Forward-Looking Disclosure and Stock Prices: Does Digital Experience Matter? Egyptian evidence.

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Abstract

Forward looking disclosures have a great impact on the creditability of the listed companies, as companies providing accurate future information tend to be more creditable for investors. On the other hand, inaccurate forward-looking disclosures would result a severely negative impact on the creditability of companies. Accordingly, stock prices would be affected consequently. For any listed company, in order to be able to provide accurate and sound forward looking disclosures, digital tools packages and artificial intelligence techniques is a must due to the variety of data sources and voluminous of data which makes it difficult to manage, analyze, and store these data and information. Digital experience represents the degree by which a company deals with digital technological tools such as big data analytics, artificial intelligence tools in a way that facilitate and enhance forward looking disclosures, which eventually affect companies stock prices. We have tested 221 Egyptian companies that are now functioning in the market and were listed between 2019 and 2022 on the Egyptian Stock Exchange (ESE). Information was manually gathered from annual reports and company websites.

Keywords: Forward looking disclosure, Digital Experience, Stock prices.

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Introduction:

Firms registered in the stock markets generally and in the Egyptian stock market particularly are very oriented to earning investors, stockholders, and stakeholders trust. These firms tend to find out any possible way to improve its creditability to them. Due to the rising pattern of criticizing the historical financial reports by claiming its inability to insure the firm's future financial position because of the economic and political fluctuations that the country and the globe is going through. Investors have insufficient information about the future value of the outstanding securities of the firms. Accordingly, the registered firms in the Egyptian stock market found themselves obliged to find out a new alternative to proof to the users of its financial reports that, the firm is investment worthy.

Starting from the need of reassuring the stakeholders specially the stockholders and its potential investors, firms began to issue forward-looking disclosures. Issuing forward-looking disclosures include a future estimations and decisions about the future of the firm. Since we are living in the digital era, it was thought that, adopting a sound AI forecasting technique, and big data analysis technological solutions, may enhance and improve the quality of the forward-looking disclosures and also may increase the trust of information users in these disclosures.

This paper will be discussing the pros and cons of forward-looking disclosures trying to find out the impact of disclosing future information on the stock prices of the firms providing such disclosures. Also, the paper will measure the impact of digital experience of firms providing forward-looking disclosures trying to find out how AI generated, and digitally analyzed and stored information and can reshape the value of these disclosures and eventually the value of the firm represented it its stock prices.

The study structure is divided into:

- General framework of the study
- Concept and dimensions of financial inclusion
- Concept and development of financial technology
- Study results
- Challenges of financial inclusion and financial technology.

Research problems and questions: Forward-looking disclosures have been severely criticized as non-reliable disclosures that cannot enhance investment decision making process and maybe biased in terms of preparation and information generation methodology.

While the revolution of artificial intelligence is going through its peak of adoption around the world, the Egyptian business environment is still way too far from taking advantage of these revolutionary technological advances, especially in financial disclosures purposes. Accordingly, this paper represents a pioneer attempt to encourage AI adoption and digital experience enhancement in order to achieve more reliable financial disclosures and accordingly a positive impact on stock prices.

Using AI forecasting techniques and other digital tools is still a vague perspective in the Egyptian business environment in terms of the effectiveness, efficiency, and applicability.

Furthermore, the tendency to neglecting or underestimating the forward-looking disclosures claiming its unreliability, deprives the financial information users from the benefits of forward-looking disclosures as an indicator of organizations' going concern, as well as from using it as a tool to support investment decision-making.

Finally, the research problems can be expressed in the following questions:

- Is the use of artificial intelligence and digital tools packages may enhance forward-looking disclosures in terms of reliability and effectiveness?
- What would be the impact of providing FLDs on stock prices?
- Does digital experience really matter in terms of the creditability of FLDs?

Research objective: The main objective of this research is to test the impact and the relationship between Forward looking disclosures and stock prices in Egypt. Also, the quality and creditability of forward-looking disclosures generated, analyzed, and stored digitally on stock prices in Egypt.

Research plausibility: There are few studies as far as the knowledge of the researcher that have examined the forward-looking disclosures through the level of digital experience in developing countries in general and in the Middle East in particular. Moreover, the research shows the difference between forward looking disclosures using different levels of digital experience in terms of stock prices stability and growth.

1. Defining the Forward-Looking Disclosures FLDs

The forward-looking disclosures are not only projected numerical information in financial statements and the accounting policies that represent the base by which these projections were made. It is a complete insight to the future of the company that enables the users to make a better insightful investment decision.

As the Egyptian Auditing standard (EAS No. 3400 for the year 2008) has defined forward-looking disclosures as "That Financial information based on future estimations, that requires a huge amount of personal judgement to make, and it could be in the form of one year predictions, or five years' predictions or both". Here arises the distinction of this research as crystal clear where we argue that, the latest introduced technologies of artificial intelligence can reshape the forward-looking disclosures from being a personal judgement of companies' future that have been criticized of bias and unreliability to become a reliable and accurate estimates made with the minimal human involvement.

The forward-looking disclosures has been defined also as realizable financial information showing the operations results of a firm, its cash flows, financial position, and the most important accounting policies that is used to generate these predictions, in addition to financial performance complementary information and overall performance related information, and these predictions could be made for short term or long term purpose (Saadeldin, 2014).

From the definitions and literature review regarding the forward-looking disclosures, it was found out that, there are some characteristics distinguishing the forward-looking information, which can by summarized as follows (Alqatamin et al, 2017):

- **Optional Disclosure.**

The forward-looking disclosure is an optional disclosure, which means companies do not have to issue forward-looking disclosures. Consequently, companies who issue forward-looking disclosures have decided voluntarily to issue such a disclosure without any pressure on it.

- **Includes the Regular Form of Financial Statements.**

The forward-looking disclosures should contain the regular form of financial statements just the same as the historical financial statements - income statement, Balance sheet, Statement of cash flows, and statement of changes in owners' equity - but for a future period to come usually from 1-3 coming years. Moreover, the forward-looking statements should be not only financial statements of predictions for a future period but also it should have an additional column for the historical information regarding the same items, so that it could be compared to it easily.

- **Not in Accordance with GAAP.**

The forward-looking disclosures are made traditionally used to be based on a huge amount of personal judgement. In other words, the forward-looking disclosures usually were made by experts who generate this information by using their personal judgement according to how they interpret the circumstances around the company and how they feel about the future. Even though, this paper represents a call to make forward-looking disclosures a more reliable disclosure through the use of artificial intelligence forecasting techniques with the minimal human interaction to these estimates, but still Using estimations or judgements does not have to be in accordance with GAAP.

- **Risky to the Company.**

The forward-looking disclosures are considered very risky to the company as, forward-looking disclosures can be considered as promises from the company to stakeholders, and after the period of forecasts ends a comparison to be done between the forecasted information and the actual information that took place during this period. In case of significant variances existence between the forecasted information and the actual information, the firm will be facing the backlash risk of losing the trust and the creditability of its stakeholders, which is just the opposite of the reason why the company had made these disclosures from the beginning.

Moreover, in case of significant variances existence between the forecasted information and the actual information when take place, the company might also face litigation risks by being legally exposed to lawsuits against its forward-looking disclosures as an official promises made and haven't kept by the company.

Many firms fear the increasing demand for forward-looking disclosures will force them to disclose sensitive information, such as profit forecasts or costing data, which will compromise their competitive position and may expose them to the threat of litigation.

2. Elaborating the Importance of the Forward-Looking Disclosures

There are many sources that may provide relevant information with the purpose of supporting investment decision-making enabling investors, and financial analysts in particular or financial reports users in general to predict the future performance of companies. Information in the historical annual report can be classified into two types of disclosures: backward-looking disclosures and forward-looking disclosures. Backward-looking disclosures are related to past financial operations, results, and their related footnotes. While forward-looking disclosures are related to future forecasted operations, results, and their related footnotes that indented to help the users of information – most probably investors, and analysts - in evaluating the future performance of companies (Hussainey, 2004).

Giving the fact that the historical audited annual reports are considered the primary source of such information, we can also claim that an accurately prepared forecasts based on a sound methodology of preparation may be considered a useful insight to companies future performance as it should be considering some of nonfinancial information or decisions that about to happen and may affect the future performance severely and consequently, should affect the investment decisions related to these forwardly disclosing companies.

Forward-looking disclosures as the historical or backward disclosures contain different types of information: financial information such as companies' non-current assets that its planning to keep or acquire and current assets as well that represent its operating position and policies. In addition to its expected current, non-current liabilities, and equity showing their financing policies and plans. Also, financial information of cash flows, profitability, changes in revenues, operating results and financial resources. It also includes non-financial information such as significant risks and uncertainties that might affected the actual results and may affect or make difference between actual results and expected results (Baroma, 2022).

There are many types of information related to forward-looking disclosures (Beretta & Bozzolan, 2004) which are: core business strategies, actual and forecasted capacity to deliver results, explanations of past and future decisions, facts that might be effective in the future, vision, strategies and objectives stated by management, future opportunities and threats that might be effective in the future, and historical results and future results.

The reporting of forward-looking disclosures is related to making almost accurate anticipation of company's future financial position, operating performance and results as well as company's stock price. In order to maintain the comparability of the reports, the forward-looking disclosures comes alongside the historical disclosures to facilitate the analytical procedures for whether the investors of analysts (Scott, 2019).

information about current and future corporate performance is considered the raw material for effective decision making in the capital markets. There are several reasons why a firm would decide to issue forward-looking disclosures (Orcutt, 2022); One of the most important situations in which a company would decide to issue a forward-looking disclosure is when the company is about to make an Initial public offering to a part of its ownership. When a company tend to make an (IPO), the company may need to reassure the investors that, they are investing their money in the right place that will bring them a valuable future benefits. The company who issue a forward-looking disclosure is more reliable for the investors than who do not as; publishing reliable projections brings trust to investors. The idea itself of a company issuing a forward-looking disclosure that come a long with a legal liability to the company about this disclosure is a trust worthy idea as, the company will not put itself in the danger of facing litigation risks so, it will not publish that information unless it is quite sure about it.

In addition, companies may decide to issue forward-looking disclosures in case of merger with other companies, as the future information included in that disclosure would reassure the merger companies that they are making the right call. Also, after mergers, companies tend to brief the investors with the new capabilities and potentials that they have after merger, and what future gains would come out of the same reason, so they decide to issue a forward-looking disclosure.

Companies may decide to issue a forward-looking disclosure in case of applying for borrowing funds. When a company apply to a loan or any kind of credit facilities, it's more likely to be asked for future projections to reassure the fund granting entity of the company's ability of paying back these funds. A forward-looking disclosure would be a valuable tool for the purpose of gaining the trust of the lender party.

3. Pillars of Forward-Looking Disclosures

After establishing the importance of forward-looking disclosures and exploring the kind of information needed to make decisions regarding company's future performance it was concluded that, there are seven pillars for a valuable forward-looking disclosure:

(1) Forward-looking disclosures are only medium-term disclosures that are not appropriate for strategic decisions of a period over 5 years (Saadeldin, 2014).

(2) Providing both quantitative and descriptive information about the available resources of the company and how the company intend to manage

these resources and how that enables it the company to achieve its objectives (Saadeldin, 2014).

(3) Describing the principal risks and uncertainties that may affect the firm's medium-term value or may represent a threat to the investment. Knowing that, disclosing that there are no major risks is also a valuable disclosure (Novitasari and Handayani, 2020).

(4) Clarifying the significant relationships with stakeholders that are likely to influence the performance of the firm and its value in the near future (Alatawi et al, 2025).

(5) Providing quantified information about trends and factors that likely to affect company's future prospects, such as, profit or sales forecasts (Saadeldin, 2014).

(6) Identifying the information that the firm consider confidential and cannot share with the public. Also identifying the degree of uncertainty whenever it exists around any piece of information provided (Saadeldin, 2014).

(7) Disclosing the targets of the company and its related key performance indicators and its evaluation activities in addition to disclosing the strategies the company decided to adopt to achieve these targets (Vasiliki and Abdlmutaleb, 2025).

(8) Providing columns of the historical information and forward-looking information side by side to demonstrate the pattern of the progress or decline if existed (Saadeldin, 2014).

4. Exploring Digital Experience Potentials in Financial and Non-Financial Disclosures

Digital experience would be discussed represented in artificial intelligence techniques, and big data and analytics. As, forecasting the future is a critical aspect of investment strategies, risk management, and economic planning. Traditional statistical methods have long been used, but the emergence of Artificial Intelligence (AI) and Machine Learning (ML) has revolutionized predictive accuracy and efficiency. Financial forecasting involves predicting future market trends, asset prices, and economic conditions to guide investment decisions. Traditional methods like ARIMA (Auto Regressive Integrated Moving Average) and linear regression rely on historical data but struggle with nonlinear patterns, high-frequency data, and market volatility (Pilla and Mekonen, 2025).

4.1 The Competitive Edge of AI in Financial and Non-Financial Forecasting

AI and ML offer data-driven, adaptive, and high-dimensional modeling capabilities that outperform conventional techniques and provide new forecasting capabilities:

Handling Complex, High-Dimensional Data as the traditional financial models struggle with High-frequency trading data, alternative data sources, and unstructured data. On the other hand, AI provide several solutions to such problems represented in modern AI tools such as, deep learning models that process image-based data, also the Natural Language Processing (NLP) tools which are set of artificial intelligence tools focuses on enabling computers to understand, interpret, and generate human language and extract sentiment from calls with >90% accuracy (Yurtay et al., 2024). A matter like this should provide a huge time saving in both quantitative and qualitative analysis stage the comes before the final forecasts, also reduces human bias in the qualitative analysis.

Capturing Nonlinear Relationships, usually Linear regression fails with volatility clustering which is a phenomenon where large price movements tend to be followed by larger movements which is a well-documented feature of financial markets (Dunis et al., 2023). Linear regression, a foundational statistical tool, performs poorly in modeling such behavior as Linear regression treats each observation or market shock as independent case. While AI tools can provide a superior pattern recognition.

Forecasting Time and Cost Saving as the financial forecasting process to be accurate depends on several sources of information such as: minutes of board of directors, economic regime information, historical financial data, etc. for any traditional forecasting techniques it takes enormous time and cost to handle and analyze all these data sources. While, AI provide automation of data processing AI significantly reduces time spent on data collection and cleaning. Traditional financial forecasting requires manual extraction and preprocessing of data from diverse sources (Davenport and Mittal, 2022).

Scenario Generation Feature, the edge of AI adoption doesn't reach only more accurate and timely forecasts, but also could provide multi-scenario analysis and forecasts which help the organization to be more responsive to any potential opportunities or threats. AI enhances scenario generation by simulating multiple plausible future states of financial markets, enabling better risk assessment and strategic planning (Chen and Zhu, 2022).

4.2 Big data Technological Solutions and Improving the Quality of FLDs

Any future forecast is as good as the input data used in the forecasting process. A better forecast is based on larger and more accurate amount of data that are efficiently generated, analyzed, and stored (Zain, 2023). The volume and complexity of data are increasing rapidly due to the numerous sources of data available making it very difficult to collect, analyze, and store the data using the traditional ways and making it a must to adopt big data technological solutions (Breur, 2016).

(Gantz and Reinsel, 2011) developed some characteristics for big data which can be expressed as (Four-Vs) paradigm; volume, velocity, variety and value. According to (Warren et al., 2015) relevant data has several forms as it maybe numeral, texts, images, audio, video, and many other types. Accordingly, majority of companies generate unstructured data. (Laney ,2001) argued that traditional software cannot deal with big data for the (first 3-Vs) paradigm: volume, velocity and variety. Although, when it comes to the fourth V (value), big data big data collection can have no meaning unless it supports a better understanding of customer needs and customize products or services (Ram et al., 2016). Therefore, big data analytics have the ability to convert unstructured data into meaningful and useful information (De Mauro et al.,2016).

5. Risks and Challenges of Digitalization

The adoption of digital solutions such as artificial Intelligence (AI) and big data analytics in financial and non-financial forecasting has introduced significant advancements in predictive accuracy and efficiency. However, its implementation is surrounded with risks, including model interpretability issues, data biases, regulatory compliance challenges, and systemic vulnerabilities (Rao et al, 2025)

5.1 Lack of Interpretability (Black-Box Problem)

AI models, and big data analyzed conclusions, often operate as "black boxes," making it difficult to understand especially for the financial personnel who are responsible for decision-making processes. Also, the financial forecasts users, not all of them are fully aware of the mechanism of AI forecasting processes which makes it difficult to verify the given forecasts (Doshi et al, 2021).

5.2 Regulatory and Compliance Risks

Financial regulators require models to be auditable, fair, and transparent—conditions that many AI models fail to meet. As deep learning models and neural networks operate as complex, nonlinear systems where decision pathways are not easily traceable. Also, AI models continuously adapt, making it difficult to "freeze" a version for auditing (Fuster et al., 2021).

5.3 Cybersecurity and Adversarial Attacks

Any system in the world no matter how strong it is, is as good as the input data used in it. As long as, digital solutions are mostly multi data source models that rely on collecting data from many sources to be used in the forecasting process, so any manipulation to the inputs may affect the out puts of the model. Digital technologies are vulnerable to data poisoning and model evasion. As, attackers might manipulate training data to corrupt AI model behavior (Goodfellow et al., 2022).

6. Mitigating the Risks of Digitalization

The integration of digital technological solutions in forward-looking disclosures for financial and non-financial forecasting presents significant opportunities for accuracy, efficiency, and unprecedented capabilities in predictive analytics, scenario generation, and real-time decision-making but also introduces risks related to model bias, regulatory non-compliance, cybersecurity vulnerabilities, and other ethical concerns.

6.1 Making the Information Explainable in Forward-Looking Disclosures

The interpretability of forecasts is as important as the forecasts itself. Accordingly, it is proposed that, every critical conclusion made on the financial analysis done to get the forecasts, there must be a brief description of the most important factors that influenced this conclusion. Also, it's important to provide a key table for the used model in which basic version of the clear rules that the AI model has followed to get his conclusions (Ribeiro et al., 2023).

6.2 Protecting the Systems from Manipulation

Digital systems face targeted attacks including data Poisoning, model Inversion, and adversarial attacks to distort forecasts. As these systems face an evolving array of cybersecurity threats that include input manipulation –data poisoning- to corrupt the forecasts, model extraction attacks that aim to steal the model itself.

Block Chain-Verified AI Systems could be considered the firewall systems to protect the system from cybersecurity risks as it provides a three-layer verification system that complicate the task for attackers by three layers' protection system that includes; input Layer in which data sources stored encrypted on block-chain platforms which doubles the security. Also a model layer, that uses smart contracts validate algorithm changes. And finally an output layer in which predictions cryptographically signed to make sure of the security of the outputs (JPMorgan, 2024).

7. Literature review and hypotheses Development:

Several studies and literature assured the impact of forward-looking disclosures on companies' stock prices (Arya and Ramanan, 2017) argued that, historical financial reports can only succeed in elaborating current profitability, but definitely fails to help in anticipating future profitability. However, historical financial reports are an important information source anyway, stock price reactions are the primary metric of how future decisions are expected to fare. Meanwhile, (Qu et al, 2015) investigated the determinants of the quality of forward-looking disclosures in a mandatory disclosure regime knowing that most forward-looking disclosures literature have been conducted as an optional disclosure (voluntary-based disclosure), the study indicated that, forward looking information are as good as its quality and its impact might be negative or positive on companies' reputations depending on the quality of forward looking information.

(Bravo, 2016) investigated whether future disclosures and corporate reputation lead to a reduction in stock prices volatility. The study has concluded that forward-looking disclosures has significant effects on capital markets reducing the effect of rumors which cause fluctuations of stock prices. (Baroma, 2022) argued that forward-looking disclosures by its traditional preparation methodology have a positive impact over stock prices only up to the quality of the sources of information used in the disclosure preparation. (Ananzeh et al., 2023) have examined the effect of corporate governance application on future CSR disclosures, and used semi-automatic analysis for available contents to measure FCSRD for a set of 94 listed firms on the Amman Stock Exchange covering a time series from 2010 and to 2016. Data generated about firm's FCSRD were manually generated from firm's annual financial and non-financial reports. The paper also found that size of the board affects FCSRD positively. On the other hand, the duality of CEOs and family businesses affects FCSRD negatively. (Al lawati and Hussainey, 2023). Used content analysis for measuring the levels of future disclosures for 48 bank / year observations of which 8 banks were listed on Securities Exchange Market of Muscat in Oman covering a time series from 2014 and until 2019. Regression analysis showed that overlapping AC membership positively affects FLD. The evidences collected in this paper suggested that a consideration of AC directors' attributes is required to the understanding of their role in the board rooms or in the committees and subcommittees as well. it could be concluded from the findings of this study that the corporate governance in Oman should provide more specifications and standards on the type the overlapping AC membership and the proportion of it.

Based on this, the study proposes the following hypothesis:

H1. There is a significant association between Forward-Looking Disclosure and Stock Prices.

Recent research has extensively explored the application of artificial intelligence (AI) in forecasting financial market trends and evaluating its practical utility for trading. (Cohen, 2022) examined advanced deep learning (DL) and machine learning (ML) methods designed to identify subtle patterns and relationships that may influence trading outcomes. These systems often integrate both linear and nonlinear modeling approaches, along with sentiment analysis derived from social media or technical pattern recognition. The majority of studies reviewed reported successful implementation of such systems in actual trading contexts.

(Faheem et al., 2024) emphasized that AI—through machine learning, neural networks, and big data analytics—enables real-time processing of large-scale financial data, revealing insights traditional methods may overlook. This enhances the ability of financial institutions to anticipate market movements, evaluate credit risk, and refine investment tactics. A key advantage noted is the adaptive capacity of AI models, which continuously improve their accuracy as market conditions change. Nevertheless, the authors also address significant challenges including data privacy, model transparency, and ethical considerations surrounding automated decision-making. Overall, their research underscores the expanding role of AI in developing a more informed and robust financial ecosystem.

In a sector-specific investigation, (Chernysh et al., 2024) analyzed the impact of AI on financial forecasting within banking. They focused on AI's ability to manage large datasets and increase predictive precision, particularly for stock prices, currency exchange rates, and general market trends. Methodologically, the study compared conventional statistical techniques, including ARIMA models, with modern machine learning algorithms such as Gradient Boosting and Random Forests. Using R for data preprocessing and model training, the research evaluated the contribution of AI to forecasting performance and risk management.

Based on this, the study proposes the following hypothesis:

H2. Digital Experience has a significant impact on the association between Forward-Looking Disclosure and Stock Prices.

8. Research design

8.1. Sample and data sources

The present study's population consists of 221 Egyptian companies that are now functioning in the market and were listed between 2019 and 2022 on the Egyptian Stock Exchange (ESE). Since banks and financial services organizations have capital structures that set them apart from non-financial businesses, they are not included in this sample. As a result, companies will become more comparable and uniform. excluding all companies with incomplete information. With 110 firm and 440 firm-year observations spanning 4 years, the final study sample is thus comprised. We manually gathered information from annual reports and company websites. Table 1 lists the companies that were part of the research's final sample along with their industry categorization.

Table 1. Sample structure.

Industry	firms	observations	%
Food, Beverages, and Tobacco	20	80	18
Contracting & Construction Engineering	8	32	7.4
Industrial Goods, Services and Automobiles	5	20	4.6
Travel & Leisure	13	52	12
Real Estate	20	80	18
Chemicals	5	20	4.6
Basic Resources	11	44	10
Textile & Durables	5	20	4.6
IT & Communication Services	4	16	3.6
Trade & Distributors	4	16	3.6
Healthcare	5	20	4.6
Building Materials	10	40	9
Total	**110**	**440**	**100%**

8.2 Variables' measurement

8.2.1 Dependent variable:

Stock prices (SP), the dependent variable in this study, are assessed by the stock prices of listed firms at the conclusion of the month in which financial statements are issued (Abdollahi et al., 2020). The stock price of listed firms three months following year-end is used to assess robustness in the analysis (Chehade and Prochazka, 2023).

8.2.2 Independent variable:

FLD, or forward-looking disclosure, is the study's independent variable. Our suggested FLD index was modified from earlier research (Abad and Bravo, 2019; Agyei-Mensah, 2017; Bravo and Alcaide-Ruiz, 2019; Kılıç and Kuzey, 2018; Abdelazim et al., 2023) and unique indexes created by professional bodies and organizations (CPA Canada, 2014; FASB, 2001). Additionally, utilizing the modified index, a content analysis method was used to look into the total, financial, and non-financial FLD of the firms. Twenty disclosure elements (including financial and non-financial information) are included in the modified index. The ratio of the number of items disclosed to the total number of items (20 items) was used to compute the suggested index.

8.2.3 Moderating variables

Digital Expertise (DE) is the moderating variable in this study. To assess a listed company's level of digital knowledge, we look at relevant buzzwords like big data, cloud computing, blockchain, artificial intelligence, and digital technology as markers of digital experience. The frequency of terms in a company's annual reports serves as a proxy for DE (Yang et al., 2020; Li et al., 2020; Rahman and Ziru, 2023).

8.2.4 Control variables

Firm size, firm profitability, firm leverage, and audit quality are among the factors that we account for since they have been shown to have an impact on stock prices (Abdollahi et al., 2020; Chehade and Prochazka, 2023).

Table 2. Variables’ definition

Variables	Symbol	*Measurement*
Independent variable		
Stock Prices	*SP*	stock price of the company at the conclusion of the month in which financial statements are released.
Dependent variable		
Forward-Looking Disclosure	*FLD*	the proportion of items in the aforementioned index that are disclosed to the total (20 items).
Moderating variables		
Digital Experience	*DE*	The frequency of terms in reports serves as an indicator of the digitization experience of listed organizations.
Control variables		
Firm Profitability	*ROA*	The ratio of net income over total assets
Firm Size	*Size*	The entire assets' natural logarithm
Firm Leverage	*LEV*	The ratio of total debt over total assets
Audit quality	*BIG4*	If the company was audited by one of the Big Four audit firms, a dummy variable with a value of 1 was assigned; if not, it had a value of 0.

8.3 The study models

Using the Pooled Ordinary Least Squares (POLS) approach, we looked into the relationship that the study hypotheses suggested. Consequently, two models are used in this study. In the first model, the relationship between FLD and SP is tested, and in the second, the moderating effect of DE on the relationship between FLD and SP is tested. As a result, two regression models were developed to represent the two hypotheses as follows:

Model 1: $SP_{it} = \beta_0 + \beta_1 FLD_{it} + \beta_2 Size_{it} + \beta_3 LEV_{it} + \beta_4 ROA_{it} + \beta_5 BIG4_{it} + \varepsilon_{it}$

Model 2: $SP_{it} = \beta_0 + \beta_1 FLD_{it} + \beta_2 DE_{it} + \beta_3 FLD{*}DE_{it} + \beta_4 Size_{it} + \beta_5 LEV_{it} + \beta_6 ROA_{it} + \beta_7 BIG4_{it} + \varepsilon_{it}$ **(Model 2)**

Where: DE stands for Digital Experience, FLD for Forward-Looking Disclosure, and SP for Stock Prices. The acronyms for firm size, firm leverage, firm profitability, and audit quality are size, LEV, ROA, and BIG4, respectively. Table 2 has definitions for every variable.

9. Regression Results

9.1. Descriptive Analysis and Correlation:

The descriptive statistics for the variables under investigation are shown in Table 3. With a range of 0.062 to 116 and a standard deviation of 14.64, the average stock price (SP) for the whole sample is 10.44, indicating significant diversity among firms. With values ranging from 0.00 to 1.00 and a standard deviation of 0.243, the complete sample's average degree of disclosure of information pertaining to forward-looking disclosure (FLD) is 40.4%. A company's digital experience (DE) has a mean value of 2.643, a standard deviation of 0.974, and values ranging from 0.00 to 3.666. For firm size, the log transformation averages 20.54 and ranges from 16.03 to 23.79. Leverage is 38.39% on average. The average profitability of the business is 6.1%. Based on 207 observations (400 × 47%), the overall sample's average audit quality is 47%.

Table 3. Descriptive statistics

Variables	*n*	Min.	Max.	Mean	S.D
SP	440	.062	166.00	10.44	14.643
FID	440	.130	1.00	.404	.243
DE	440	.000	3.666	2.643	.974
Size	440	16.033	23.791	20.544	1.634
LEV	440	.004	1.46	.389	.215
ROA	440	-.481	.449	.061	.117
Big4	440	.000	1.00	.47	.499

The findings of the correlation matrices are shown in Table 4, which does not indicate multicollinearity and shows a low degree of correlation between the independent variables. The variance inflation factor (VIF) further supports this; it is less than 10. Additionally, the results show that, at the 1% level, stock prices (SP) have substantial positive correlations with FLD, DE, Size, ROA, and BIG4, with correlation values of 0.327, 0.157, 0.260, 0.169, and 0.234, respectively.

Table 4. Pearson's correlation Matrix

Variables	SP	FLD	DE	Size	LEV	ROA	BIG4	VIF
SP	1							------
FLD	0.327***	1						1.029
DE	0.157***	0.073	1					1.346
Size	0.260**	0.062	0.026	1				1.071
LEV	0.010	-0.099**	0.028	0.182***	1			1.069
ROA	0.169***	0.125***	0.115**	0.107**	-0.073	1		1.036
BIG4	0.234**	0.029	0.179***	0.425***	0.184***	0. 088*	1	1.337

Notes: ***, **, and * denote statistical significance at the 1, 5, and 10 % levels, respectively.

9.2. Multivariate Analyses

9.2.1. FLD and SP (Model 1)

Table 5 presents the results of the regression that examines the relationship between Forward-Looking Disclosure (FLD) and Stock Prices (SP) using Model (1). The model was judged fit and statistically significant when the computed F value was 20.330 at a significant level, which was 0.000 below the authorized level of significance of 0.05. Additionally, adjusted R2 (=18.3%) showed that around 18.3% of the variance in the dependent variable (stock prices) can be explained by changes in the independent variables. Additionally, table (5)'s findings show a substantial positive correlation between FLD and stock prices. The value of (t) = 6.826 at a significance level (Sig) = 0.000 less than the authorized level of significance 5% is found when the FLD's (β) value is positive and equals 17.97. This finding indicates that stock prices are positively and significantly impacted by information pertaining to forward-looking disclosure. Thus, the first research hypothesis (H1) of the study is supported by these findings. These results are in line with other research that found that greater disclosure of information pertaining to forward-looking disclosure raises stock prices. Whereas a higher FLD reduces investor uncertainty and raises market value. For the control variables, at the 1% and 5% levels, stock prices have a substantial positive correlation with business size, profitability, and audit quality (Abdollahi et al., 2020; Chehade and Prochazka, 2023).

Table 5: The relationship between FLD and SP - Model 1

Predictor	Coefficient	t-value	P-value
FLD	**17.976*** **	6.826	**0.000**
Size	1.483***	3.301	0.001
LEV	-0.570	-0.188	0.851
ROA	12.630**	2.295	0.022
BIG4	4.002***	2.733	0.007
Constant	-29.542***	-3.334	0.001
Adjusted R^2	0.183		
F-value	20.330***		
Obs.	440		

9.2.2. Digital Experience Moderating Role (Model 2):

Table 6 summarizes the results of the Pooled OLS regression that we used to look into the relationships between FLD, DE, and stock prices. As the table illustrates, our analysis reveals a strong and favorable correlation between DE and stock prices. This suggests that businesses with better digital experiences are associated with greater stock prices. We spoke about how digital experience might moderate the link between FLD and SP. This model represents (FLD*DE) as the interaction term between forward-looking disclosure and digital experience. With a value of (t) = 4.014 at a significance level (Sig) = 0.000 below the authorized level of significance 5%, the results in table (6) show that the interactional variable (FLD*DE) has a positive significant effect on the relationship between the forward-looking disclosure and stock prices. The interactional variable's (β) value is positive and equals 10.83. Thus, the second hypothesis of the study is supported by these findings.

The study's results imply that the association between forward-looking disclosure and stock prices is strengthened by the moderating effect of digital experience. To put it another way, in companies with a high degree of digital experience, information about the future is made easier to access, transparent, and user-friendly through digital platforms. This improved accessibility lowers information asymmetry, boosts investor confidence, and speeds up the incorporation of disclosed information into stock prices. As a result, digital experience works as a trigger to increase the impact of forward-looking disclosure in influencing stock market reactions in addition to being an extra corporate capacity (Fedorova et al., 2024; Liu et al., 2025).

Table 6: The relationship between FLD, DE and SP - Model 2

Predictor	Coefficient	t-value	P-value
FLD	15.373***	5.832	0.000
DE	1.611**	2.545	0.015
FLD*DE	**10.834**	**4.014**	**0.000**
Size	1.595***	3.598	0.000
LEV	-0.717	-0.242	0.809
ROA	9.470*	1.746	0.081
BIG4	3.129***	2.134	0.033
Constant	-34.625***	-3.800	0.000
Adjusted R^2	0.217		
F-value	18.420***		
Obs.	440		

10. Sensitivity Analysis: Alternate measurements of the dependent variable:

We re-estimated the models using the stock price of listed businesses three months after year-end as an alternate proxy to guarantee the robustness of the primary studies (Chehade and Prochazka, 2023). This method aids in determining if the main conclusions are affected by the stock price measuring method selected. Even when this alternative measure is used, the results, as shown in Table 7, show that the primary conclusions are still true and consistent.

Table 7: Results of sensitivity analysis

Predictor	Model (1)		Model (2)	
	Coefficient	t-value	Coefficient	t-value
FLD	**14.913*****	**5.861**	12.943***	5.041
DE	---------	---------	1.616**	2.527
FLD*DE	---------	---------	**7.735*****	**2.943**
Size	1.447***	3.336	1.572***	3.640
LEV	-0.424	-0.145	-0.462	-0.160
ROA	10.403*	1.957	7.762*	1.870
BIG4	3.103**	2.194	2.252**	2.044
Constant	-27.209***	-3.178	-32.817***	-3.698
Adjusted R^2	0.145		0.171	
F-value	15.903***		13.893***	
Obs.	440		440	

11. Summary of findings:

The following table summarizes the results of hypotheses tests as follows:

N	Hypotheses	Main Analyses	Sensitivity Analysis
H1	There is a significant association between Forward-Looking Disclosure and Stock Prices.	accepted	accepted
H2	Digital Experience has a significant impact on the association between Forward-Looking Disclosure and Stock Prices.	accepted	accepted

12. Conclusions, Limitations, and Future Research:

It was found that, forward looking disclosures have a significant impact on firm's stock prices. This impact comes from the creditability earned in companies providing future information about their operations, plans, and financial decisions, and financial position. The research has shown that, investors tend to get future forecasts to ensure them they are investing in the right place. Also, investors prefer to have an insight to companies' future before investing in it. Although, there is still a substantial doubt about the accuracy of this future information, and here comes the role of digital experience of companies, as the more digital experience a company may have, the more reliable its future disclosures would be. Digital experience represents companies' ability to adopt technological solutions such as big data analysis tool packages and AI techniques for data collection, storage, and analysis. Accordingly, companies with higher digital experience are more reliable in providing forward looking disclosures, a matter like that would eventually affect companies' stock demand and consequently stock prices.

This research was only oriented to measuring the effect of digital experience on the reliability of forward-looking disclosures in investment decision-making in the Egyptian business environment and eventually on stock prices.

The research findings tested only on the companies listed in the Egyptian stock exchange market. Moreover, this research is addressing the financial impact on companies represented by its stock prices.

It is recommended to further investigate the applicability and application mechanism of using AI and other digital tool packages in forecasting a forward-looking financial reports in Egyptian business environment. Also, it is recommended to investigate the impact of the moderating role of digital experience on the association between budgeting and earnings quality.

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