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Human Vs AI Summaries of Exploratory Data Analysis: Trust, Accuracy, And Decision Impact

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Abstract- ***The recent progress of artificial intelligence has dramatically changed the environment of data analysis, especially with the introduction of large language models (LLMs) into the process of analysis. Such systems are also becoming able to produce automated summaries of Exploratory Data Analysis (EDA) output and can give narrative explanations of statistical trends, correlations, and anomalies in datasets. With the use of AI-assisted analytics in organizations to enhance efficiency and scalability, concerns have arisen as to the relative reliability and interpretability of summaries prepared by human analysts compared to summaries prepared by AI systems. Recent studies point to the increased role of the analytical tools based on LLM in scientific research, business-level, as well as decision-support settings, both in terms of their transformative power and obstacles to the implementation of such tools in the context of a critical decision-making process (Mienye et al., 2025; Mishra et al., 2024). The paper analyzes the relative features of EDA summaries produced by human analysts and those produced by the LLM, in terms of four dimensions of evaluation, including factual accuracy, analytical completeness, expression of uncertainty, and perceived analytical trustworthiness. The construction of EDA narratives is usually based on domain knowledge, the reasoning of contexts, and interpretive judgment by human analysts, but the construction of EDA narratives based on probabilistic language generation and pattern recognition is based on massive amounts of training data by the systems that are built using the LLM. Though AI-based summaries have their benefits in terms of speed and scalability, their interpretive accuracy and the capacity to make reasonable statements about uncertainty are still on a scholarly research agenda. In addition to correctness in the analysis, the research additionally reviews the way such differences affect the way stakeholders make decisions. The summaries of EDA can be used as a formal linkage between complicated data and strategic actions by managers, policy makers, and other parties involved. As a consequence, misinterpretation or decision bias, or lack of uncertainty in summaries due to inaccuracies, incomplete interpretations, or poor communication of that uncertainty, can occur. The current body of research on AI-driven decision systems states that AI analytics integration can have a significant effect on the quality of decisions, organizational trust in automated systems, and user confidence calibration in the outputs of analytical systems (Guan et al., 2022). This article, by exploring the interaction between human analytical thinking and AI-generated narrative summaries, contributes to the wider debate on an ethical introduction of AI in the data-driven decision-making sphere. Particularly, the paper identifies the benefits and disadvantages of both methods of analysis and explains how the hybrid human-AI work processes can enhance the reliability, openness, and credibility of the EDA-based decision support. The results will be used to guide the development of stronger analytical models that will match the speed at which AI systems can compute with the ability of human analysts in their context.***

Keywords: Exploratory Data Analysis (EDA) Summarization, Large Language Models (LLMs), Human–AI Analytical Comparison, Decision Support Systems, Analytical Trust and Reliability, Uncertainty Communication in Data Analysis, Stakeholder Decision Impact

I. INTRODUCTION

The adoption of artificial intelligence (AI) as a part of the data analysis processes has been rising exponentially during the last decade due to the development of computational capabilities, machine learning algorithms, and access to large volumes of data. Large language models (LLMs) are some of these AI technologies that have become highly useful AI tools that can produce human-like narrative summaries, understand intricate data trends, and assist a decision-making process in a variety of areas (Mienye et al., 2025). They have been used in more fields, such as healthcare, as well as business intelligence, proving their ability to supplement or even enhance the conventional human analytical processes (Mishra et al., 2024; Zhang and Goyal, 2024).

Exploratory Data Analysis (EDA) is a very important process in the interpretation of datasets and the revealing of actionable information. According to the definition provided by Hinterberger (2009), EDA is the organized study of data that aims at identifying trends, outliers, or connections without having any hypotheses. Good EDA summaries help stakeholders with understandable and clear narratives, which make them strategic and operational decisions (Barsalou, 2023). These summaries serve as a liaison between raw data and organizational decision-making, and therefore, the quality of clarity, completeness, and reliability of the analytical narrative is very important to make informed decisions.

The increasing utilization of LLMs in EDA has added another layer to the analytical processes, where automated tools are able to create textual summaries that previously needed the human analyst's expertise in the domain. Although AI-generated summaries are beneficial in terms of speed, scalability, and consistency, it is still of concern that factual accuracy, completeness, and the capacity to convey uncertainty are not properly addressed (Guan et al., 2022). Human analysts, on the other hand, are able to use contextual knowledge, domain expertise, and critical thinking, although they might be constrained by time and cognitive biases.

This contrast brings the human vs AI analysis issue: What is the relationship between the accuracy, comprehensiveness, reliability, and the influence of the LLM-generated EDA summaries and the human analysts on the stakeholder decision-making? This question is critical to developing hybrid analytical frameworks that would allow integrating the computational benefits of AI with the interpretive benefits of human reasoning to make sure that organizational decisions are efficient and reliable (Zhang and Goyal, 2024).

Through systematic assessment of these dimensions, the study will give an idea of the responsible use of AI in the process of data analysis by identifying the trade-offs, advantages, and drawbacks of both human and AI-generated EDA summaries. This knowledge is essential to the development of theoretical studies and practice in the AI-assisted decision support systems.

II. ROLE OF EDA SUMMARIES IN DATA-DRIVEN DECISION MAKING

Exploratory Data Analysis (EDA) summaries in the contemporary data-driven world are an essential tool towards converting complex data into information that can be used to make strategic and operational decisions. Organizations are finding it more and more necessary to utilize analytic outputs to aid in planning, the establishment of policies, and the revision of operations. Nonetheless, raw data do not often give a significant indication to the stakeholders who may not have the necessary statistical knowledge. Consequently, EDA summaries work as an interpreting platform to transform unstructured numerical trends into explanation-based understandings that are capable of making decisions (Barsalou, 2023).

An essential component of EDA summaries is the application of summary statistics, which summarize huge data in a form of interpretable numerical indicators like mean, median, variance, and distribution characteristics. These statistical measures will give a broad overview of the data and enable analysts to see trends in the data in the first position, including skewness, central tendencies, and variability (Brereton, 2021). Although the summary statistics provide a succinct description of the data, their applications in decision-making are largely defined in the explanations and contextualization. Unless the stakeholders interpret the statistical indicators properly, they might be misinterpreted, or important implications hidden within the data distribution can be overlooked.

In addition to the use of numerical measures, visual exploration is also instrumental in EDA. Scatter plots, box plots, heat maps, and distribution charts are visualization tools that allow an analyst to determine trends, clusters, correlations, and anomalies, which would not necessarily be apparent using a numerical summary. Visual exploration enables the decision-maker to see the relationship in the data in a more intuitive format that enhances the understanding and makes the analytical outcomes easier to interpret (Lode et al., 2024). Visualizations usually constitute the initial artifact of analytical review by stakeholders in the majority of organizational settings; thus, they are a key element of EDA communication.

Narrative explanation is another very important element in EDA summaries, which connects statistical results with the practical application. Human analysts usually decode analytical results in descriptive accounts that support why some patterns take place and what they possibly imply for their future judgments. Such stories combine both statistical findings with contextual knowledge and allow stakeholders to place analytical findings into the larger operational or strategic context (Putatunda et al., 2019). By comparison, automated AI-generated summaries are based on pattern recognition algorithms to produce textual explanations of analytical results. Although these summaries are easily and uniformly generated, they can be devoid of more detailed contextual interpretation without well-developed prompts or training data of the domain model.

Very similar to narrative explanation is the term of data storytelling, which means an organized unveiling of analytical findings in a manner that relates data discoveries to organizational goals and decision priorities. Good data storytelling focuses on the most pertinent insights, draws attention to the essential trends, and conveys uncertainty or limitations of the analysis (Hongoh et al., 2016). Such a method of storytelling will allow the stakeholders to know not only what the data indicates but also how the findings are expected to change the decision-making. Summaries of EDA can also be a huge boost to the performance of analytical systems when included in intelligent decision support environments by providing interpretable insights to lead policy development, operational changes, and overall strategy (Wang and Liang, 2023).

In general, EDA summatives can be considered as a layer of translation between raw data and processed actionable decisions. They integrate statistical analysis, visual interpretation, and narrative explanation in order to enable the stakeholders to interpret complex analytical outputs. Regardless of the method used to create the summaries (human analysts or artificial intelligence), the usefulness of any such summary, at the end of the day, is determined by whether the summaries convey the information accurately, clearly, and in a format that suits the needs of the stakeholders in terms of decision-making.

TABLE 1: Core Functions of Exploratory Data Analysis Summaries in Decision Contexts

Function	Human Analyst	Automated AI Summary
Summary Statistics	Provides context and interprets significance; may highlight domain-specific anomalies	Quickly computes statistics; presents standard measures without contextual emphasis
Visual Exploration	Designs visuals to emphasize key patterns; adapts plots for stakeholder comprehension	Generates consistent visual outputs; may lack adaptive emphasis on critical insights
Narrative Explanation	Integrates domain knowledge and interpretive judgment; contextualizes findings	Produces coherent, grammatically correct narratives; relies on learned patterns, may miss nuanced interpretation
Data Storytelling	Crafts compelling stories linking analysis to decisions; emphasizes critical insights	Generates structured explanations; may be limited in persuasive or context-aware storytelling

The roles of EDA summaries are much deeper than the mere statistical reporting; it is an interpretation process that transforms the results of the analysis into knowledge to be used in decision-making. To demonstrate the effective uses of the EDA summaries in the process of analytical work, Table 1 provides a comparison of the fundamental functions that human analysts and AI-based automated summarization systems serve. The table showcases the two methods of handling important activities like statistical interpretation, visualization, narrative description, and data storytelling. Although automated processes are more concerned with computational efficiency and consistency when producing summaries, human analysts offer more contextual explanations and more domain-based explanations that can enhance the relevance of insights in decision-making by stakeholders.

III. ANALYTICAL CAPABILITIES OF HUMAN ANALYSTS VS LARGE LANGUAGE MODELS

Analytical capability assessment is the key to comprehending the weaknesses and strengths of human analysts in comparison to large language models (LLMs) in the process of generating EDA summaries. Although the two methods strive to derive meaning out of intricate datasets, the mechanisms behind them are fundamentally different, and they affect the process of interpreting and communicating the trends in data.

Human analysts have domain reasoning as one of their strengths. The analysts apply specialized knowledge and contextual information to their analysis and, thus, discover subtle connections, anomalies, and trends that are not evident at the surface level of the raw data (Baker et al., 2020). The experience they gain allows them to make decisions in advance to avoid pitfalls, doubt the unexpected outcomes, and incorporate external information that could be of value in the context of the decision. By contrast, LLMs are based on statistical associations and trends that are acquired on large-scale training data. Although these models are able to handle large datasets in a short time and detect general trends efficiently, the models do not possess inherent domain knowledge, which restricts them to decode specialized or novel situations with the help of a human expert (Mienye et al., 2025).

Contextual interpretation is also very closely related to domain reasoning, yet it is focused on the perception of the environment and the purpose of the data. Human analysts are able to make their interpretations according to the needs of stakeholders, organizational priorities, or by the historical background of the dataset (Konieczny and Sporek, 2025). However, LLMs are created with the help of probabilistic text generation that creates outputs that are coherent and linguistically natural, which may not always be relevant in the context of finer tasks or decision priorities of stakeholders (Venkatesh et al., 2024).

Pattern recognition is a subject on which both humans and AI are good at differing. Human analysts can identify non-linear trends, rare events, and interdependencies that have a multifaceted nature and demand logic among several variables at a time (Baker et al., 2020). With the help of the advanced architectures, LLM can detect the common patterns in a short period of time and summarize the relationships in very large data (Li et al., 2025). Nevertheless, they might overlook some fine-grained interactions or occasional but vital anomalies that might need a contextual interpretation or knowledge.

Last but not least, the usage of the LLMs as automated language generators is a distinguishing element. The models have the ability to decode data patterns into structured, coherent, and readable narratives in seconds, which makes them very scalable to perform large-scale reporting (Mienye et al., 2025). Human analysts, though slower, offer interpretive richness, and the story is not just accurate but has a sense as well as something that stakeholders should act on. This difference brings out one major trade-off, which is that LLMs are efficient and consistent, compared to human analysts who are rich in interpretation and judgment.

In general, it can be noted that human analysts are superior in contextualized reasoning and subtle interpretation, whereas LLMs are fast, scalable, and capable of synthesizing text automatically. It is important to understand these complementary strengths in developing hybrid frameworks to make the best out of accuracy and usability in the EDA summaries.

TABLE 2: Comparison of human analytical reasoning and llm-based eda summarization

Dimension	Human Analyst	LLM-Generated Summary
Domain Reasoning	Applies expertise and contextual knowledge; identifies subtle patterns	Relies on learned statistical correlations; may miss domain-specific nuances
Contextual Interpretation	Adjusts insights based on organizational goals and stakeholder priorities	Generates coherent text but may lack alignment with specific context
Pattern Recognition	Detects rare events, non-linear trends, and complex relationships	Efficiently identifies common patterns across large datasets; may miss subtle anomalies
Automated Language Generation	Narrative is crafted manually; slower but rich in interpretation	Produces rapid, structured, and fluent textual summaries; may lack depth or nuanced reasoning

To be able to see the differences between human analytical reasoning and AI-generated summaries, it is necessary to inspect the capabilities that influence the way in which insights are generated and communicated. Table 2 is a systematic analysis of the analytical tasks of human analysts and large language model (LLM)-based summarization systems in terms

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of crucial aspects, such as domain reasoning, contextual interpretation, pattern recognition, and automated language generation. This analogy can be used to demonstrate the complementary advantages of the two methods: human analysts can provide contextual knowledge and interpretive judgment; on the other hand, LLMs can have computational scalability and can produce analytical narratives at a rapid speed. Such differences are vital in determining the quality of the EDA summaries and the possible impact on the decision-making procedures of the stakeholders.

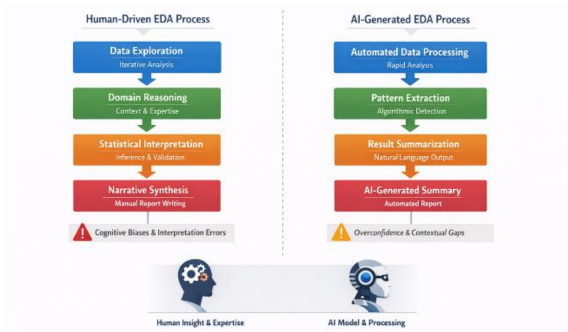

Figure 1: Workflow comparison between human-driven and AI-generated exploratory data analysis (EDA) summarization.

IV. ACCURACY AND COMPLETENESS IN EDA INTERPRETATION

Factual accuracy and analytical completeness are the two fundamental attributes of the Exploratory Data Analysis (EDA) summaries to be reliable. These features will result in the knowledge being shared with stakeholders to actually be indicative of the trends in the dataset, or to inject inaccuracies that may have a detrimental impact on the decisions made. In summarizing data by analysts or AI systems, the analysts need to have the ability to interpret statistical outputs correctly and to recognize pertinent patterns and prevent misguided conclusions, which are based on incomplete or biased analysis.

Factual accuracy is one of the significant factors of EDA interpretation and is termed the validity of the statements regarding the data. Proper summaries should accurately reflect statistical measurements, correlations between variables, and trends in data observed in the data. Studies point out that analytical conclusions can be markedly misrepresented when statistical signs are misinterpreted: by wrongly comprehending the correlations or inadequately depicting the distribution patterns (Brereton, 2021). To validate the validity of their interpretations, human analysts usually use statistical training and experience. Nevertheless, even highly trained analysts sometimes can commit interpretive mistakes because of cognitive biases or assumptions regarding the data set. In comparison, AI systems are capable of processing statistical outputs quickly and creating summaries, but the interpretations rely entirely on learned patterns and not true reasoning about the information (Mugaanyi et al., 2024).

Analytical completeness is another significant aspect that determines whether an EDA summary provides all the valuable information that is present in the dataset. A summary note should draw prominent relationships, outliers, distributions, and possible anomalies, which can affect interpretation. It is not uncommon to see human analysts develop several interpretations of analysis before making conclusions to enable them discover a very thin layer of relationship across the variables (Konieczny and Sporek, 2025). Conversely, AI-generated summaries can give preference to the patterns that are common in the data, but they do not consider other, less apparent associations that need to be arrived at through reasoning or prior knowledge.

Statistical reasoning is also important in the assessment of EDA summaries. Statistical reasoning is normally applied with the help of human analysts to interpret the correlation between variables, the difference between correlation and causation, and to determine the significance of observed patterns. These are the logic processes that enable analysts to perceive information with a degree of caution and understand the weakness of statistical findings (Brereton, 2021). Even though the systems that are based on the use of LLM can create statistically informed narratives, they are predominantly not analytical in their reasoning. It implies that they can give certain explanations despite the fact that the underlying statistical evidence is weak or ambiguous (Venkatesh et al., 2024).

One issue that is also connected to it is the interpretation bias, and it can influence human and AI-generated summaries. When interpreting the results of an analysis, human analysts are subject to confirmation bias, organizational expectations, or preconceived hypotheses. On the other hand, AI systems can produce biased interpretations when their training material has patterns that are not relevant to a particular situation of the analyzed dataset (Baker et al., 2020). In both scenarios, prejudiced interpretations may give biased conclusions and eventually may affect the stakeholder decision-making in a negative manner.

Since the summaries provided by EDA may be utilized as the basis of the strategic decision-making process, the accuracy and completeness of the analyses that are

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provided analytically must be assessed. Through the comparison between the human and AI-generated summaries, organizations will determine the possible risks related to automated analysis, as well as the opportunities to enhance the efficiency of the analytical processes with the help of hybrid human-AI processes.

TABLE 3: Accuracy and Completeness Evaluation Framework for EDA Summaries

Evaluation Metric	Human Analyst	AI-Generated Summary	Potential Risk
Factual Accuracy	Verifies statistical outputs through analytical reasoning and domain expertise; may cross-check calculations and assumptions	Generates interpretations from detected patterns in the dataset; may describe statistical results without deeper verification	Incorrect interpretation of statistical measures or misleading descriptions of relationships
Insight Completeness	Explores multiple analytical perspectives and investigates subtle relationships or anomalies	May highlight dominant patterns but overlook less obvious insights	Important patterns or anomalies may remain undiscovered
Statistical Reasoning	Applies reasoning to evaluate correlations, distributions, and significance of results	Produces statistically framed explanations but relies on probabilistic text generation	Overconfidence in interpretations without sufficient statistical justification
Interpretation Bias	May be influenced by prior expectations or organizational context	May reflect biases present in training data or algorithmic patterns	Biased conclusions leading to misleading analytical insights

The reliability of EDA summaries needs to be measured in terms of a structured framework that would take into account the accuracy of the interpretation and the fullness of the insights obtained with the help of the data. In order to demonstrate the major criteria applied to evaluate these qualities of analysis, Table 3 provides an evaluation system comparing human analysts with AI-generated summaries based on various measures, such as factual accuracy, completeness of the insight, use of statistical analysis, and interpretation bias. The framework successfully indicates how every analytical method works through and analyzes the patterns of data, as well as exposing the possible risks that could be presented by missing or false interpretations. Such a comparison can be used to explain the weaknesses and strengths of both human and AI-generated EDA narratives in decision-support situations.

Figure 2: Conceptual framework for evaluating accuracy, completeness, and uncertainty communication in EDA summaries.

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V. COMMUNICATION OF UNCERTAINTY AND ANALYTICAL CONFIDENCE

When it comes to exploratory data analysis, uncertainty and analytical confidence have been accepted as a crucial message that stakeholders need to interpret the information that specific data provides accurately. The summaries produced by EDA can help in making strategic or operational decisions; thus, an analyst should not only present the findings to the audience but also explain the limitations, assumptions, and uncertainty of the analysis. A failure to express uncertainty in the right manner might cause decision-makers to respond to analytical outputs as a sure conclusion, as opposed to a probabilistic understanding.

Statistical uncertainty is one of the main elements of uncertainty communication; it is caused by sampling error, incomplete information, and randomness of the data generation process. This uncertainty is typically measured using statistics like the confidence interval, probability distribution, and error margins to make stakeholders aware of the analytical investigation's reliability (Padilla et al., 2021). Such indicators are usually included by human analysts in their intended explanations, and it explains when results are to be addressed with a lot of care or when more information might be needed before arriving at any significant conclusion.

The other critical dimension is the visualization uncertainty that is associated with the possibility of misinterpreting the graphical representation of data. The visual representations, like charts and graphs, could be effective in terms of showing the trends and patterns, but they can also conceal the uncertainty, in case they do not reflect variability or error margins explicitly. Studies on visualization of uncertainty focus on the need to create graphical models with the capability to visually convey central tendencies as well as how diverse they can be (Weiskopf, 2022). The uncertainty can be depicted by advanced visualization methods, such as the use of shading, confidence bands, or probabilistic overlays, which aid the viewers in seeing the extent of possible outcomes (Wu et al., 2012).

EDA summaries should also deal with probabilistic interpretation, especially where analysis conclusions are made that are either predictions, associations or model-generated. In most analytical settings, the relationships found in EDA can denote statistical relations as opposed to causal relations. It is of importance to properly communicate probability and likelihood to avoid the fact of overestimation of the certainty of the analytical findings by the stakeholders (Bian et al., 2011). Such distinctions are normally highlighted by human analysts who clarify the assumptions made on the interpretation of the statistics and also raise the factors that can affect the credibility of the findings.

An almost similar concept is that of confidence calibration, the relationship between what the stakeholders believe to be the confidence of the analysis and the actual reliability of the analysis. Trust in the outputs of a given analytical procedure may cause failure in making appropriate decisions, particularly when the data used to infer the results are filled with noise, values are missing, and unobserved factors are present. On the other hand, too much skepticism can make the stakeholders disregard valuable insights obtained from the data. Sound EDA summaries thus strive to tune the confidence to the right level by showing insights in addition to describing their shortcomings and unpredictability (Conroy et al., 2024).

The creation of AI-generated EDA summaries creates new factors in the communication of uncertainty. Although large language models can produce fluent descriptions of statistical patterns, in most cases, they do not describe uncertainty or limitations unless they are specifically asked to do so. Human analysts, in their turn, have a higher chance to contextualize findings in the wider context of the analytical environment and obscure the provisionality of exploratory insights. Consequently, uncertainty communication to human and AI-generated summaries needs to be evaluated to determine the accuracy of the analytical narratives and their role in influencing the decision-making of the stakeholders.

TABLE 4: Comparison of Uncertainty Communication in Human and AI EDA Narratives

Aspect	Human Analyst	AI-Generated Summary
Statistical Uncertainty	Explains variability using confidence intervals, error margins, and statistical reasoning; often highlights limitations of the dataset	May reference statistical measures but may not consistently emphasize uncertainty unless prompted

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Visualization Uncertainty	Designs visualizations that incorporate uncertainty indicators such as confidence bands or error bars	Generates standard visualizations or descriptions that may omit explicit representation of uncertainty
Probabilistic Interpretation	Distinguishes between correlation, probability, and causation; provides contextual explanations	May describe statistical relationships fluently but may not fully explain probabilistic limitations
Confidence Calibration	Adjusts the tone and interpretation of results to match the reliability of the analysis	May present insights confidently even when underlying evidence is uncertain, depending on mod

Doubt in communication is one of the important aspects in ensuring that stakeholders address analytical understandings appropriately. In situations where the uncertainty is ineffective in communication, the decision-makers can gain false confidence in the analytical conclusions. Table 4 gives a comparative summary of the manner in which human analysts and AI-generated summaries express uncertainty in the context of EDA narratives, paying attention to such aspects of uncertainty as statistical uncertainty, visualization uncertainty, probabilistic interpretation, and confidence calibration. Through the analysis of these dimensions, the table indicates differences between the ways these two approaches communicate the constraints of analyses and the extent to which each of the approaches includes uncertainty in the narrative explanations. These differences are important in understanding the reliability of EDA summaries and their impact on the process of decision-making by the stakeholders.

VI. TRUST AND RELIABILITY IN AI-GENERATED ANALYTICAL NARRATIVES

With the growing integration of artificial intelligence into analytical workflows, issues of trust and reliability have become the key factors of consideration in the application of AI-generated analytical narratives. When organizations are using automated systems to generalize the exploratory data analysis (EDA), the stakeholders need to be assured that the generalizations are precise, transparent, and reliable. Lack of enough trust in the analytical results of AI systems implies that decision-makers will not only dismiss useful information but can also infer false information without proper examination. Therefore, it is important to note that to build trust in AI-generated summaries, one should consider such aspects as explainability, reliability, verification practice activity, and transparency.

Explainability is also one of the most vital elements of trust in AI analytics, which is the process whereby an AI system can present comprehensible explanations of the insights it produces. The results of the analysis will be more credible to the decision-makers when they can easily comprehend the derivation process of those results. Explainability in the EDA context summaries entails explaining how patterns were determined, how statistical associations were understood, and how inferences were drawn using the data. Studies on reliable AI systems underscore the way explainability increases the level of confidence in automated analytical systems by rendering their line of reasoning more understandable and transparent (Devalla and Yogi, 2023). Analytical outputs might be opaque and hard to decode, thus raising questions for the stakeholders about their validity, regardless of whether the result is correct or not statistically significant.

The concept of explainability goes hand in hand with another, which is the concept of reliability, which can be defined as the consistency and dependability of AI-generated analytical narratives. Consistent analytical systems ought to yield consistent and precise results when tested using diverse datasets and analysis situations. Research that investigates the human-AI interaction implies that the credibility of AI systems plays a significant role in the motivation of users to use automated insights in the decision-making process (Maier et al., 2022). When the AI-made summaries are full of discrepancies, missing details, or false interpretations, it is possible that the stakeholders will lose trust in the technology. That is why, to provide reliability, it is necessary to engage in extensive testing, constant reviewing of the models, and integration of quality assurance processes into AI-based analysis devices.

The other dimension of trust towards AI-generated narratives that is significant is the incorporation of verification practices. According to many scholars, the AI-generated output should not be accepted without human intervention, especially in such situations when the analytical findings are going to be reflected in a strategic or high-stakes decision. The most common practices constituting verification include human verification of AI-generated summaries, comparison of the statistical interpretations, and confirmation of the conclusions in automated reports. These methods are consistent with the principle of trust but verify that has been listed numerous times in the literature on human-AI collaboration (Khan et al., 2025). With the help of verification systems implemented in the workflow of the analysis, organizations can reduce the possible risks of automated summarization and achieve the efficiency of AI systems.

The second aspect is transparency, which will allow developing trust in AI-generated analytical narratives. Transparency is the ability to expressly communicate the practices, assumptions, and boundaries of AI-based insights. When users of a system know the way the system works and what factors determine its outputs, chances are high that they will critique and be responsible in the evaluations. Reliable AI is discussed in philosophical texts whereby transparency helps people to determine whether the conclusions provided by AI are sufficiently plausible and suitable to be used in a situation of decision-making (Duran and Pozzi, 2025; Robertson, 2025). Transparency can be practiced in the context of analysis, which can include the provision of explanations about the behavior of the model, documentation of data origin, and making clear uncertainty in the context of analytical summaries.

The recent research in AI-driven business analytics also indicates that trust towards automated analytical systems is built over time as the user is increasingly exposed to the technology and realizes that it performs in a consistent, reliable manner over time (Luchian et al., 2025). Companies that have embraced AI-enabled analytics are thus left with two aspects to take into account, namely technical reliability and human understanding of reliability. Even the most accurate systems could be doubted when users are not completely aware of their functionality or when they feel that they are not responsible.

Altogether, automation and human supervision are key elements that must be established in a fine balance when it comes to the incorporation of AI-generated EDA summaries into decision-making settings. Explainability, reliability, verification practices, and transparency are the factors that define the degree of trust that the stakeholders have in the AI-generated analytical narratives. Considering these dimensions, organizations will be able to enhance the responsible use of AI in data analysis and make sure that automated insights contribute to high-quality decisions and do not harm them.

VII. DECISION IMPACT OF HUMAN VS AI EDA SUMMARIES

The summaries of the Exploratory Data Analysis (EDA) are vital in determining data-based decision-making. Both AI and human interpreters derive narrative explanations of a dataset, and these interpretations may have a substantial impact on an organization's decision by the stakeholders. With the rising adoption of Large Language Models (LLMs) in organizational analysis processes, it is necessary to comprehend how the narratives generated by artificial intelligence affect the decisions made by people.

The wrong takeaway rate is one of the primary aspects in measuring the impact of the decision; it is the probability of a reader making an incorrect conclusion based on a summary of data. Contextual reasoning and domain expertise are usually used by human analysts when they interpret patterns in data, and this may decrease the chances of misleading conclusions. Nevertheless, human analysts can also be the cause of cognitive biases or may miss out on the complicated patterns of data in big datasets. On the contrary, AI summaries tend to require less time to digest large volumes of data, but they can make overconfident conclusions and/or fail to take fundamental contextual factors into account, further reducing the chances of being misinterpreted without thoroughly validating their outputs (Almadani et al., 2025).

Decision bias is another dimension that is important. Human analysts can find themselves framing the results in a manner that supports the already existing organizational beliefs or expectations. This is a commonly termed confirmation bias, and it can influence the interpretation of analytical findings by the stakeholders. Although AI-generated narratives are not open to human cognitive bias in their conventional meaning, they still have the potential to recreate any biases that exist in the training data or other outputs. It has been demonstrated that automated explanations of analytics tend to enhance patterns that, although statistically significant, are not practically significant and may prompt decision-makers to adopt strategies that are suboptimal (Hassan et al., 2024).

The type of decisions made based on the EDA summaries also depends on the clarity, format, and depth of the review story. Human analysts can tend to give contextual explanations to assist the stakeholders in interpreting the causal relationship and what it might mean. This interpretive richness is able to improve the quality of decisions, especially in a complicated analytical setting. On the other hand, AI-generated summaries can give brief accounts of statistical relationships, but are at times not as domain explanatory. Because of this, decision-makers who use automated summaries only can overlook important information that can be used in strategic planning (Ko et al., 2025).

Another factor is the calibration of confidence that is described as the extent to which decision-makers evaluate the reliability of the information provided to them. It has been shown that the explanations provided by AI may sometimes prompt the user to trust automated results too much, especially when the explanation is presented in authoritative or technical form. The given phenomenon may contribute to the overconfidence in AI-driven insights even in cases when underlying assumptions or methodological constraints remain not completely visible (Manulak et al., 2024). Conversely, human analysts can communicate more analysis constraints or other interpretations, which would allow the stakeholders to make more balanced decisions.

Recent research claims that the combination of human skills and AI-aided summarization can be offered as a hybrid analytical approach, which can be the most reliable background for making decisions. Through the fast identification of patterns provided by AI and human analysts confirming and contextualizing the results, the risk of misinterpretation can be minimized, but the efficiency of the analysis will remain high (Wang and Liang, 2023).

Altogether, the impact of EDA summaries on the outcomes of the decision-making process is not only based on the accuracy of the analysis but also on the communication of insights, their situationalization, and being believed by the stakeholders. This is because the comparison of the strengths and weaknesses of human and AI-generated narratives will be critical to the responsible and effective data-driven decision process.

VIII. STAKEHOLDER INTERACTION AND DECISION INTERPRETATION

The value of Exploratory Data Analysis (EDA) summaries cannot exist in isolation, but rather they are created by the interpretation and use of insights by stakeholders in decision-making processes. Data scientists are not the only ones who review the analytical results and are able to use the summaries to make strategic decisions in a variety of organizational settings. Therefore, whether EDA narratives are created by a human analyst or an AI system, the effectiveness of EDA narratives will greatly rely on how stakeholders will interpret and engage with the findings provided.

Participatory decision-making is one of the aspects of stakeholder engagement, whereby various stakeholders can be involved in interpreting analytical findings. Participatory frameworks focus on the work of collaboration between analysts and decision-makers in order to make sure that the output of analysis is consistent with the real-life operational conditions. Studies indicate that stakeholders can enhance the applicability and relevance of the analytical insights when they are engaged in the interpretation process because stakeholders can also give contextual knowledge that might otherwise be overlooked by statistical models (Neef and Neubert, 2011). This process is usually aided by human analysts providing information on the assumptions made in the analysis and defining the unknowns in the data.

The idea of collaborative interpretation is closely connected with the concept of participatory processes as another means of understanding, in which stakeholders explore the analysis narratives jointly in order to obtain common sense. Collaborative interpretation prevents the risk of misinterpretation by giving several points of view an opportunity to challenge or refine the initial conclusions. Decision science research shows collaborative analysis has the potential to strengthen a decision through the combination of technical data analysis with knowledge of the domain (Thokala and Madhavan, 2018). Although the summaries obtained using AI as an EDA can be effective in displaying the statistical results, they do not provide the interactive discussion that would be needed to facilitate the collaborative interpretation in the absence of further human mediation.

The other key element is stakeholder trust in analytics. Trust also determines how far the stakeholders go to trust the analytical insights in making decisions. In cases where stakeholders have confidence in the analytical process and its products, they tend to make use of the results in the strategic planning process and their operations. The human analysts frequently develop trust based on transparency, articulation of analytical thinking, and openness to questions posed by the stakeholders. Nonetheless, the expanding utilization of AI-based summaries presents new problems in the formation of trust. Stakeholders might place too much trust in automated systems because of their technological high level or too little because of the lack of knowledge about the way AI-generated narratives are generated (Starks et al., 2015).

Moreover, the stakeholders' interaction process should be effective, and that is why analytical summaries have to be presented in a manner that fits the decision-making context. Actionable insights instead of purely statistical descriptions are usually given priority by decision-makers. Accordingly, EDA stories need to put analytical results to valuable policy, business strategy, or business operations planning. A study of decision-support systems also indicates that analytical communication must be customized to the requirements and level of expertise of the stakeholders to make correct interpretations and follow-up decisions (Vriens et al., 2025).

Lastly, interdisciplinary cooperation among analysts and stakeholders can empower the whole process of decision-making. The incorporation of different knowledge will empower the organizations to interpret analytical results in a better manner and to counter uncertainties and situational influences that can alter the findings. Such a cooperative model has been demonstrated to increase the plausibility and applicability of the analytical results in multifaceted decision-making settings (Hongoh et al., 2016).

To conclude, stakeholder interaction is a very critical part in defining the impact that EDA summaries have in real-life decisions. Regardless of whether analytic stories are compiled by human spectators or AI systems, they are to uphold participatory interpretation, trust, and collaborative decision-making to make sure that the data-driven perspectives provide effective and responsible responses.

IX. INTEGRATED HUMAN–AI ANALYTICAL FRAMEWORK

The most important challenge to overcome with the implementation of AI-assisted analytics, as organizations embrace them more and more, is the ability to balance the efficiency of automated systems with the interpretive capabilities of human analysts. According to the analysis of the human and AI-generated EDA summaries above, it can be concluded that both methods have complementary capabilities: AI systems can process data faster and with a larger volume of data, and human analysts can generate contextual reasoning, domain expertise, and interpretative judgments. The combination of these capabilities can help optimise the analytical processes and improve the quality of decisions.

The integrated human-AI framework proposed will include three stages, which are connected, namely, AI-driven summary generation, analyst verification, and stakeholder interpretation. At the initial stage, big language models (LLMs) or other AI systems create a preliminary EDA summary, such as statistical information, visualizations, and narrative descriptions. This automation is a major time-saving measure in big data processing and the achievement of consistency when repeated analyses are carried out (Zhang and Goyal, 2024). The fact that AI-generated summaries enable exploratory analysis of various scenarios is also helpful because it allows organizations to quickly discover possible patterns and areas of interest.

The second level is the verification of human analysts, during which domain experts check the accuracy, completeness, and relevance of the context of AI-generated summaries. Analysts evaluate the rationale of statistics, test the insights in accordance with the knowledge of the domain, and revise the interpretations in a way that the overall organizational goals are met (Wang and Liang, 2023). Such a verification process removes the risks related to the limitations of AI, that is, the misunderstanding of nuanced patterns, the absence of anomalies, or overconfident claims. It is also a chance to combine qualitative knowledge that might not be reflected in the dataset but is essential to make a proper decision.

The last step focuses on the interpretation of stakeholders, in which validated EDA summaries are shared with the decision-makers and the appropriate stakeholders to be used in the strategic or operational setting. Through stakeholder involvement in analytical results interpretation, organizations could promote participative decision-making, improve confidence in AI-supported processes, and make sure the insights are practical and oriented towards organizational goals (Luchian et al., 2025). The insights can be contextualized by stakeholders to further enable confidence and comments that lead to future analysis refinement, and this will become a cycle of continuous learning among AI systems, analysts, and decision-makers.

The combined structure, therefore, embraces the mutual strengths of AI and human analysis, which improves both efficiency and reliability of EDA summaries as well as promotes responsible and effective data-driven decisions. Studies indicate that these hybrid models will enhance commitment to analytics, minimize the chances of misinterpretation, and enhance the overall quality of choices made in organizational settings that are complex (Guan et al., 2022). Through integrated application of automated summarization, expert validation, and stakeholder involvement, organizations would be able to gain the greatest value out of EDA outputs and reduce the risks related to relying either on human or AI analysis.

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To summarize, this framework highlights the promise of human-AI collaboration as a best practice in exploratory data analysis, especially in high-stakes decision-making situations where the accuracy, completeness, and communication of uncertainty and trust are of utmost importance.

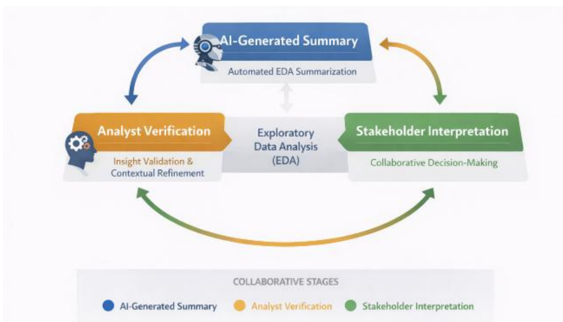

Figure 3: Integrated human–AI framework for exploratory data analysis and decision support.

X. IMPLICATIONS FOR AI-ASSISTED DATA ANALYSIS

The growing use of AI-based exploratory data analysis (EDA) summaries presents significant concerns of responsible analytics and governance, as well as human supervision. Although AI systems have the potential to enhance efficiency and offer regular summaries of extensive datasets, their application in the decision-making processes should be supported by accountability mechanisms, transparency, and trust from stakeholders.

One of the implications is responsible AI in analytics, which is the focus on ethical, correct, and open application of automated systems. The summaries produced using AIs should follow the principles protecting against misinterpretation of information, bias, or overconfidence when making a decision (Robertson, 2025). The accountable aspects of AI require the creation of models that are explainable, documented, and clearly present the uncertainty in the underlying data. This methodology will help the AI tools to aid the process of informed decision-making, and not unwittingly put errors or misinformation to the stakeholders.

Another very important consideration is trust calibration. When the AI-generated summaries seem fluent or authoritative, the stakeholders tend to overvalue the accuracy and reliability of this type of information. Trust calibration demands that AI system users must be aware of the strengths and weaknesses of the systems (Duran and Pozzi, 2025). The introduction of verification steps, uncertainty communication, and human-AI collaboration will allow matching the confidence of stakeholders with the true reliability of analytical outputs and, therefore, minimizing the threat of making misconductive decisions.

It is also required that governance structures be put in place to regulate AI-supported analytics. The organizations should create a clear policy on data management, model validation, and ethical implications, and analytical workflow documentation (Devalla and Yogi, 2023). Governance structures ensure that AI outputs are accountable, verifiable, and consistent with business standards to ensure accountability of the decision-making process.

Last but not least, the role of analysts cannot be eliminated even in the most automated analytical settings. The human analysts are involved in the contextual interpretation, domain knowledge, and critiques of AI summaries. Supervision makes the insights accurate and actionable to ensure that the information gaps between automated computation and the real-world decision-making needs are bridged (Robertson, 2025). With the help of AI efficiency and human judgment, organizations will be in a position to increase the trustworthiness of the data-driven decisions without compromising ethical and operational values.

Altogether, AI incorporation into EDA processes has major implications for accountable, reliable, and accurate data analysis. To achieve the benefits of AI-assisted analytic processes to the fullest and reduce the risks associated with it, organizations need to strike a balance between automation and human control, develop governance frameworks, and have transparency and trust calibration measures.

XI. CONCLUSION

This paper has discussed the relative advantages and drawbacks of human analysts and artificial intelligence-generated summaries in exploratory data analysis (EDA), and the role that both can play in the decision-making process. Contextual reasoning, domain knowledge, and interpretive judgment are provided by human analysts, which allow subtle understanding and bias avoidance of subtle biases in data. AI-generated summaries, especially those made by large language models, offer fast processing, scalability, and pattern recognition consistency, and are useful in quickly analyzing large amounts of data.

Although the above benefits exist, the two methods have the risk of being misinterpreted. Human analysts can cause cognitive bias or not notice patterns because of time constraints or inadequate computing power. Although generated by AI, AI-generated narratives can be excessively confident, may miss out on facts in the context, or may repeat biases within their training data. These dangers highlight accuracy, completeness, uncertainty reporting, and trust as significant risks to be considered when using EDA summaries because these are the aspects that directly affect the outcomes of the decision made by stakeholders (Guan et al., 2022).

The results justify the use of mixed workflows of analysis, where AI systems are used to create the first summaries that are then confirmed and put in context by human analysts before being interpreted by stakeholders. This human-AI model is highly efficient in terms of analysis and still reliable, transparent, and actionable (Luchian et al., 2025).

Lastly, the paper outlines the opportunities for future work, such as the creation of standard evaluation measures of AI-generated EDA summaries, the study of trust calibration processes in different organizational settings, and longitudinal research on the outcomes of decisions in hybrid analytical processes. Also, further development of AI explainability, uncertainty communication, and stakeholder engagement strategies will enhance the successful application of automated analytics in high-stakes decision-making environments (Mienye et al., 2025).

To sum up, it can be argued that responsible integration of AI into EDA procedures with human supervision and involvement of stakeholders is a potential way towards more informed, reliable, and accountable data-driven decision-making and a precursor to further development of AI-aided analytics.

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