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Designing Data Visualization for Non-Expert Users: Balancing Aesthetics and Usability

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***Abstract*—*In modern enterprises, master data platforms such as Dun & Bradstreet's unified data solutions provide a "single source of truth" that integrates fragmented customer, supplier, and partner information into consistent, high-quality records to support analytics and decision-making. Yet even when the underlying data foundation is robust, non-expert business users often struggle to interpret complex dashboards and derive actionable insights from the consolidated data. This article, Designing Data Visualization for Non-Expert Users: Balancing Aesthetics and Usability, addresses this gap by proposing a practical design framework for turning enterprise master data into visualizations that are both engaging and easy to understand for non-technical stakeholders. Grounded in real-world enterprise scenarios, the framework outlines five design dimensions—user and context analysis, visual encoding and chart choice, color and layout, textual and narrative support, and lightweight interaction with progressive disclosure—and demonstrates through a small-scale study and a dashboard redesign case that "balanced" visualizations can improve comprehension, confidence, and adoption among non-expert users. By aligning visual design with the realities of master data management, the article shows how organizations can fully leverage trusted enterprise data assets to enable broader, more inclusive data-driven decision-making.*

***Keywords*—** *Data Visualization for Non-Experts ; Aesthetics and Usability ; Enterprise Master Data ; User-Centered Dashboard Design.*

I. INTRODUCTION

In today's data-driven world, data visualization has become an indispensable tool for making complex information more accessible and actionable. However, for non-technical users, understanding and creating compelling visualizations remain significant challenges. The China Data Analytics Industry Development Report (2023) notes that over 70% of enterprise users engaged in data analysis lack professional technical backgrounds, yet they are directly involved in business decision-making. This reality raises a central question: how can "non-experts" effectively use data to support accurate, data-driven decisions rather than relying solely on technical specialists?

Despite the widespread availability of reporting and dashboard tools, many business professionals still describe data visualization as "too difficult," "too advanced," or "hard to learn." In practice, however, data analysis should not be the exclusive domain of technical experts. It should function as an efficient, empowering capability for every business stakeholder. Making data visualization genuinely accessible to non-expert users, therefore, requires not only lowering technical barriers but also designing visual representations that are easy to understand, engaging to explore, and aligned with real-world enterprise needs.

This article focuses on these practical needs by using real-world enterprise scenarios to examine how data visualization can be designed for non-expert users. We analyze key design paths and verifiable methods for helping non-technical personnel interpret data with minimal barriers, and we pay particular attention to how designers can balance aesthetic appeal with usability. By doing so, we aim to provide a set of actionable principles and design guidelines that make data visualization more inclusive, intuitive, and effective for a broad range of non-expert users.

II. RELATED WORK

2.1 Non-Professional Users and Graphical Literacy

Currently, after evolving from professionally generated content to user-generated content and content co-generated by professional users, content production is entering a stage of AI-generated content, namely, content generated with the assistance of generative artificial intelligence (AIGC) or automatically. Generative AI, based on artificial intelligence, uses large-scale model training and big data learning to produce meaningful content products in response to user instructions. Generative AI not only constructs a new paradigm for content production but also significantly changes the social information structure, profoundly impacting our production and lifestyles.

Generative AI encourages greater user participation in content production. It provides technological availability to bridge the "capability gap." In the era of mass communication, differences in economic resources, cultural levels, and cognitive frameworks among users lead to unequal access to information, resulting in phenomena such as the "knowledge gap" and "information gap" among audiences. The widespread adoption of the internet has provided ordinary users with more opportunities for information and knowledge. In fact, some have seized these opportunities to start businesses and expand their businesses.

In contrast, others have become addicted to entertainment such as online dramas and games, leading to a "capability gap." Although the rapid development of social media has empowered people to express opinions and produce information, the ability to quickly and massively produce high-quality content has become a crucial criterion for distinguishing ordinary users from professional media organizations. Without improving the quality of content products, it will be difficult to change the reality that ordinary users remain content recipients, and user-generated content will only be a derivative of user social behavior. The emergence of generative artificial intelligence (AI) helps ordinary users compensate for their shortcomings in content production through AI technology, including the mastery and application of professional knowledge, languages, and programming. Generative AI provides ordinary users with almost the same level of technological access as professional content producers, significantly improving their ability to use social media, generate various types of text, and solve practical problems.

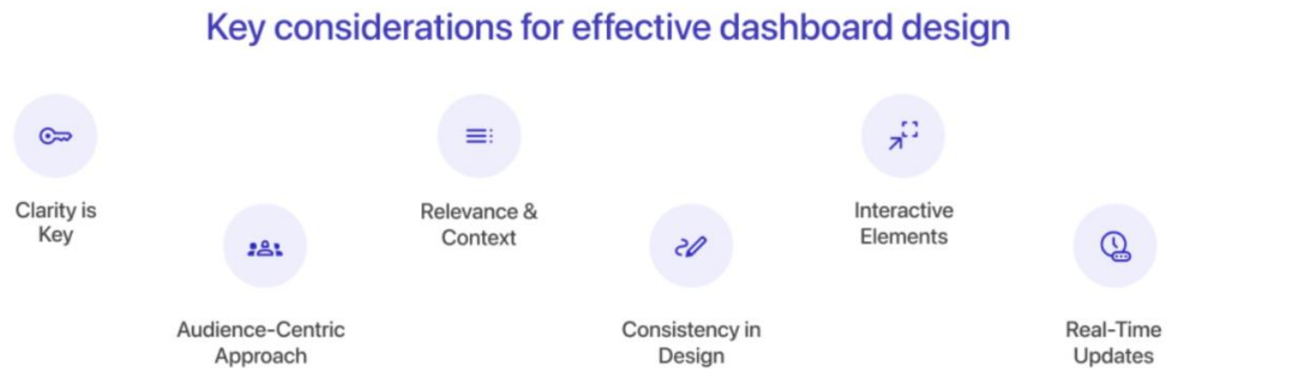
What does the AI literacy framework provide? The AI literacy framework, currently in draft form, defines AI literacy as a fusion of knowledge, skills, and attitudes that helps students use AI responsibly and effectively. The framework revolves around four areas of practice:

1. Interacting with AI – Understanding when and how AI appears in everyday tools and rigorously evaluating its output.
2. Using AI for Creativity – Collaborating with AI tools to support problem-solving, foster creativity, and consider ethical issues such as ownership and bias.
3. Managing AI Behavior – Responsibly delegating tasks to AI, developing guidelines, and ensuring human oversight.
4. Designing AI Solutions – Understanding how AI works and exploring how to build or adapt systems to address real-world problems.

Each area includes 23 competencies and classroom learning scenarios, making the framework both visionary and practical. It applies not only to computer science courses but also to disciplines ranging from languages and arts to social studies, further demonstrating AI's status as an interdisciplinary topic in education.

2.2 Overview of Usability Principles in Data Visualization

In the era of widespread artificial intelligence and machine learning, data visualization is crucial for understanding model performance and optimizing processes. It has become an essential component of successful data dashboard analysis strategies and is vital for maintaining competitiveness in a dynamic market.



Key Considerations for Effective Dashboard Design:

Clarity is Paramount: Ensure your visualizations are clear and easy to interpret. Avoid unnecessary complexity, focusing on simplicity without sacrificing depth of information.

Audience-Centered Approach: Understand your audience and tailor your visualizations to their needs. Different stakeholders may require different views of the data, so customize your dashboard accordingly.

- Relevance and Context: Provide context for the data by integrating relevant details. This helps users understand the importance of the information and its impact on decision-making.
- Design Consistency: Maintain a consistent design throughout the dashboard. Consistency facilitates the smooth delivery of information and ensures a consistent user experience.
- Interactive Elements: Integrate interactive elements to allow users to explore the data further. Features such as filters and in-depth options enhance user engagement and promote a deeper understanding of the data.
- Real-Time Updates: Consider integrating real-time data updates where applicable. This ensures up-to-date information, enhancing its relevance and reliability.

Big data visualization is a crucial element of modern data analysis. By transforming complex data into easily understandable charts and graphs, it helps decision-makers quickly gain insights. This article will explore the fundamental principles of big data visualization in detail, helping you better present the value of data in practical applications. Here are the core points of this article:

Define the Purpose: Before starting any visualization project, be sure to clearly define what information you want to convey through the data.

Choose the Appropriate Chart Type: Different data types and presentation purposes require different chart types.

Prioritize Data Accuracy: Data accuracy is the foundation of visualization; any errors can mislead decision-making.

Focus on User Experience: Good visualization should not only be aesthetically pleasing but also easy for users to understand and use.

Continuous Optimization and Updates: Data is dynamic, and visualizations also require continuous updates and optimization.

Through the detailed explanation in this article, you will be able to master the practical application of these principles, improving the effectiveness and quality of your data visualizations.

I. Define the Purpose:

Defining the purpose is the most critical step before starting any big data visualization project. Data visualization is not just about aesthetics; its core lies in conveying information graphically, helping users quickly understand key information and trends in the data.

Defining your purpose can be approached from several aspects:

Identify your target audience: Understand who your primary audience is, their background, needs, and expectations.

Define the problem: Clarify what problem you hope to solve or answer through data visualization.

Set goals: Determine what effect you hope to achieve through visualization—is it to show data trends, compare data differences, or reveal anomalies in the data?

A clear purpose helps you maintain consistency in selecting data, designing charts, and adjusting presentation methods.

II. Choosing the Appropriate Chart Type

Different data types and presentation purposes require different chart types. Choosing the appropriate chart type is one of the essential principles of big data visualization. Common chart types include line, bar, pie, scatter, and heat maps.

1. Line chart: Suitable for showing data trends over time.
2. Bar chart: Suitable for comparing different categories of data.
3. Pie chart: Suitable for showing the proportion of each part to the whole.
4. Scatter plot: Suitable for showing the relationship between two variables.
5. Heatmap: Suitable for showing the spatial distribution and density of data.

Choosing the right chart type not only improves the clarity of data presentation but also better conveys the information behind the data.

III. Emphasize Data Accuracy

Data accuracy is the foundation of visualization. Emphasizing data accuracy not only increases its credibility but also avoids misleading decision-makers. Data accuracy includes data completeness, consistency, and reliability.

1. Data Completeness: Ensure the data source is reliable and the data collection process is complete.
2. Data Consistency: Ensure data remains consistent across different systems and platforms.
3. Data Reliability: Ensure data is not damaged during transmission and storage.
4. Before visualizing data, it is essential to clean and verify it to ensure accuracy.

IV. Focus on User Experience

Good data visualization should not only be aesthetically pleasing but also easy for users to understand and operate. Focusing on user experience can be approached from the following aspects:

- Simplicity and Clarity: Avoid excessive embellishment; keep charts simple and clear.
- Ease of Understanding: Use easy-to-understand chart types and labels to help users quickly comprehend the data.
- Interactivity: Provide features that let users explore the data themselves.

Focusing on user experience not only improves the effectiveness of data presentation but also enhances users' understanding and trust in the data.

2.3 The Role of Aesthetic and Emotional Design in Visualization

How humans experience the beauty of nature and thus live in harmony with the natural environment has become a crucial topic in design studies in recent years. In an era of information overload and redundancy, visual communication has gradually become an effective way to receive information. Information visualization design involves transforming complex and massive amounts of textual information into easily understood graphic symbols and quickly conveying them to the target or potential audience. This dramatically improves the speed of information dissemination, making information visualization a widely used and accessible method of information communication in contemporary times. In the post-carbon era, people seek both a more harmonious aesthetic concept with nature and a more precise understanding of it.

Through information visualization design, the public can gain a more comprehensive understanding of nature, thereby alleviating the antagonistic relationship between humans and nature. Simultaneously, as a form of graphic design, information visualization design itself possesses specific aesthetic value. Through reasonable graphic transformation, color matching, and layout, a picture showcasing the harmonious coexistence of humans and nature can be constructed. However, there is currently a lack of research exploring the value of information visualization design in ecological aesthetics. Therefore, this paper attempts to combine information visualization design with ecological aesthetics theory, elucidating the aesthetic value of information visualization design and providing a research paradigm for improving public awareness of nature, presenting aesthetically pleasing images, and constructing a post-carbon world of harmonious coexistence between humans and nature.

In his paper "A Mathematical Theory of Communication," mathematician Claude Elwood Shannon defined information as "something that eliminates uncertainty." Based on this, information visualization is a research field that combines logical empirical methods with visual design, aiming to explore how to transform complex, abstract data into intuitive, emotional visual forms. Its core objective is to improve the logic, functionality, artistry, and readability of information through formal design and artistic expression, making it easier for the audience to accept and understand. Its fundamental purpose is to enhance the audience's reception of information, demonstrating a potent combination of functional and artistic

qualities. Information visualization design includes the following characteristics: 1) Functionality. Information visualization presents complex information graphically, making it clear and easy to understand, lowering the cognitive threshold for the audience. Information visualization serves as a communicator across multiple disciplines, translating professional information into artistic visual forms or other sensory representations, eliminating barriers to information exchange, transforming data into sensory education, and promoting knowledge dissemination and acquisition.
2) Symbolism. Symbols are perceptions that carry meaning, and design itself is a symbolic activity; the effect of design is a change in symbolic meaning. Information design is a symbol-based approach that aims to disseminate information efficiently. In the design process, cognitive elements are transformed into symbolic visual graphics, including basic shapes, logos, charts, data, and images. Based on the characteristics of the information, the design endows these graphics with various visual features such as proportion, position, color, and texture, making them visual symbols that convey information. People can intuitively understand the meaning of information through these symbols, achieving equivalence between symbolic presentation and information delivery.
3) Cognitiveness. The design methods and presentation formats of information visualization need to align with the cognitive habits of the audience. The brain, as the space for information storage, is responsible for receiving, processing, storing, and outputting information. The speed of this process is closely related to the brain's inherent cognitive patterns. The success of information transmission depends on the audience's mental level, and a deep understanding of the visual patterns within that cognitive level is one of the key steps in achieving information visualization. The primary task of information visualization design is to meet the visual needs of the audience, enabling them to read and understand the information easily. Therefore, in the process of designing and transmitting information, it is essential to ensure that the information has a clear purpose so that it is readily accepted and remembered by the public.

III. DESIGN FRAMEWORK: BALANCING AESTHETICS AND USABILITY

This section presents a practical design framework for creating data visualizations that are both aesthetically appealing and highly usable for non-expert users. Rather than focusing on advanced visualization techniques, the framework emphasizes clear decision points that designers, product teams, and business professionals can apply in everyday projects. The core idea is to start from the needs and limitations of non-expert audiences, and then systematically adjust chart choices, visual styles, and interaction patterns to support accurate understanding with minimal cognitive burden.

The framework is organized into five dimensions: user and context analysis, visual encoding and chart selection, color and layout decisions, textual and narrative support, and interaction design. Each dimension highlights typical trade-offs between “looking good” and “working well,” and proposes concrete principles to help designers balance these forces. The following subsections describe each dimension in detail.

3.1 User and Context Analysis

Designing visualizations for non-expert users begins with a clear understanding of who the users are and the context in which they will encounter the charts. Non-expert users often vary widely in statistical literacy, domain knowledge, and familiarity with digital tools. For example, a sales manager who occasionally reads dashboards may have strong intuition about business trends but limited experience interpreting confidence intervals or complex chart compositions. By explicitly describing user profiles—such as typical roles, goals, and pain points—designers can better anticipate where misunderstandings are likely to occur and where additional guidance is needed.

Contextual factors are equally important. Visualizations may be consumed in very different settings: quick-glance views on mobile phones, scheduled reporting meetings, public-facing websites, or internal self-service analytics platforms. Each context imposes constraints on time, attention, and screen space, which, in turn, influence the amount of visual complexity considered acceptable. Within this framework, aesthetic richness is deliberately adjusted to the usage context: in fast-paced environments, clarity and simplicity are prioritized, while in slower, exploratory contexts, more expressive visual elements can be introduced without sacrificing usability.

3.2 Visual Encoding and Chart Choice

For non-expert users, the choice of visual encoding and chart type often determines whether a visualization is immediately understandable or confusing. The framework advocates a “low-threshold first” strategy: begin with widely familiar chart types—such as bar, line, and simple pie charts—before introducing more complex encodings like stacked area charts, treemaps, or network diagrams. Priority is given to encodings that rely on position and length, which humans perceive more accurately than area, angle, or color saturation. This approach helps ensure that users can extract core trends and comparisons without needing specialized training.

Aesthetic concerns should be addressed within the boundaries of perceptual accuracy. Designers are encouraged to avoid visually impressive yet ambiguous elements, such as unnecessary 3D effects, distorted baselines, or overly dense overlays, which can make it difficult to identify patterns. Instead, minor stylistic enhancements—such as soft grid lines, subtle background shapes, or consistent iconography—can be layered on top of simple encodings to improve the perceived quality of the visualization without introducing confusion. In this way, beauty is treated as an enhancement of clarity rather than a competing objective.

3.3 Color and Layout: Aesthetics with Readability

Color is one of the most powerful tools for making visualizations attractive, but it is also one of the easiest to misuse. For non-expert users, the framework recommends using a limited and consistent color palette with clear functional roles: for example, one primary color for key data series, a secondary color for comparison groups, and neutral tones for background elements. High contrast between foreground and background is prioritized to maintain legibility, especially on small screens or in low-quality display environments. At the same time, color choices should respect standard conventions (e.g., red for decline or risk, green for growth or success) to reduce cognitive friction.

Layout decisions shape the overall reading experience. A clean layout with sufficient white space, precise alignment, and a visible information hierarchy helps non-expert users quickly identify where to start and how to proceed. The framework encourages designers to treat titles, subtitles, charts, legends, and annotations as parts of a single visual narrative rather than separate components placed arbitrarily. Decorative elements—such as illustrations or background patterns—should be added only when they support the message, for instance by reinforcing the data's theme, and should never compete with the data marks themselves. The ultimate goal is to create visual harmony where aesthetics guide attention rather than distract from information.

3.4 Textual and Narrative Support

For non-expert audiences, well-crafted textual elements are essential companions to visual encodings. The framework emphasizes the role of clear, descriptive titles that explicitly state the main message of the chart, rather than merely repeating axis labels. Subtitles can be used to summarize key insights in plain language, bridging the gap between raw data and business implications. Labels, legends, and axis descriptions should avoid technical jargon whenever possible, replacing terms like "variance," "standard deviation," or "log scale" with more intuitive phrases or short explanations when such concepts are necessary.

Narrative structure further enhances comprehension. Instead of presenting a collection of independent charts, designers are encouraged to arrange visualizations into a logical sequence that supports a story: context, trend, comparison, and implication. In this sequence, annotations can highlight critical points, turning points, or anomalies, guiding users' attention to what matters most. For non-experts, this narrative layer is often the difference between "seeing a chart" and "understanding a story." Within the framework, textual and narrative support is not an optional decoration, but a core mechanism for transforming aesthetic visuals into meaningful, actionable representations.

3.5 Interaction and Progressive Disclosure

Interactive features can significantly improve the usability of visualizations for non-expert users when designed with simplicity in mind. The framework advocates for lightweight interactions such as hover tooltips, simple filters, and toggle switches that allow users to explore details without altering the fundamental structure of the chart. These interactions should be discoverable, clearly labeled, and reversible, avoiding complex gesture combinations or multi-step configuration panels that can overwhelm non-technical audiences. Interaction is treated as a way to customize the depth of information, not as a way to offload design decisions onto the user.

Progressive disclosure is a central principle in this dimension. Instead of presenting all available data and options at once, the visualization first displays a clear, high-level view that conveys the main message. Additional details, breakdowns, or alternative views are revealed only when the user actively chooses to explore further. This approach helps manage cognitive load and prevents interface clutter, while still respecting the curiosity of users who want to dig deeper. When applied consistently, progressive disclosure creates a sense of control and safety for non-expert users: they can engage with complex data step by step, within an interface that remains visually coherent and aesthetically pleasing.

IV. Evaluation and Case Studies

4.1 Study Design and Procedure

To examine the practical value of the proposed framework, we conducted a small-scale evaluation with non-expert users in an enterprise-like setting. Participants were recruited from business and administrative roles who regularly view reports but do not have formal training in statistics or data visualization. Each participant completed a series of interpretation tasks based on three sets of visualizations: a visually elaborate but usability-poor baseline design, a highly utilitarian but visually plain design, and a "balanced" design created according to the framework described in Section 3. Tasks included identifying key trends, comparing categories, and drawing simple business-relevant conclusions (e.g., which product line requires attention, or which region shows the most stable growth). For each condition, we recorded task completion time, response accuracy, and subjective ratings of clarity, aesthetic appeal, and overall confidence in the conclusions. A short semi-structured interview followed each session to gather qualitative feedback on which design elements helped or hindered understanding, and how comfortable participants felt using the visualizations for real-world decision-making.

4.2 Findings and User Feedback

Overall, the balanced design condition outperformed the purely aesthetic and purely utilitarian baselines in both objective and subjective measures. Participants generally completed tasks more quickly and made fewer interpretation errors when interacting with visualizations that combined familiar chart types, constrained color palettes, clear textual guidance, and lightweight interaction features such as tooltips and simple filters. While the visually elaborate baseline attracted initial attention, many participants reported feeling "unsure what to look at" or "afraid of missing something important," especially when faced with dense decoration and complex compositions. Conversely, the utilitarian baseline was described as "clear but boring," with several participants indicating they would be less inclined to engage with such dashboards regularly. In contrast, the balanced designs were frequently characterized as "easy to read," "professional," and "trustworthy," with users noting that the combination of straightforward charts, structured layout, and concise annotations made it easier to connect the visuals to concrete business actions. Qualitative feedback also highlighted the importance of narrative cues—such as descriptive titles and callout annotations—for guiding non-expert users through the data.

4.3 Case Illustration and Design Implications

To further ground the evaluation in realistic practice, we applied the framework to redesign an internal sales performance dashboard used by a mid-sized organization. The original dashboard prioritized visual richness, featuring multiple bright colors, 3D effects, and complex combined charts in a single view, leading to frequent misinterpretations and low adoption among non-technical staff. Using the principles outlined in Section 3, we simplified chart choices to a small set of bar and line charts, standardized the color scheme, reorganized the layout into a clear top-down narrative (overview, key drivers, regional breakdown), and added short textual summaries under each major visual. After deployment, informal usage metrics and stakeholder interviews indicated a noticeable increase in dashboard consultation during weekly meetings and a reduction in the need for data specialists to "translate" the charts for business teams. This case, together with the user study findings, suggests that a balanced approach to aesthetics and usability not only improves comprehension in controlled tasks but also supports sustained, confident use of data visualization in everyday decision-making. For practitioners, these results imply that investing in a structured design process—even without complex analytics or large-scale experiments—can yield meaningful improvements in how non-expert users engage with and act upon data.

V. Conclusion

This article has examined how data visualization can be deliberately designed to support non-expert users by balancing aesthetics and usability. Starting from the observation that a large share of enterprise decision-makers lack formal technical training yet increasingly rely on data in their daily work, we argued that visualizations must be not only accurate and information-rich, but also approachable, engaging, and easy to interpret. The proposed framework translates this requirement into five practical design dimensions: understanding users and context, selecting low-threshold visual encodings, using color and layout to enhance readability, strengthening textual and narrative support, and applying interaction and progressive disclosure in a lightweight way. Together, these dimensions show that aesthetic quality and usability need not be competing goals. When aesthetics is constrained by perceptual principles and anchored in clear communication, it can guide attention, increase engagement, and enhance perceived professionalism without compromising comprehension.

Our empirical observations and case illustration suggest that a "balanced" design approach is more effective for non-expert users than either visually elaborate but confusing dashboards or extremely plain but uninspiring reports. Visualizations created under the proposed framework helped participants complete interpretation tasks more quickly and accurately, and were perceived as more trustworthy and pleasant to use. For practitioners, this implies that investing in structured design decisions—such as simplifying chart types, standardizing color schemes, and adding clear narrative cues—can meaningfully improve how non-technical audiences interact with data in real organizational settings. For researchers, the work highlights the need for further studies on how cultural factors, device constraints, and domain-specific conventions influence the aesthetics–usability balance for different user groups. Overall, the study reinforces the central message implied in the title: effective data visualization for non-expert users is not simply about making charts look beautiful or technically sophisticated; it is about crafting visual experiences where aesthetic appeal and usability work together to make complex information accessible, interpretable, and actionable for everyone.

References

[1]. Cleveland, W. S., & McGill, R. (1984). Graphical perception: Theory, experimentation, and application to the development of graphical methods. Journal of the American Statistical Association, 79(387), 531–554.

[2]. Mackinlay, J. (1986). Automating the design of graphical presentations of relational information. ACM Transactions on Graphics, 5(2), 110–141.

[3]. Few, S. (2013). Information Dashboard Design (2nd ed.). Analytics Press.

[4]. Shneiderman, B. (1996). The eyes have it: A task-by-data-type taxonomy for information visualizations. In Proceedings of the IEEE Symposium on Visual Languages (pp. 336–343). IEEE.

[5]. Hu R, Jian X, Zhao H, et al. Design and Realization of Computer Vision-Assisted Human Rehabilitation Training System[J]. 2025.

[6]. Yang J, Hu R, Wu C, et al. Sensor Infused Emperor Penguin Optimized Deep Maxout Network for Paralyzed Person Monitoring[J]. IEEE Sensors Journal, 2024.

[7]. Lu J, Zhao H, Zhai H, et al. DeepSPG: Exploring Deep Semantic Prior Guidance for Low-light Image Enhancement with Multimodal Learning[C]//Proceedings of the 2025 International Conference on Multimedia Retrieval. 2025: 935-943.

[8]. Zhao H, Chen Y, Dang B, et al. Research on Steel Production Scheduling Optimization Based on Deep Learning[C]//2024 4th International Symposium on Artificial Intelligence and Intelligent Manufacturing (AIIM). IEEE, 2024: 813-816.

[9]. Heer, J., & Bostock, M. (2010). Crowdsourcing graphical perception: Using mechanical turk to assess visualization design. In Proceedings of CHI '10 (pp. 203–212). ACM.

[10]. Borkin, M. A., Vo, A. A., Bylinskii, Z., Isola, P., Sunkavalli, S., Oliva, A., & Pfister, H. (2013). What makes a visualization memorable? IEEE Transactions on Visualization and Computer Graphics, 19(12), 2306–2315.

[11]. Brewer, C. A., Hatchard, G. W., & Harrower, M. (2003). ColorBrewer in print: A catalog of color schemes for maps. Cartography and Geographic Information Science, 30(1), 5–32.

[12]. Segel, E., & Heer, J. (2010). Narrative visualization: Telling stories with data. IEEE Transactions on Visualization and Computer Graphics, 16(6), 1139–1148.

[13]. Yang W, Zhang B, Wang J. Research on AI Economic Cycle Prediction Method Based on Big Data[J]. 2025.

[14]. Yuan Y, Xue H. Cross-Media Data Fusion and Intelligent Analytics Framework for Comprehensive Information Extraction and Value Mining[J]. 2025.

[15]. Lam, H., Bertini, E., Isenberg, P., Plaisant, C., & Carpendale, S. (2012). Empirical studies in information visualization: Seven scenarios. IEEE Transactions on Visualization and Computer Graphics, 18(9), 1520–1536.

[16]. Sedlmair, M., Meyer, M., & Munzner, T. (2012). Design study methodology: Reflections from the trenches and the stacks. IEEE

Transactions on Visualization and Computer Graphics, 18(12), 2431–2440.
[17]. Xu, Ivonne. "Computer Vision-Enabled Inventory Management System: A Cloud-Native Solution for Retail Cost Reduction." (2025).
[18]. Yang J, Wu Y, Yuan Y, et al. Llm-ae-mp: Web attack detection using a large language model with autoencoder and multilayer perceptron[J]. Expert Systems with Applications, 2025, 274: 126982.
[19]. Yang W, Lin Y, Xue H, et al. Research on Stock Market Sentiment Analysis and Prediction Method Based on Convolutional Neural Network[J]. 2025.
[20]. Yuan Y, Xue H. Multimodal Information Integration and Retrieval Framework Based on Graph Neural Networks[C]//Proceedings of the 2025 4th International Conference on Big Data, Information and Computer Network. 2025: 135-139.
[21]. Li Z, Ji Q, Ling X, et al. A comprehensive review of multi-agent reinforcement learning in video games[J]. Authorea Preprints, 2025.
[22]. Zhang Z, Wang J, Li Z, et al. AnnCoder: A mti-Agent-Based Code Generation and Optimization Model[J]. 2025.
[23]. Hu R, Jian X, Wang J, et al. Construction of a Prediction Model for Rehabilitation Training Effect Based on Machine Learning[J]. 2025.
[24]. Sha F, Ding C, Zheng X, et al. Weathering the Policy Storm: How Trade Uncertainty Shapes Firm Financial Performance through Innovation and Operations[J]. International Review of Economics & Finance, 2025: 104274.
[25]. Sha F, Meng J, Zheng X, et al. Sustainability Under Fire: How China-US Tensions Impact Corporate ESG Performance?[J]. Finance Research Letters, 2025: 107882.
[26]. Sha F, Ding C, Zheng X, et al. Weathering the Policy Storm: How Trade Uncertainty Shapes Firm Financial Performance through Innovation and Operations[J]. International Review of Economics & Finance, 2025: 104274.
[27]. Deng X. Cooperative Optimization Strategies for Data Collection and Machine Learning in Large-Scale Distributed Systems[C]//2025 4th International Symposium on Computer Applications and Information Technology (ISCAIT). IEEE, 2025: 2151-2154.
[28]. Tan C, Gao F, Song C, et al. Proposed Damage Detection and Isolation from Limited Experimental Data Based on a Deep Transfer Learning and an Ensemble Learning Classifier[J]. 2024.
[29]. Tan C. The Application and Development Trends of Artificial Intelligence Technology in Automotive Production[J]. Artificial Intelligence Technology Research, 2024, 2(5).
[30]. Zhang, Lijun, and Qian Meng. "User Portrait-Driven Smart Home Device Deployment Optimization and Spatial Interaction Design." (2025).
[31]. Gonzalez, Jean, Vinh Tran, John Meredith, Ivonne Xu, Ritviksiddha Penchala, Laura Vilar-Ribó, Natasia Courchesne-Krak et al. "How it begins: Initial response to opioids strongly predicts self-reported opioid use disorder." medRxiv (2025): 2025-03.
[32]. H. Yang et al., "Research on Model Parallelism and Data Parallelism Optimization Methods in Large Language Model-Based Recommendation Systems," arXiv preprint arXiv:2506.17551, 2025.
[33]. Han X, Dou X. User recommendation method integrating hierarchical graph attention network with multimodal knowledge graph[J]. Frontiers in Neurorobotics, 2025, 19: 1587973.
[34]. Zhuang R. Evolutionary Logic and Theoretical Construction of Real Estate Marketing Strategies under Digital Transformation[J]. Economics and Management Innovation, 2025, 2(2): 117-124.
[35]. Z. Yang et al., "RLHF Fine-Tuning of LLMs for Alignment with Implicit User Feedback in Conversational Recommenders," arXiv preprint arXiv:2508.05289, 2025
[36]. Deng, Xiaoyu, and Jinzhu Yang. "Multi-Layer Defense Strategies and Privacy Preserving Enhancements for Membership Reasoning Attacks in a Federated Learning Framework." In 2025 5th International Conference on Computer Science and Blockchain (CCSB), pp. 278-282. IEEE, 2025.
[37]. Tan C, Gao F, Song C, et al. Highly Reliable CI-JSO based Densely Connected Convolutional Networks Using Transfer Learning for Fault Diagnosis[J]. 2024.
[38]. Gonzalez, Jean, John Meredith, Ivonne Xu, Ritviksiddha Penchala, Laura Vilar-Ribó, Natasia Courchesne-Krak, Daniel Zoleikhaeian et al. "M82. Subjective Response to Opioids Predicts Risk for Opioid Use Disorder." European Neuropsychopharmacology 99 (2025): 150-151.