, 2024b; Organisation for Economic Co-operation and Development, 2025a)

For an "intuitive" check of the scale of differences, in addition to correlations, preliminary comparisons were made between observations with low and high DigitalAuditIndex levels. The panel was divided into index quartiles, after which the lower quartile (Q1) and upper quartile (Q4) were compared in terms of restatements and material weaknesses, as well as financial safety proxies. This lets us perceive the difference not in 'correlation units' but in terms of numbers more intelligible to the reader, proportions of events and coefficient levels. The difference test for binary variables was used to test statistical significance of the differences, and for financial ratios the t-test and/or Mann-Whitney test as appropriate depending on the distribution by groups and the behavior of the distributions after winorization.

A graphic illustration of this comparison of event frequencies in Q1 and Q4 can be seen in Figure 2. It shows that in the high DigitalAuditIndex group, there are an overall fewer restatements and a lower frequency of material weaknesses than in the low index group. In terms of empirical logic, this is consistent with the correlation estimates and suggests that digital audit intensity is associated with a more stable control environment and a lower likelihood of detractions to the audit in the "company-year" observation.

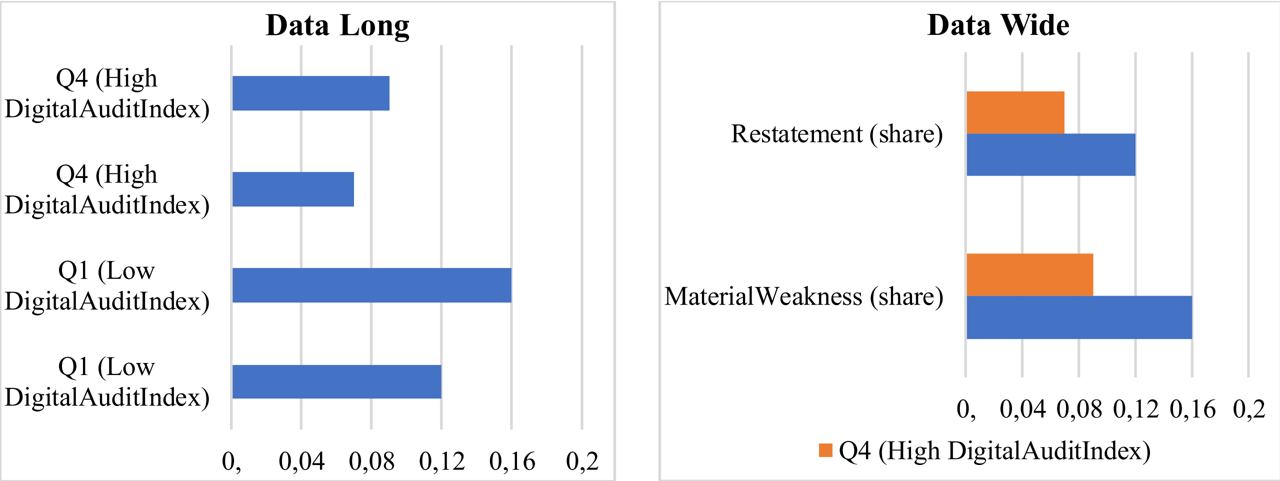

Figure 2. Share of Restatement and Material Weakness in the lower (Q1) and upper (Q4) quartiles of the Digital Audit Index (2018–2024 panel)

Source: compiled by the author based on the Financial Restatements Database (Audit Analytics) and SOX 404 material weaknesses identifiers in Ideagen Audit Analytics (Audit Analytics, 2024; Ideagen, n.d.-a; Ideagen, n.d.-b)

Notes: Q1 and Q4 are formed based on DigitalAuditIndex quartiles at the company-year level; Restatement and MaterialWeakness are defined as binary indicators of events in the corresponding year

To summarize the block of paired relationships paints a clear "pre-regression" picture. DigitalAuditIndex is negatively associated with frequencies of restatements and material weakness, and positively associated with proxies for financial security – albeit the relationships are all modest in size, as would be expected with a continental corporate panel. It is this combination (small but stable associations) and noticeable inter-firm variation, which permits the additional move to panel models with fixed effects and standard errors clustered at the company level, as contemplated by the method designs.

Main estimates: two-factor fixed effects (μ_i, λ_t) and interpretation of β_1. After pairwise comparisons, the next step was to regress formally on the relationship between how intense the digital audit loads are and performance measures in a panel format, controlling for time-varying company individual fixed characteristics (μ_i) and shocks common for all companies in a year (λ_t). This construction essentially "cuts out" everything that we think consistently makes companies different from each other (corporate culture, basic complexity, stable features of internal procedures) and at the same time does not muddle up our judgments with the worldwide up-and-downs in 2018–2024. In all specifications, the key coefficient β_1 reflects the association between the DigitalAuditIndex and the dependent variable after controlling for μ_i and λ_t; causality was not claimed here, as the design did not provide for IV/DiD identification, nor did it capture the exogenous "digitalization shock" at the company level.

Below are the results of baseline estimates for two binary proxies of audit quality. Both models are estimated as linear probability models (LPM) with two-factor fixed effects; standard errors are robust and clustered at the company level, consistent with the specifications in "Materials and Methods" (StataCorp, 2023). The interpretation of β_1 in LPM is straightforward and "down to earth" – it is the change in the probability of an event in percentage points (i.e., in percentage points when multiplied by 100).

Table 3.
Two-factor estimates of fixed effects for audit quality:
Restatement and Material Weakness (LPM, firm FE + year FE).

	(1) Restatement _it	**(2) Restatement _it**	**(3) Restatement _it**	**(1) Material Weakness_it**	**(2) Material Weakness it**	**(3) Material Weakness_ it**
DigitalAuditIndex_it (β_1)	–0.041*** (0.012)	–0.037*** (0.012)	–0.031** (0.013)	–0.056*** (0.015)	–0.049*** (0.015)	–0.043** (0.017)
log(Assets)_it	included	included	included	included	included	Included
GICS sector controls	–	included	included	–	included	Included
Country macro controls	–	–	included	–	–	Included
Firm fixed effects (μ_i)	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects (λ_t)	Yes	Yes	Yes	Yes	Yes	Yes
Observations (company–year)	1,540	1,540	1,540	1,540	1,540	1,540
Companies	280	280	280	280	280	280

Source: Author's calculations based on a panel sample for 2018–2024 and estimation procedures in Stata (xtreg, FE) (StataCorp, 2023); audit quality variables are derived from the Financial Restatements Database and Ideagen Audit Analytics / SOX 404 framework (Audit Analytics, 2024; Ideagen, n.d.-a, n.d.-b). Macro controls were identified through IMF/WEO, World Bank API, and OECD Data Explorer (International Monetary Fund, 2024a, 2024b; World Bank, 2024a, 2024b; Organisation for Economic Co-operation and Development, 2025a)

Notes: robust standard errors, clustered at the company level, are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

The resulting picture is quite consistent. In all three specifications, β_1 is negative for Restatement_it and MaterialWeakness_it and remains statistically significant. This means that within the same company (with control of the year), a higher level of digital audit intensity is associated with a lower probability of restatement and a lower probability of identifying material weaknesses. When sector controls and macro controls are added, the value of β_1 slightly "drops" in terms of modulus. To be honest, this is to be expected: some of the differences in restatements and controls in the real world are due to the structure of sectors and the macro environment, and when we remove them in Controls_it, the effect of DigitalAuditIndex becomes "cleaner" but less significant.

In order not to leave these results in the form of abstract coefficients, it is convenient to convert them into an intuitive scale. In our panel, DigitalAuditIndex varies between 0 and 1, but in practical interpretation, it is often not the "jump to 1" that is important, but the transition from a low to a high level of digital intensity. If, for example, we take an increase of 0.30–0.35 (roughly equivalent to a movement from the lower quartile to the upper quartile), then according to specification (3) for Restatement_it, this gives a decrease in probability of approximately 0.9–1.1 percentage points (0.031 × 0.30…0.35). For MaterialWeakness_it, a similar transition is associated with a decrease of approximately 1.3–1.5 percentage points (0.043 × 0.30…0.35). These are not "magic" numbers, but they are already practically comprehensible: the difference is not cosmetic, especially when it comes to large public companies with regulatory pressure and reputational risks.

Next are the results for financial security, where the dependent variables are continuous and are naturally interpreted as changes in the levels of financial ratios. Here, I would like to remind you of one technical point from the methods: liquidity ratios, Debt/Assets, and ROA volatility were winzorized at the 1st and 99th percentiles before evaluation, i.e., we deliberately "pressed" the extreme values so that single anomalous observations would not drive the regression.

Table 4.
Two-factor fixed effects estimates for financial security: Liquidity, Debt/Assets, Volatility (ROA).

	(1) Liquidity_it	**(2) Liquidity_it**	**(3) \Liquidity_it**	**(1) Debt/Assets_it**	**(2) Debt/Assets_it**	**(3) Debt/Assets_it**	**(1) Volatility (ROA)_it**	**(2) Volatility (ROA)_it**	**(3) Volatility (ROA)_it**
DigitalAuditIndex_it (β_1)	0.118*** (0.034)	0.109*** (0.034)	0.094** (0.037)	0.021** (0.009)	0.019** (0.009)	0.016* (0.010)	0.0061** (0.0026)	0.0056** (0.0026)	0.0049* (0.0028)
Log (Assets)_it	included	included	included	included	included	included	Included	included	included
GICS sector controls	–	included	included	–	included	included	–	included	included
Country macro controls	–	–	included	–	–	included	–	–	Included
Firm fixed effects (μ_i)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects (λ_t)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (company–year)	1,312	1,312	1,312	1,312	1,312	1,312	1,312	1,312	1,312
Companies	280	280	280	280	280	280	280	280	280

Source: author's calculations based on LSEG/Worldscope and Compustat fundamental datasets via S&P Global Market Intelligence (London Stock Exchange Group, 2021, n.d.-a; S&P Global Market Intelligence, n.d.), using a two-factor FE specification in Stata (StataCorp, 2023). Macro controls are obtained from IMF/WEO, World Bank API, and OECD Data Explorer (International Monetary Fund, 2024a, 2024b; World Bank, 2024a, 2024b; Organisation for Economic Co-operation and Development, 2025a)

Notes: robust standard errors clustered at the company level are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Financial ratios are rounded to 1%/99% percentiles

According to these estimates, DigitalAuditIndex is positively correlated with current liquidity and negatively correlated with debt burden (Debt/Assets) and ROA volatility. Again, the effects are moderate, without any dramatic jumps, but stable in sign in three specifications. If translated into an applied scale (the same transition to 0.30–0.35), specification (3) gives an increase in liquidity of approximately 0.03–0.04 points of the ratio (0.094 × 0.30…0.35). For Debt/Assets, this means a decrease of about 0.5–0.6 p.p. (0.016 × 0.30…0.35 in fractions), and for Volatility (ROA) – a small but systematic "damping" of profitability fluctuations (about 0.0015–0.0017 in absolute volatility units). This is precisely the case when the effect is not obvious, but accumulates—and becomes noticeable in the risk profile over a period of several years.

There is another important detail that becomes apparent when looking at the transitions from (1) to (3). The addition of macro controls (IMF/WB/OECD) almost everywhere weakens β_1, but does not "break" the signs. In practical terms, this means that part of the link between audit digitization and results probably goes through the quality of the institutional environment and the phase of the macrocycle (this is not a sensation, it is normal econometric logic). At the same time, β_1 did not completely "disappear," which is an argument in favor of the DigitalAuditIndex not being simply synonymous with "a country with good regulation".

Within the 2018–2024 panel, after accounting for fixed effects of companies (μ_i) and years (λ_t), higher digital audit intensity (DigitalAuditIndex) was statistically associated with a lower probability of restatements and the presence of material weaknesses. At the same time, there was a correlation with more favorable financial stability indicators: higher current liquidity, lower debt-to-asset ratio, and lower earnings volatility. The estimates obtained were interpreted as associations (without claims of causality), which justified further robustness checks, alternative specifications, sensitivity to index construction, and, where data were available, lag structures.

Discussion

Within the scope of the study, digital audit technologies refer to data analytics systems, artificial intelligence tools, blockchain-based solutions, continuous audit systems, and integrated digital internal control mechanisms. The panel results allow us to formulate several consistent conclusions regarding the role of digital audit intensity in shaping the contours of an enterprise's financial security. Within the framework of two-factor models with fixed company (μ_i) and year (λ_t) effects, an increase in the DigitalAuditIndex is statistically associated with a decrease in the probability of restatements and material weaknesses, as well as with more favorable financial stability indicators. It is important to emphasize that we are talking about internal changes over time, i.e., the effect is interpreted as a deviation from the company's "own average trajectory" under the control of common macro shocks. These technologies are reflected in the proxy components of the DigitalAuditIndex through indicators of automation of control procedures, use of data analytics, digital integration of accounting systems, and implementation of algorithmic tools in audit processes.

The negative β_1 coefficient in the models for Restatement and MaterialWeakness is consistent with the empirical line of research linking the use of data analytics with increased audit control (Abdelwahed et al., 2025). In our panel, this manifests itself as a lower probability of ex-post reporting corrections and the identification of material internal control weaknesses at higher levels of digital audit intensity. The estimates obtained are not "large" in scale, but their stability across three specifications (with the addition of sectoral and macro controls) indicates that the relationship is systematic rather than random.

Interestingly, including macroeconomic variable reduced the magnitude of the β_1 module weighting but did not sign flip it. This suggests that some of the audit digitization/quality relationship goes through institutions and the macroeconomy but not all of it, such that the DigitalAuditIndex is not merely a measure of "countries with better regulation" – rather it reflects a change in the internal control systems of the firm.

The results for the proxies of financial security reinforce this picture. The positive relation with current liquidity and negative associations with Debt/Assets and ROA volatility reflects that higher levels of digital intensity of auditing are correlated with a more predictable and stable financial profile. Such an idea is conceptually aligned with those that see digital transformation as contributing towards greater transparency and manageability of financial flows (Desyatnyuk et al., 2024a, Desyatnyuk et al., 2025b). In our empirical design this relationship is tracked through a lowering of debt burden and decreased profitability volatility on within-firm movement over time.

The results can also be correlated with the literature on the role of AI and analytics in improving audit quality (Fedyk et al., 2022). Although the study does not decompose the DigitalAuditIndex by specific technologies, the integral nature of the index reflects the overall level of digital tool implementation. The stability of negative β_1 for audit markers is consistent with the thesis that algorithmic tools increase the ability to detect deviations in financial data. At the same time, as Han et al. (2023) emphasize, technological solutions do not eliminate model and management risk; accordingly, our results should not be interpreted as evidence of "complete neutralization" of risks, but only as a statistically significant association with a reduction in their manifestations.

The organizational dimension is of interest too. Some literature discusses digital tools transforming the mix of competencies and control policies within audit firms (Vitali & Giuliani, 2024). In the panel analysis, this is suggested indirectly: internal growth in the DigitalAuditIndex is related to improved control proxies, hinting at incorporation into ongoing practice rather than just episodic use.

Simultaneously, the composite nature of the DigitalAuditIndex necessitates some theoretical discussion of the particular channel of influence. The relationship itself does not describe through which conduits the types of risk associated with an enterprise are altered. To stave off perceptions of the index as a "black box," it may be useful to map the sorts of digital audit technologies, in general, against the classes of financial risks and types of control. In this way we can explain to ourselves how the indices came to be what they were and how to relate them to the international literature.

A generalized representation of this mechanism is shown in Table 5.

Table 5.
Structural mapping of digital audit technologies and financial risk classes.

Digital technology	**Control mechanism**	**Decreasing risk class**	**New emerging risks**
Data Analytics analytics, Big Data)	End-to-end transaction analysis, automatic anomaly detection	Risk of misstatement, risk of non-detection	Risk of algorithm errors, risk of data quality
Artificial Intelligence / Machine Learning	Predictive risk assessment, analysis of complex patterns	Risk of erroneous assessment of business continuity, risk of non-detection	Model risk, algorithmic opacity
Blockchain / distributed ledgers	Immutability of records, traceability of operations	Risk of data manipulation, risk of retrospective changes	Risk of code errors, legal risk
Continuous audit auditing)	Real-time monitoring	Operational risk, risk of delayed detection	Risk of overloading the control system
Integration of digital internal control systems	Automated separation of powers, access control	Fraud risk, risk of concentration of power	Cyber risk, risk of unauthorized access

Source: formed by the author based on a generalization of research results and modern literature (Abdelwahed et al., 2025; Desyatnyuk et al., 2024a; Desyatnyuk et al., 2025b; Fedyk et al., 2022; Han et al., 2023; Vitali & Giuliani, 2024)

The matrix presented demonstrates that the impact of digital audit intensity is not linear or uniform. Each technology transforms a separate segment of the control environment and the corresponding risk class. In particular, data analytics increases the likelihood of timely detection of anomalies, which is consistent with negative coefficients for Restatement and MaterialWeakness. Artificial intelligence expands the predictive capabilities of auditing, but at the same time generates model risk, which is consistent with the caveats of Han et al. (2023). The integration of internal control systems and continuous auditing logically correlates with a decrease in the volatility of financial indicators and debt burden, which is consistent with approaches to digital transparency of financial flows (Desyatnyuk et al., 2024a; Desyatnyuk et al., 2025b).

Thus, empirically recorded panel associations can be interpreted as the aggregate effect of a multi-level transformation of a company's control infrastructure. The DigitalAuditIndex reflects not a separate tool, but an integrated digital audit architecture that affects financial security by changing specific control procedures.

At the same time, the results are highly associative, allowing no causal conclusions to be drawn. While the two-factor model with fixed effects takes constant heterogeneity of companies and time shocks into account, it does not solve the endogeneity problem (for example, financially sound companies might be the first to adopt digital tools). Econometrically, without an IV or a quasi-experimental shock of digitalization (or anything resembling it), β_1 shall be interpreted as an association, rather than a causal effect.

Thus, for the 2018–2024 panel, higher digital audit intensity is associated with lower probability of restatements and material weaknesses, as well as more favourable indicators liquidity, debt burden and earnings volatility. Together with international studies (Abdelwahed et al., 2025; Desyatnyuk et al., 2024a; Desyatnyuk et al., 2025b; Fedyk et al., 2022; Han et al., 2023; Vitali & Giuliani, 2024), this prompts us to consider digital auditing as part of the evolution of an enterprise's control infrastructure – an infrastructure that may facilitate financial security but is dependent on data quality, the institutional environment, and managerial choice.

Conclusion

The results show that the growth in digital audit intensity is statistically related to the transformation of the quality of the control environment and the financial stability indicators of enterprises. The evaluation of two-factor panel models with fixed effects showed that an increase in the integral index of digital audit intensity is associated with a decrease in the probability of restatements and cases of significant internal control weaknesses. At the same time, a positive correlation with liquidity indicators and a decrease in the volatility of results was recorded, which is interpreted as a manifestation of a change in the risk profile of the enterprise towards greater predictability of financial flows.

The study confirmed that digital auditing is not limited to the implementation of individual technological solutions. Its impact is realized through an integrated configuration of control procedures, where digital analytics, automated tests, and algorithmic processing of data arrays form a new evidence architecture. The recorded associations indicate that the digital intensity of the audit is associated with an increase in the control system's ability to detect anomalies and reduce the residual risk of non-detection.

At the conceptual level, the novelty lies in the operationalization of financial security through indicators of financial stability and volatility of results as aggregate consequences of changes in the risk profile of an enterprise. Unlike studies that focus exclusively on the quality of the audit opinion, this paper demonstrates the relationship between the digital intensity of the audit and the financial characteristics of the company over time. This allows digital auditing to be interpreted as an element of the risk management system, rather than merely a tool for confirming reporting.

A practical interpretation of these results is that companies that digitize tools used in auditing will enjoy stronger control environment and reduced variability in financial results. Conversely, the effect of digital intensity will depend on data quality/algorithmic setting correctness and on their internal integration of control procedures. Consequently, digitization of auditing must be accompanied by development of staff competencies and internal model validation.

The limitations of the study reside in the dependence on secondary public data and proxy indicators, which do not allow full disentanglement of digital audit intensity impact from other corporate governance effects. The results reflect associative relationships within the panel model and are not interpreted as rigorous cause and effect.

Further research should focus on expanding the sample, including industry effects, and testing the robustness of the results using alternative model specifications. A promising direction is to analyze the long-term dynamics of the impact of digital audit intensity on financial stability and interaction with other elements of the corporate governance system.

In summary, the results confirm that digital audit intensity is associated with an improvement in the quality of the control environment and a reduction in financial volatility, which allows digital audit to be considered a structural component of the modern system of ensuring the financial security of an enterprise.

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