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LINGUISTIC MARKERS OF MANIPULATION IN TEXT-BASED DEEPFAKE FINANCIAL DISCOURSE: A COMPARATIVE STUDY OF ENGLISH AND RUSSIAN CORPORA

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BSTRACT

Advances in artificial intelligence have increased the use of text-based deepfakes in financial communication. At the same time, their linguistic features remain much less studied than audiovisual formats or technical detection methods. This gap is addressed through a comparative analysis of English and Russian-language corpora, focusing on linguistic manipulation in financial deepfakes. The research follows a corpus-oriented approach within Critical Discourse Analysis, combining quantitative corpus data with qualitative interpretation. The material consists of four subcorpora of natural and AI-generated financial media texts in Russian and English, analyzed using Voyant Tools. The analysis reveals recurrent lexical, semantic, and

pragmatic patterns reflecting strategies of emotional amplification, simulated authority, reduced epistemic modality, metaphorical dramatization, and manipulation of textual coherence. The findings demonstrate stable differences between natural and synthetic financial discourse in both languages. According to the results, natural texts rely on institutional attribution, restrained evaluativity, and low emotional intensity, whereas synthetic texts are characterized by heightened emotional density, rigid categorical framing, metaphorical excess, and the effect of simulated "expertise". The cross-linguistic consistency of the identified patterns suggests that manipulation in text-based financial deepfakes operates through shared discursive strategies rather than language-specific features. By regarding language as a key instrument of manipulation in AI-mediated financial communication, the study contributes to research on digital disinformation and offers insights relevant to forensic linguistics, media analysis, and risk assessment in digital financial environments.

KEYWORDS: Text-Based Deepfakes; Financial Discourse; Corpus-Assisted Analysis; English And Russian Corpora; AI-Generated Content.

1. LITERATURE REVIEW

Financial discourse is commonly conceptualized as a specialized form of professional communication embedded within economic discourse and closely interconnected with political and media discourses. It comprises discussions of financial market development, forecasting, stock exchange operations, cash-flow analytics, taxation, lending and other financial instruments. While the primary audience consists of trained financiers, entrepreneurs, and journalists, its reach extends to the broader public interested in economic processes (Apresyan, 2022).

This expansion is reinforced by the rapid digitalization of everyday practices: recent socio-economic data indicate that digital technologies are most actively used by the population in financial and public services, with digital platforms and online environments forming a routine infrastructure of daily economic interaction. Social networks play a particularly significant role in the digitalization of interpersonal communication, with approximately 78% of Internet users in Russia registered on such platforms, substantially widening the audience exposed to digitally mediated financial information (Kapranova, 2025).

Because of this hybrid audience and high-stakes content, financial discourse is exceptionally sensitive to credibility threats, hence the salience of deepfake technologies.

In the Russian context, this sensitivity is reinforced by long-standing traditions in political economy that emphasize moral and ethical principles—such as justice, honesty, and social responsibility—as foundational expectations in economic interaction, shaping heightened public sensitivity to perceived deception and legitimacy breaches in financial communication (Tsvetkov & Yadgarov, 2025).

This vulnerability is further intensified by the large-scale transition of banking and financial services from offline to digital formats. Research on digital banking development emphasizes that the expansion of online financial interaction significantly increases cyber risks for credit institutions, requiring heightened attention to the stability and security of digitally mediated financial communication (Gumerov et al., 2025).

Recent corpus-based studies confirm that sentiment and emotional polarity in financial journalism play a crucial role in shaping investor expectations and anticipating market instability (Vargas-Sierra & Orts, 2023). Deepfakes, highly realistic synthetic audio, video and images produced with deep learning, have moved from novelty to mainstream concern (Katarya, 2020). The contemporary media environment magnifies their impact, as online platforms shape attitudes and trust at scale (Jiang, 2021). New forms of technology-enabled fraud are arising, among them practices referred to as "con game" (or "info-scam") and deceptive schemes centered on low-value information products (Smirnova, 2024; Shekhovtseva, Kozhukhova, 2025). Trend analyses show a sharp rise in deepfake-related reporting between 2000 and 2022, with more than 500 news sources contributing to the discourse. These studies chart regional publication patterns, thematic clusters and shifting narrative frames; overall sentiment skews negative or neutral, mirroring anxieties around misinformation, manipulation and technological opacity (Tang, Yin, & Goh, 2023). Within business contexts, journalistic coverage highlights threats to marketing, advertising, and brand reputation (Kietzmann; Whittaker, 2020).

Synthetic media, including deepfake audio and video, are increasingly used to disseminate fabricated news and deceptive content (Seow et al., 2022). Scholars warn of an erosion of institutional trust and an amplification of misleading information, with deepfake-based financial communication posing specific risks to market credibility and institutional legitimacy (Krishna J. Patel; Kaushik et al., 2024). Importantly, expert fact-checkers emphasize that “cheap fakes” and *decontextualized* materials may pose more immediate, scalable risks than high-end audiovisual forgeries. Legislative debates are also widening to cover text-based synthetic content (e.g., artificial transcripts and multilingual deepfake subtitles), acknowledging their potential to shape public understanding (Synthetic Media & Deepfakes).

This regulatory attention forms part of a broader international discussion on artificial intelligence governance. Recent studies on international AI regulation show that, despite the growing number of policy frameworks and guidelines, regulatory efforts remain fragmented, while the risks posed by AI-generated content continue to develop faster than institutional coordination (Revenko & Revenko, 2025).

Recent studies highlight that deepfake texts produced by large language models pose a growing threat, particularly through fake news, social media content, and financial commentary that can influence public opinion (Diel et al., 2024). Introduced in 2017, the term *deepfake* blends “deep learning” and “fake,” pointing to its algorithmic origins (Ürmösné, 2017). Growing interest in text-based deepfakes has led to the view that AI-generated language should be studied as a distinct linguistic phenomenon. Micallef (2025) proposes *linguistics of neural networks* as an interdisciplinary framework that treats neural networks as producers of meaningful texts rather than mere technical tools. This perspective provides a theoretical basis for analyzing AI-generated financial texts as discourse and for examining their manipulative potential. From a linguistic perspective, A.P. Chudinov, N.N. Koshkarova, and N.B. Ruzhentseva conceptualize *fake*, *deepfake*, and *post-truth* as destructive social phenomena. Their approach integrates linguopragmatic, discursive, and linguoculturological analysis, at the same time it is grounded in Fairclough's three-dimensional model of Critical Discourse Analysis (text–interaction–context), which connects textual form with interactional dynamics and the broader sociocultural environment (Fairclough, 2015). Contextual factors, including communicative roles, social status, sphere of activity, and cognitive characteristics, play a decisive role in shaping how fabricated messages are interpreted (Shapochkin, 2013). This is particularly important in financial communication, where cues of authority, urgency, and expertise can strongly influence perception and decision-making.

Recent research has shifted attention from visual fabrication to the linguistic content of AI-generated materials. This shift draws on psycholinguistic research, which treats emotionality as an inherent property of language rather than as a peripheral stylistic feature. It is widely acknowledged that language possesses a broad range of tools for expressing emotions, with emotive vocabulary among the dominant means, and that emotionality manifests across all linguistic levels; accordingly, researchers argue that there are no fully neutral units in language (Konurbaev M.E., Andreeva E.Yu., Smakhtin E.S., 2024, p. 387). A. Martinek and E. Bartuzi-Trokielewicz show that deepfake ads and transcripts are often identifiable through *grammatical irregularities, stylistic inconsistencies and social-engineering tactics.* Linguistic features such as urgency, authority simulation, and social proof have been identified as key indicators of manipulative and fraudulent synthetic communication, particularly in financial advertising and scams (Martinek & Bartuzi-Trokielewicz, 2025). They propose a four-part typology: *tension-building rhetoric, language-style layering, motivational appeals and sociological targeting*. They also note recurring persuasive tropes in synthetic financial scams (exaggerated promises, emotional urgency, fabricated testimonials) (Biela, 2016; Ferreira et al., 2015). Linguistic anomalies such as illogical sequencing and inconsistent register are common and amenable to automated detection (Prelipceanu, 2013). Parallel studies confirm that deepfake emails and transcripts exploit social proof and urgency markers (Anafo & Ngula, 2020; Modzelewski et al., 2024). In computational linguistics, detection pipelines leverage part-of-speech profiles, named-entity patterns and stylometry to capture syntactic and stylistic anomalies consistent with AI generation (Hassan et al., 2015; Boididou et al., 2018; Okulska et al., 2023; Wood, 2024).

Research on public perception applies computational tools such as topic modeling (LDA) and sentiment analysis (TextBlob, VADER) to trace how discussions of deepfakes develop and shift over time (Zhaoxiang Xu, 2025). Findings from social psychology highlight a consistent pattern of attitude congruence: people are more inclined to trust and disseminate synthetic content that aligns with their existing beliefs and values (Dobber, 2020). Experimental studies further demonstrate that deepfakes portraying faces with more natural and expressive features tend to be perceived as more competent and likable, thereby enhancing their persuasive potential. At the same time, perceptions of ethical acceptability rise significantly when audiences are assured of transparency, including clear consent, identifiable origin, respect for privacy, and the absence of deception (Renier et al., 2024).

Artificial intelligence has profoundly transformed the digital media landscape, affecting both the production and detection of content (Hussain, 2024; Passos et al., 2024). With growing advances in synthetic text generation, the boundary between human-written and AI-generated content is becoming harder to discern (Pink, 2022; Habgood-Coote, 2023; Zaidi, 2020). The interaction between content generation and detection is often described as an "arms race" (Chauhan, 2024), reflecting ongoing adaptation by both producers and analysts of synthetic media. In financial discourse, often perceived as rational and data-driven, deepfakes pose a particular risk by exploiting pragmatic and emotional cues to influence judgment and credibility. The scale of this threat is illustrated by documented cases, including a 2019 CEO voice-cloning fraud involving USD 243,000 and a 2024 incident in Hong Kong with losses of approximately USD 25 million. Deepfake technologies have increasingly been used in financial fraud in recent years, including executive impersonation, market manipulation, and even the fabrication of corporate data, posing systemic risks to the integrity of financial markets (Mehta et al., 2025). Subsequent forensic linguistic analysis identified a number of characteristic indicators of synthetic origin, including unnatural pause durations, limited pitch variability, and atypical vowel formant patterns, which collectively indicate that the recordings were generated by artificial intelligence.

Accordingly, researchers are developing multi-level detection strategies that combine linguistic and acoustic analysis:

- Prosodic analysis: examination of pause patterns, intonation contours and pitch variation;
- Lexical–statistical profiling: analysis of function-word frequencies, modal verbs and evaluative vocabulary;
- Semantic–pragmatic diagnostics: identification of contradictions, narrative gaps and breaches of Gricean maxims.

Hybrid models integrating these features consistently outperform single-modality systems, especially in high-stakes financial communication.

A further, underexplored vulnerability lies in translation and multimodal communication. Synthetic speech and transcripts frequently introduce distortions such as unnatural accent adaptation, omission of cultural cues, and semantic hallucinations. This problem is compounded when translation is performed at a purely linear level, without comparative-cognitive transformation. Research in interpreting studies shows that such linear transfer often results in syntactically and stylistically degraded output marked by features of uncontrolled spontaneous speech, including repetitions, self-interruptions, slips of the tongue, and non-lexical fillers. By contrast, translation operating at a higher cognitive level, based on the transformation of the underlying thought rather than surface form, produces more coherent and perceptually fluent speech in the target language (Konurbaev M.E., Ganeeva E.R., 2023). Since listeners depend on paralinguistic markers – breathing, background noise and micro-delays – to assess authenticity, the artificial regularity or absence of these cues can shift perceived stance, diminishing hedging and amplifying certainty or confidence.

Insights from publicistic linguistics clarify how deepfakes achieve persuasive impact. P. V. Prikhodko (2025) demonstrates that persuasive discourse operates across multiple linguistic levels: phonetic (alliteration, pausing), lexical (emotionally charged vocabulary, metaphors, jargon, clichés), morphological (modality, imperatives, evaluative and diminutive suffixes) and syntactic (rhetorical questions, parallelism, inversion, repetition, parcelling). I. S. Gavrilina (2003) adds that paratextual strategies, especially headline design and question framing, guide interpretation through desire-eliciting and reason-seeking formulations. Broader media-linguistic research further identifies adversarial labelling, scare quotes, euphemization, pronoun deixis, borrowings, and alternation between active and passive voice as tools for ideological framing.

In financial deepfakes, language directly shapes how messages are interpreted and acted upon. Strategic wording can make fraudulent requests appear legitimate, shape investor confidence, and obscure responsibility. Urgency is often created through rhetorical questions and headline-style phrasing, which guide audiences toward predefined interpretations of market events.

2. Empirical Study

2.1. Corpus description and Methodology

The empirical research employs a comparative, corpus-assisted discourse analysis of English- and Russian-language financial media texts to identify linguistic patterns of manipulation in both natural and AI-generated communication. It combines quantitative corpus data with qualitative discourse analysis, ensuring a balance between empirical evidence and theoretical interpretation. As it was mentioned before, the analysis is conducted within the framework of Critical Discourse Analysis (CDA) and draws on Fairclough's three-dimensional model (text–interaction–context), which makes it possible to interpret linguistic patterns as socially and ideologically embedded communicative practices.

The research material consists of four subcorpora:
(1) natural financial texts in Russian;
(2) synthetic (or AI-generated) financial texts in Russian;
(3) natural financial texts in English;
(4) synthetic financial texts in English.

This design enables systematic comparison along two analytical dimensions: authorship (human vs. synthetic) and language (Russian vs. English). The choice of English and Russian is motivated by their broad communicative reach and relevance to contemporary financial discourse. English functions as the dominant international language of global finance, media, and digital communication, and is widely used in transnational financial reporting and investment analysis. Russian, while serving as the state and majority language of the Russian Federation, also functions as a transethnic language across a wide post-Soviet and Eurasian communicative space. Together, these languages represent two influential financial-information ecosystems with different institutional, cultural, and media traditions, making them suitable for identifying both universal and language-independent mechanisms of manipulation in text-based financial deepfakes.

~~F~~The natural subcorpora comprise human-authored financial news articles published in authoritative media outlets and characterized by institutional norms of credibility, attribution, and analytical restraint. The synthetic subcorpora consist of AI-generated financial texts designed to imitate journalistic discourse while varying in evaluative intensity, narrative framing, and emotional charge. All texts were originally produced in their respective languages and were not translated, in order to preserve language-specific lexical, stylistic, and pragmatic features.

Corpus preprocessing included tokenization, removal of stop words, and normalization of word forms. Identical preprocessing and analytical procedures were applied to all four subcorpora to ensure methodological symmetry and comparability across languages and authorship types.

The corpus analysis was conducted using Voyant Tools[1], which was employed as a corpus-assisted diagnostic and heuristic interface rather than as an automated statistical modeling system. Voyant Tools facilitated multi-level linguistic observation through frequency analysis, collocation mapping, keyword-in-context exploration, word trees, and visualization modules (Cirrus, Bubblelines, Trends, TextualArc). These tools were not used for inferential statistical testing or automated topic modeling; instead, their quantitative outputs served as indicators guiding qualitative interpretation within the CDA framework.

The identification and interpretation of recurrent lexical clusters draws on the concept of lexico-semantic fields, which allows frequency-based patterns to be interpreted as discursively meaningful conceptual domains (Zagidullina et al., 2023). From this perspective, statistically salient lexical groupings are treated not as isolated numerical phenomena, but as manifestations of underlying discursive strategies related to evaluativity, epistemic stance, metaphorical framing, and authority construction. This approach is consistent with text-linguistic models that view coherence as a dynamic system of connections whose density and structure vary depending on functional style and communicative intent. Konurbaev and Andreeva propose a universal text coherence scale that constrains textual analysis to objectively measurable types of connections, ranging from formal to pragmatically motivated ones, thereby allowing the logical coherence and perceptual integrity of a text to be systematically assessed (Konurbaev M.E., Andreeva E.Yu., 2025).

Quantitative observations were therefore integrated with close contextual reading, enabling the analysis to link lexical regularities to broader communicative functions and ideological effects in both natural and synthetic financial discourse.

2.2. Linguistic Characteristics of Natural Financial Discourse (Russian Corpus)

The analysis shows that natural Russian-language financial texts are mainly focused on presenting factual information. They regularly refer to economic actors, institutions, and numerical data, while evaluations remain neutral and are usually supported by official sources. According to the analyzed data, the most frequent lexical items include the following lexemes: *цена* (price), *рынок* (market), *рубль / рубли* (ruble[s]), *компания / компании* (company / companies), *активы* (assets), *банк / банки* (bank[s]), *счёт* (account). These terms help structure the text around concrete economic facts rather than personal opinions. Collocational analysis shows that these terms typically appear in neutral, technical, and institutionalized contexts, such as *финансовая стабильность* (financial stability), *динамика цен* (price dynamics), *рыночные условия* (market conditions), and *структура активов* (asset structure). These collocations reinforce an analytical style and help avoid ambiguity in interpretation. Verbs in the corpus mostly refer to change and development, not to evaluation or opinion, for example, *расти* (to grow), *снижаться* (to decline), *увеличиваться* (to increase), *корректироваться* (to adjust), *сохраняться* (to remain). These verbs are frequently used in impersonal or passive constructions, making the text sound less personal and emotionally neutral.

In the Russian natural texts corpus, adjectives and adverbs are used mainly to specify quantity, scale or temporal change rather than to express emotion or evaluation. General modifiers include such terms as *умеренный* (moderate), *высокий* (high), *постепенный* (gradual), *значительный* (significant), *незначительный* (minor). These descriptors are generally neutral and contribute to analytical clarity rather than subjective evaluation.

[1] Voyant Tools. (n.d.). Voyant-Tools.org. https://voyant-tools.org

Natural financial discourse consistently relies on epistemic hedging and attribution to sources. Evaluative and predictive statements are typically framed through references to external authorities, such as *аналитики отмечают* (analysts note), *по оценке экспертов* (according to experts), and *по данным Банка России* (according to data from the Bank of Russia). This practice distributes epistemic responsibility, softens categorical claims, as well as aligns with journalistic norms of credibility and accountability.

Table 1. Key Linguistic Features of Natural Russian Financial Discourse

Linguistic level	Russian examples	English translation	Discourse function
Key nouns	цена, рынок, рубль, компании, активы, банки, счёт	price, market, ruble, companies, assets, banks, account	Referential anchoring, objectivity
Technical collocations	финансовая стабильность, динамика цен, рыночные условия, структура активов	financial stability, price dynamics, market conditions, asset structure	Analytical framing
Verbs (processual)	расти, снижаться, увеличиваться, корректироваться, сохраняться	grow, decline, increase, adjust, remain	Description of change
Adjectives/adverbs	умеренный, высокий, постепенный, значительный	moderate, high, gradual, significant	Quantification, specification
Hedging & attribution	аналитики отмечают; по оценке экспертов; по данным	analysts note; according to experts; according to data	Epistemic caution
Metaphorization	минимальная / отсутствует	minimal / absent	Emotional neutrality

2.3. Linguistic Features of Manipulation in Synthetic (AI-generated) Financial Discourse (Russian Corpus)

The next stage of the study focuses on synthetic Russian-language financial texts to identify linguistic deviations from the baseline described in Section 2.2, with particular attention to features that enhance manipulative and persuasive effects.

Synthetic texts rely heavily on metaphors taken from non-economic domains, such as weather (e.g., *финансовая оттепель* (financial thaw), *шторм (storm), турбулентность* (turbulence)), war (e.g., *фронт* (front), *окопы* (trenches), *шоковая неделя* (shock week)), and physical states (e.g., *крах* (*collapse*), *давление* (pressure), *напряжение* (tension)). As a result, market processes are presented as matters of survival or salvation, which intensifies emotion and reduces interpretive flexibility. A second notable feature is the illusion of expert consensus. Although synthetic texts often refer to analysts, experts, and market participants, these actors are usually left unnamed or described in very general terms. Third, synthetic discourse tends to use fewer markers of uncertainty. In contrast to natural texts, modal verbs and hedging expressions occur far less frequently, while categorical formulations such as *на грани краха* (on the verge of collapse), *неизбежно приведёт* (will inevitably lead), and *рынок вступает (в)* (the market is entering) become more distinguished. This heightened linguistic certainty projects confidence and authority, discouraging critical evaluation. Fourth, synthetic texts exhibit emotional polarization and scenario splitting, often structuring narratives around binary oppositions such as recovery versus collapse or stability versus catastrophe.

From a discourse-analytic perspective, such concentration and polarization of evaluative language supports the notion of an emotional dominant guiding text interpretation (Ionova, 2023). This technique simplifies complex economic realities and channels reader interpretation toward predetermined conclusions. Finally, lexical analysis reveals a higher density of emotionally coloured vocabulary, both positive *успешный* (successful), *стабильная прибыль* (stable profit), *лидеры рынка* (leaders of the market) and negative, e.g.: *мифы* (myths), *ловушки* (traps), *заблуждения* (delusions), *паника* (panic).The identification of emotionally charged lexical items corresponds to current developments in emotion linguistics, where emotion recognition in text is treated as a central analytical task in both natural and synthetic discourse (Iaroshenko & Loukachevitch, 2025). Visualization tools such as Bubblelines show that these elements cluster at evaluative peaks in the text, indicating deliberate emotional framing.

Table 2. Linguistic Features of Manipulation in Synthetic Russian Financial Discourse

Linguistic level	Feature	Typical realizations (examples)	Manipulative function
Metaphorical	Metaphorical dramatization	Weather (*финансовая оттепель, шторм, турбулентность*); war (*фронт, окопы, шоковая неделя*); physical states (*крах, давление, напряжение*)	Reframes economic processes as existential threats or moments of salvation, intensifying emotional response

Pragmatic	Illusion of expert consensus	Generalized references to analysts, experts, and market participants without attribution	Creates an appearance of collective agreement while weakening accountability
Modal	Reduction of epistemic modality	Categorical constructions (*на грани краха, неизбежно приведёт, рынок вступает (в)*)	Simulates certainty and authority, discouraging critical evaluation
Discursive	Emotional polarization and scenario splitting	Binary oppositions (*восстановление / крах, стабильность / катастрофа*)	Simplifies complex economic realities and directs interpretation toward predefined conclusions
Lexical	Emotional saturation	Positive (*успешный, стабильная прибыль, лидеры рынка*); negative (*мифы, ловушки, заблуждения, паника*)	Amplifies affective engagement and reinforces evaluative framing
Text-structural	Emotional clustering	Evaluative peaks identified via *Bubblelines* visualization	Signals deliberate emotional framing and guided interpretation

2.4. Comparative Analysis of Natural and Synthetic Russian Discourse

The comparison of natural and synthetic financial texts highlights fundamentally different discourse strategies. Natural financial writing tends to be cautious and balanced, grounding claims in institutional sources and presenting market developments as complex and uncertain. Synthetic texts, in contrast, rely on emotionally charged and dramatized language that simplifies market dynamics and presents them as urgent and sharply defined. Agents in natural texts are clearly identifiable, but in synthetic texts agency is often blurred through the use of generalized expressions and passive constructions. Taken together, these differences indicate that manipulation in synthetic financial discourse relies less on factual distortion and more on linguistic framing that heightens categorical certainty, reduces specificity, and accelerates emotional response.

2.5. Linguistic Characteristics of Natural Financial Discourse (English Corpus)

The English-language corpus consists of a single consolidated document comprising 11,910 tokens and 2,907 unique word forms, with a lexical diversity index of 0.244. A stop list and a white list were applied to remove function words and highlight domain-specific vocabulary. The corpus shows a readability index of 12.557 and an unusually high average sentence length (130.9 words). Natural English-language financial texts are generally oriented toward formal, balanced and cautious presentation of information. Lexical frequency analysis reveals a predominance of nouns referring to economic processes, market actors and measurable indicators, such as *business*, *stocks*, *market*, *economy*, *company*, *shares*, *prices*, *investment*, *banks*, and *financial*. Frequency data support this observation: the most frequent items include *business* (36), *stocks* (34), *market* (33), and *economy* (29), alongside references to institutional actors (*banks*, *investors*, *CEO*), regulatory bodies (*Fed*), and scale markers (*billion*, *trillion*). These terms help anchor the discourse in concrete economic facts and indicators, avoiding subjective evaluation or emotional interpretation.

Collocational analysis indicates that key economic terms most often occur in neutral and technical contexts, such as *stock market performance*, *economic outlook*, *investment strategy*, *interest rates*, and *financial results*. When risk or instability is discussed, it is typically framed through empirical data, historical comparisons, or references to institutional sources rather than emotive language. Emotionally charged vocabulary appears with relatively low frequency in the natural corpus, indicating that affective framing is tightly constrained and subordinated to informational and institutional priorities.

At the grammatical level, the discourse is dominated by verbs describing evidence-based change and evaluation (*rise, fall, increase, decline, remain, report, expect*), frequently accompanied by modal verbs (*may, could, likely*) and hedging expressions (*according to analysts, data suggests*). Together, these features limit categorical certainty and conform to established professional norms of financial journalism.

Table 3. Key Linguistic Features of Natural English Financial Discourse

Linguistic level	Dominant features	Discursive function
Lexical	High frequency of nouns denoting economic processes, institutions, and indicators (*business, market, stocks, economy, banks, investment*)	Grounds discourse in observable economic reality
Collocational	Neutral, technical, explanatory frames (*stock market performance, interest rates, financial results*)	Limits evaluative interpretation and emotional framing
Grammatical	Verbs of evidence-based change (*rise, fall, increase, decline*) with modal verbs and hedging (*may, could, data suggests*)	Reduces categorical certainty and supports analytical caution
Pragmatic	Institutional attribution and low emotional saturation	Enhances credibility and accountability
Overall orientation	Analytical, informational, institutionally grounded	Establishes a non-manipulative baseline

2.6. Linguistic Features of Manipulation in Synthetic Financial Discourse (English Corpus)

The frequency analysis indicates a noticeable rise in abstract and forward-looking vocabulary with ideological overtones, including *AI* (22), *market(s)* (24), *global* (18), *data* (14), *financial* (11), *retail* (10), *company* (10), *risk* (8), and *trading* (8). Instead of focusing on concrete economic indicators, these lexical choices promote narratives of large-scale change, technological inevitability, and strategic urgency.

Thematic clustering and discursive functions

The synthetic texts are structured around recurring themes, each serving a specific manipulative function.

1. Lending and risk framing

The *lending* cluster (8) is frequently embedded in speculative and metaphorical constructions such as "bullish wave in automated lending", "hazardous derivative", and "rewriting the yield curve for digital lending". Financial processes are thus reframed as high-stakes market gambles, amplifying emotional engagement and speculative anticipation.

2. Economy as a living or collapsing system

The *economy* cluster (7) is characterized by metaphors of physical stress and existential threat, including "the global economy is holding its breath" , "on life support", "tectonic plates shifting", and "cascading system failures". Such imagery replaces analytical explanation with dramatized scenarios of survival or collapse.

3. Corporate and competition narratives

Clusters related to *corporate* (6), *competition* (6), and *capital* (6) frame market dynamics in confrontational and militarized terms. Expressions such as "corporate superpowers", "high-voltage capital battle", and "unstoppable corporate triad" construct an antagonistic worldview in which economic actors are positioned within zero-sum struggles, intensifying ideological polarization.

4. Simulated authority and expert consensus

Frequent references to *analysts* (6) and *CEO* statements (5) function as authority simulators. Although such actors are regularly invoked ("market analysts say", "according to the CEO"), attribution often lacks institutional specificity, creating an illusion of expert consensus without verifiable sources.

5. Emotional escalation and metaphor saturation

Across all thematic clusters, synthetic texts exhibit pronounced metaphor saturation, drawing on domains of war, natural disasters, physiology, and apocalypse. Visualizations reveal that emotional language concentrates at key points in the texts, guiding interpretation ahead of factual analysis.

Table 4. Linguistic Characteristics of Synthetic English Financial Discourse

Linguistic level	Dominant features	Manipulative function
Lexical	Abstract, future-oriented, ideologically loaded terms (*AI, global, risk, market*)	Constructs inevitability and urgency
Metaphorical	War, disaster, physiological metaphors	Amplifies emotional response
Pragmatic	Simulated authority, vague expert attribution	Enhances persuasion, reduces accountability
Discursive	Polarized, dramatized narratives	Suppresses nuance and alternative interpretations
Overall orientation	Persuasive, affect-driven	Facilitates manipulation without factual falsification

2.7. Comparative Analysis of Natural and Synthetic English Discourse

Natural financial discourse focuses on reliability and careful analysis, using factual data, technical terms, and cautious wording. Synthetic texts adopt a different approach: they favor emotionally charged, metaphor-rich, and forward-looking language that frames financial processes as urgent and unavoidable. The comparison shows that manipulation in synthetic financial discourse does not primarily depend on false information, but on systematic linguistic framing. By amplifying certainty, simulating expert authority, and concentrating emotional language, synthetic texts restrict interpretive flexibility and intensify emotional response, while still appearing informationally credible. The fact that these patterns recur across linguistic levels suggests they are core features of AI-generated financial discourse, not accidental stylistic choices. This underscores the importance of approaching text-based deepfakes not only as a technical problem, but as a discursive phenomenon that requires ongoing linguistic and pragmatic analysis.

3. DISCUSSION AND CONCLUSIONS

Natural financial discourse in both languages follows professional journalistic norms, emphasizing caution, clear source attribution, and analytical balance. By relying on verifiable sources and restrained language, such texts present economic processes as complex rather than categorical, building credibility through transparency and measured expression.

Synthetic financial discourse follows a different communicative logic. Instead of highlighting uncertainty and analytical nuance, AI-generated texts simplify financial reality through emotionally charged and metaphor-rich narratives. Hedging is reduced, expert authority is simulated, and evaluative language is densely clustered. Together, these features create a strong sense of confidence. Importantly, manipulation does not rely on false information. It works through discursive framing that limits interpretation, accelerates emotional response, and directs readers toward predefined conclusions.

One of the key findings of the study is that these patterns remain consistent across both Russian and English corpora. Despite linguistic and cultural differences, synthetic financial texts in both languages use similar strategies of emotional amplification, simulated authority, and metaphorical dramatization. This indicates that text-based financial deepfakes rely on transferable discursive templates rather than language-specific stylistic features. LLM therefore reproduce not just surface linguistic forms, but shared persuasive structures rooted in contemporary financial and media discourse. Metaphorical framing plays a central role in this process: by drawing on images of war, natural disasters, or physical collapse, synthetic texts turn abstract economic processes into vivid and emotionally charged scenarios. Such framing shifts attention away from probabilistic analysis toward urgency and threat, which is particularly effective in financial contexts where audiences often lack specialized expertise.

Methodologically, the study highlights the effectiveness of combining corpus-based analysis with CDA. Quantitative measures, such as frequency data, collocational patterns, and visualizations, become more informative when interpreted in relation to discourse functions, communicative roles, and socio-economic context. This combined approach helps uncover subtle but consistent features of synthetic texts that are likely to be missed by purely technical detection methods or intuitive reading.

The results point to clear practical applications: identifying linguistic cues such as excessive certainty, metaphor saturation, emotional polarization, and vague authority claims can strengthen forensic linguistic analysis, media monitoring, and financial risk assessment. Recognizing these features can support earlier identification of manipulative synthetic texts and contribute to the development of linguistic awareness in digital financial environments. At the same time, the results caution against relying on surface fluency or stylistic smoothness as indicators of authenticity, as these qualities are easily reproduced by advanced language models.

Several limitations of the study point to directions for future research. The analysis focuses on publicistic financial texts and does not account for genre variation within financial communication, such as regulatory documents, investment advisory platforms, or social media discourse. In addition, while the study identifies linguistic mechanisms of manipulation, it does not directly measure their persuasive impact on audiences. Experimental and reception-based studies could clarify how specific discursive strategies influence trust, decision-making, and risk perception.

In conclusion, the findings suggest that addressing text-based financial deepfakes requires more than technical detection tools alone. Regulatory measures, professional norms, and media literacy efforts must also take into account the linguistic and discursive strategies through which AI-generated texts construct credibility and persuasive force. As synthetic financial communication continues to develop, sustained attention to language as a key mechanism of manipulation will be essential for preserving trust in digitally mediated financial discourse.

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Contribution / Originality

This study advances research on deepfakes by shifting attention from audiovisual detection to the linguistic mechanisms of manipulation in text-based financial discourse. Through English-Russian corpus comparison of AI-generated content vs natural texts it shows persuasion relies on discursive strategies rather than factual distortion—extending Critical Discourse Analysis to synthetic communication.

REFERENCES

1. Anafo, C., & Ngula, R. S. (2020). On the grammar of scam: Transitivity, manipulation, and deception in scam emails. *Word, 66*(1), 16–39.
2. Apresyan, K. G. (2022). Key concepts of financial discourse finance (Finansy) and money (Den'gi) in diachrony and synchrony. *LUNN Bulletin*, 1(57), 9–27. https://doi.org/10.47388/2072-3490/lunn2022-57-1-9-27
3. Biela, B. (2016). Typy i mechanizmy manipulacji w mediach. *Studia Pastoralne, 12*, 286–311.
4. Boididou, C., Middleton, S. E., Jin, Z., et al. (2018). Verifying information with multimedia content on Twitter. *Multimedia Tools and Applications, 77*(12), 15545–15571.
5. Chauhan, P. S. (2024). Deepfake: Risks and opportunities. *Computer, 57*(6), 141–144. https://doi.org/10.1109/MC.2024.3392992
6. Chudinov A. P., Koshkarova N. N., & Ruzhentseva N. B. (2019). Linguistic interpretation of Russian political agenda through fake, deepfake, post-truth. *Zhurnal Sibirskogo federal'nogo universiteta. Gumanitarnye nauki, 12* (10), 1840-1853. Retrieved from https://cyberleninka.ru/article/n/linguistic-interpretation-of-russian-political-agenda-through-fake-deepfake-post-truth
7. Diel et al. (2024). Human performance in detecting deepfakes: A systematic review and meta-analysis of 56 papers. *Computers in Human Behavior Reports, Volume 16*: 100538. https://doi.org/10.1016/j.chbr.2024.100538
8. Dobber, T., Metoui, N., Trilling, D., Helberger, N., & Vreese, C. D. (2020). Do (microtargeted) deepfakes have real effects on political attitudes? *International Journal of Press/Politics, 26*, 69–91.
9. Fairclough, N. (2015). *Language and power* (3rd ed.). Routledge.
10. Gavrilina, I. S. (2003). O vybore yazykovyh sredstv rechevogo vozdejstviya. *Uspekhi sovremennogo estestvoznaniya*, (5), 34–36.
11. Gumerov M.F., Rizvanova I.A., Belova M.T. (2025). Cyber Resilience of Credit Institutions in the Context of Digital Banking Business Development. *Finance: Theory and Practice*. *29*(6):148-163. https://doi.org/10.26794/2587-5671-2025-29-6-148-163
12. Habgood-Coote, J. (2023). Deepfakes and the epistemic apocalypse. *Synthese, 201*(3), 103. https://doi.org/10.1007/s11229-023-04097-3
13. Hassan, N., Li, C., & Tremayne, M. (2015). Detecting check-worthy factual claims in presidential debates. *In Proceedings of the 24th ACM International Conference on Information and Knowledge Management* (pp. 1835–1838). ACM.
14. Hussain, A. A. (2024). The impact of artificial intelligence on digital media content creation [Master's thesis, *International Journal of Innovative Science and Research Technology*].
15. Iaroshenko P.V., Loukachevitch N.V. (2025). *RusEmoLex: Russian Emotion Lexicon. Russian Journal of Linguistics. Vol. 29*. no. 3. P. 659-687. https://doi.org/10.22363/2687-0088-44439
16. Ionova, Svetlana V. (2023). Emotional dominant of the text: Some linguistic aspects of research. Science Journal of Volgograd State University. *Linguistics, 22* (1). 13–27. (In Russ.).
17. Jiang, T., Li, J. P., Haq, A. U., Saboor, A., & Ali, A. (2021). A novel stacking approach for accurate

detection of fake news. *IEEE Access, 9*, 22626–22639. https://doi.org/10.1109/ACCESS.2021.3056079
18. Kapranova L.D. Digital transformation of society and the standard of living of the population. (2025). *Economics, taxes & law.18*(3):81-91. (In Russ.). https://doi.org/10.26794/1999-849X-2025-18-3-81-91
19. Katarya, R., & Lal, A. (2020). A study on combating emerging threat of deepfake weaponization. *In Proc. 4th International Conference on IoT Soc. Mobile, Anal. Cloud (ISMAC)* (pp. 485–490). https://doi.org/10.1109/I-SMAC49090.2020.9243588
20. Kietzmann, J., Mills, A. J., & Plangger, K. (2020). Deepfakes: Perspectives on the future "reality" of advertising and branding. *International Journal of Advertising, 40*(3), 473–485. https://doi.org/10.1080/02650487.2020.1834211
21. Konurbaev M.E., Andreeva E.Yu. (2025). On cohesion and coherence in timbral text analysis. *Lomonosov Linguistics and Intercultural Communication Journal, no. 1*(28), pp. 21–36. https://doi.org/10.55959/MSU-2074-1588-19-28-1-2. (In Russ.)
22. Konurbaev M.E., Andreeva E.Yu., Smakhtin E.S. (2024). A Comparative Analysis of Emotional-Expressive Potential of Oriental Allegorical Writing. *International Journal of Arabic-English Studies, 24 (*1), pp. 383-400. doi: https://doi.org/10.33806/ijaes.v24i1.563
23. Konurbaev M.E., Ganeeva E.R. (2023) Functional notional types of spontaneous speech in simultaneous interpreting. *Lomonosov Linguistics and Intercultural Communication Journal, 4* (26), pp. 9–24. (In Russ.)
24. Martinek, A., Bartuzi-Trokielewicz, E. (2025). Detecting deepfakes and false ads through analysis of text and social engineering techniques. *In Proceedings of the 31st International Conference on Computational Linguistics* (pp. 8432–8448). Association for Computational Linguistics. https://aclanthology.org/2025.coling-main.564/
25. Micallef, L. O. (2025). Linguistics of neural networks as a paradigm of modern language science. *Mir nauki, kul'tury, obrazovaniya, 1*(110), 468–469. DOI: 10.24412/1991-5497-2025-1110-467-469
26. Modzelewski, A., Da San Martino, G., Savov, P., Wilczyńska, M., & Wierzbicki, A. (2024). Mipd: Exploring manipulation and intention in a novel corpus of Polish disinformation. *In Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing* (pp. 19769–19785).
27. Okulska, I., Stetsenko, D., Kołos, A., Karlińska, A., Głabińska, K., & Nowakowski, A. (2023). Stylometrix: An open-source multilingual tool for representing stylometric vectors [Preprint]. arXiv. https://arxiv.org/abs/2309.12810
28. Passos, L. A., Jodas, D., Costa, K. A., Souza Júnior, L. A., Rodrigues, D., Del Ser, J., & Papa, J. P. (2024). A review of deep learning-based approaches for deepfake content detection. *Expert Systems, 41*, e13570.
29. Patel, K. J., & Desai, M. B. (202X). AI-driven advances and challenges in deepfake technology: A comprehensive review. *Journal of Electrical Systems, 20*(11s), 1388–1400. https://doi.org/10.52783/jes.7451
30. Pink, S. (2022). *Emerging technologies. Life at the edge of the future* (First ed.). Routledge. https://doi.org/10.4324/9781003182528
31. Prelipceanu, C. M. (2013). Advertising and language manipulation. *Diversité et Identité Culturelle en Europe, X*(2), 247–254.
32. Prihod'ko, P. V. (2025). YAzyk publicisticheskogo teksta kak sredstvo vozdejstviya na chitatelya. *Vestnik nauki, 2*(1(82)), 804–809.
33. Renier, L. A., Shubham, K., Vijay, R. S., Mishra, S. S., Kleinlogel, E. P., & Jayagopi, D. B. (2024). A deepfake-based study on facial expressiveness and social outcomes. *Scientific Reports*. https://doi.org/10.1038/s41598-024-53475-5
34. Revenko L.S., Revenko N.S. (2025). Artificial Intelligence: Modern Approaches to Multilateral Regulation. *Economics, taxes & law. 18*(5):165-177. (In Russ.) https://doi.org/10.26794/1999-849X-2025-18-5-165-177
35. Seow, J. W., Lim, M. K., Phan, R. C. W., & Liu, J. K. (2022). A comprehensive overview of deepfake: Generation, detection, datasets, and opportunities. *Neurocomputing, 513*, 351–371. https://doi.org/10.1016/j.neucom.2022.09.135
36. Shapochkin, D. V. (2013). Metod kognitivnogo analiza diskursa v lingvistike [Method of cognitive analysis of discourse in linguistics]. *Bulletin of Chelyabinsk State University, 10*(301), 76, 101–107.
37. Shital Mehta, Harshali Patil, Mehek Meghani. (2025). Deepfake Technology & Financial Frauds: Awareness, Risks and Prevention Strategies. *European Economic Letters (EEL), 15*(2), 2472–2477. https://doi.org/10.52783/eel.v15i2.3095.

https://eelet.org.uk/index.php/journal/article/view/3095

38. How do we protect societies from synthetic media and "deepfakes"? *Synthetic Media & Deepfakes.* (n.d.). (2025). Retrieved from https://cnti.org/article/synthetic-media-deepfakes/
39. Tang, Z., Yin, S. X., & Goh, D. H. L. (2023). Understanding major topics and attitudes toward deepfakes: An analysis of news articles. In H. Mori, Y. Asahi, A. Coman, S. Vasilache, & M. Rauterberg (Eds.), HCI International, *Late Breaking Papers* (pp. 25). Springer. https://doi.org/10.1007/978-3-031-48044-7_25
40. Tsvetkov V.A., Yadgarov Y.S. (2025). Traditions of Dominance of Moral Foundations in Russian Political Economy (Second Half of the XIX — First Third of the XX Century). *Finance: Theory and Practice*, *29*(6):121-131. https://doi.org/10.26794/2587-5671-2025-29-6-121-131
41. Ürmösné, G. S., & Nyitrai, E. (2021). The phenomena of epidemic crime, deepfakes, fake news, and the role of forensic linguistics. *Információs Társadalom XXI,* (4), 86–101.https://doi.org/10.22503/inftars.XXI.2021.4.5
42. Vargas-Sierra C, Orts MÁ. (2023) Sentiment and emotion in financial journalism: a corpus-based, cross-linguistic analysis of the effects of COVID. *Humanit Soc Sci Commun;10*(1):219. doi: 10.1057/s41599-023-01725-8. Epub 2023 May 9. PMID: 37192939; PMCID: PMC10169163.
43. Whittaker, L., Letheren, K., & Mulcahy, R. (2021). The rise of deepfakes: A conceptual framework and research agenda for marketing. *Australasian Marketing Journal, 29*(3), 204–214. https://doi.org/10.1177/1839334921999479
44. Wood, T. A. (2024). *Fast stylometry* (Version 1.0.4) [Software].
45. Xu, Z., Wen, X., Zhong, G., et al. (2025). Public perception towards deepfake through topic modelling and sentiment analysis of social media data. *Social Network Analysis and Mining, 15*, 16. https://doi.org/10.1007/s13278-025-01445-8
46. Zagidullina M.V., Ghodrati A., Shafaghi M. (2023). Linguacultural aspects of the value and semantic attitude to the speech act of promise in Russian. *Russian Journal of Linguistics, 27*(2), 418-443. doi: 10.22363/2687-0088-30603
47. Zaidi, L. (2020). The only three trends that matter: A minimum specification for future-proofing. *Journal of Futures Studies, 25*(2), 95–102.