



Empowering Non-Technical Users Through Self-Service Data Visualization in Oracle Analytics

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Article Info

ISSN (online): 3049-1215

Impact Factor (RSIF): 8.25

Volume: 03

Issue: 03

Received: 08-03-2026

Accepted: 06-05-2026

Published: 04-06-2026

Page No: 132-143

Abstract

This study investigates the impact of structured training on the ability of non-technical business users to effectively utilize self-service data visualization (SSDV) capabilities within Oracle Analytics. A mixed-methods research design was employed involving ten participants from Sales, Human Resources, and Marketing departments. Participants completed a structured training intervention consisting of guided tutorials, video resources, and hands-on dashboard development activities using an HR analytics dataset. Quantitative findings revealed substantial improvements in participant confidence, with average self-reported competency scores increasing from 2.8 to 4.2 on a 5-point Likert scale. Dashboard evaluations produced an average score of 79.4 out of 100, with eight of ten participants achieving scores above 75, demonstrating successful application of core visualization and analytical principles. Qualitative findings indicated that while participants experienced increased confidence, independence, and data literacy, challenges remained in utilizing advanced analytical features such as calculated fields and multi-measure prompts. The findings suggest that structured training serves as a critical enabler of self-service analytics adoption by improving user competency, dashboard quality, and decision-making effectiveness. The study contributes empirical evidence supporting the role of training as a key mechanism for achieving successful data democratization and organizational agility in enterprise analytics environments.

DOI: <https://doi.org/10.54660/IJFEI.2026.3.3.132-143>

Keywords: Self-Service Data Visualization (SSDV), Oracle Analytics, Structured Training, Data Literacy, Data Democratization

1. Introduction

The ascendancy of big data and advanced analytics has fundamentally redefined the operational and strategic paradigms of the modern enterprise, establishing data-driven decision-making not merely as a competitive advantage but as a core tenet of organizational survival and growth. In this new environment, the ability to rapidly synthesize information, identify patterns, and derive actionable insights from vast and complex datasets is paramount. However, a persistent and critical chasm exists between the potential of data and its practical application. While data warehouses brim with valuable information, access to it has traditionally been gated by a technical specialists of data scientists, engineers, and analysts who possess the specialized coding skills required to query and manipulate data. This bottleneck inevitably creates latency, stifles innovation at the departmental level, and leaves a vast reservoir of institutional knowledge and frontline experience untapped because the individuals who possess that contextual understanding—the marketing managers, financial officers, and operations leads—are disempowered from directly engaging with the data that could inform their decisions.

It is within this context that the promise of self-service data visualization (SSDV) platforms, such as Oracle Analytics, Tableau, and Microsoft Power BI, has emerged as a transformative solution. These tools are explicitly engineered to democratize data analytics by providing intuitive, graphical user interfaces that allow non-technical business users to create sophisticated visualizations, dashboards, and reports without writing a single line of code. The theoretical benefits are profound: by decentralizing analytical capabilities, organizations can accelerate their decision-making cycles, foster a more pervasive culture of evidence-based inquiry, and unlock innovative insights from unexpected quarters of the business. The vendor narrative surrounding these platforms often paints a picture of effortless empowerment, suggesting that simply provisioning the software will spontaneously catalyze a company-wide analytical revolution.

The evolution of self-service analytics is increasingly intertwined with advances in artificial intelligence, machine learning, and automated insight generation. Modern analytics platforms now incorporate natural language querying, predictive analytics, recommendation engines, and AI-assisted visualization capabilities that further lower technical barriers for business users. While these innovations promise to enhance accessibility and accelerate insight discovery, they also introduce new challenges related to transparency, explainability, governance, and user trust. Consequently, understanding how non-technical users develop analytical competency within increasingly intelligent analytics environments has become an important area of research.

Yet, the practical reality of SSDV adoption frequently falls short of this ideal. The mere availability of a powerful tool does not automatically confer the competence or confidence required to use it effectively. Non-technical users, often possessing limited statistical training or data literacy, can quickly become overwhelmed by the complexities of data model relationships, appropriate chart selection, filter logic, and the fundamental principles of visual encoding and design. Without adequate guidance, the outcome can be a proliferation of poorly constructed, misleading, or utterly irrelevant dashboards that obfuscate rather than illuminate the truth, potentially leading to costly misinformed decisions. This gap between the theoretical promise and the practical challenge of SSDV tools reveals a critical, yet under-examined, factor in the equation of successful data democratization: the role of structured training and enablement. Moreover, as analytics capabilities become increasingly decentralized, organizations must ensure that democratized access to data is accompanied by appropriate governance, ethical oversight, and transparency mechanisms to support responsible decision-making.

Therefore, this study is positioned to address a significant research gap that lies at the intersection of technology, pedagogy, and organizational behavior. While considerable scholarly attention has been paid to the technical architectures of SSDV platforms and the cognitive science of data visualization itself, there is a comparative dearth of empirical research investigating how formalized training interventions directly influence the proficiency and efficacy of non-technical users.

The central research question guiding this inquiry is: How does structured, pedagogical training influence the ability of non-technical business users to leverage self-service data visualization tools for effective and accurate decision-making? To answer this multifaceted question, our investigation will proceed along four primary, interconnected vectors of analysis.

The significance of this study extends beyond the evaluation of a single software platform. As organizations increasingly pursue data democratization strategies, understanding how to effectively train and empower non-technical users has become a strategic priority. The findings of this research may assist organizations in designing more effective analytics adoption programs, improving data literacy initiatives, and maximizing returns on investments in self-service analytics technologies. Furthermore, the study contributes to the broader discourse on digital transformation by examining the human and organizational factors that influence successful technology adoption.

This study makes four primary contributions to the existing literature. First, it provides empirical evidence regarding the effectiveness of structured training interventions for non-technical users of self-service analytics platforms. Second, it develops and applies a systematic framework for evaluating the quality of user-generated dashboards. Third, it identifies persistent usability and learning barriers that remain even after training interventions. Fourth, it examines the organizational implications of self-service analytics adoption, including impacts on decision-making efficiency, collaboration, and data literacy.

First, we will rigorously evaluate the effectiveness of specific SSDV training methodologies and materials. This involves moving beyond simplistic satisfaction surveys to assess knowledge retention, skill acquisition, and the ability to apply learned concepts to novel analytical scenarios. We will compare different pedagogical approaches, such as video tutorials, interactive workshops, structured documentation, and community-based learning, to determine which modalities most effectively translate into practical competency. Second, the study will critically assess the qualitative output of this training by developing a robust framework to evaluate the quality of user-generated dashboards. This framework will move beyond aesthetics to measure analytical depth, logical coherence, narrative clarity, and adherence to best practices in data visualization, thereby providing an objective measure of whether training translates into superior tangible artifacts.

Third, we will conduct a deep qualitative analysis to identify the persistent user experience barriers and cognitive friction points that users encounter even after initial training. This involves understanding the emotional and psychological journey of the novice user—where confusion arises, where confidence falters, and what specific features or concepts continue to pose challenges, thus providing crucial feedback for both platform designers and training curriculum developers. Finally, the research will scale its perspective to examine the broader organizational impact of successful SSDV adoption, seeking to measure its effects on decision-making velocity, the diffusion of data literacy, cross-departmental collaboration, and the return on investment on both the software and the training programs themselves.

By synthesizing findings across these four domains, this study aims to provide a comprehensive, evidence-based blueprint for organizations seeking to move beyond simply deploying a tool and toward genuinely cultivating a data-empowered workforce.

2. Literature Review

The burgeoning field of self-service analytics (SSA) represents a significant paradigm shift in organizational data culture, moving away from centralized, IT-controlled reporting towards a democratized model of information access. As Achanta (2023) ^[1] emphasizes, the core promise of SSA is to empower non-technical business users to explore, visualize, and interpret data independently, thereby alleviating the burden on specialized IT departments and accelerating the pace of insight generation. This democratization, as noted by Daradkeh (2019) ^[24], is not merely a technical implementation but an organizational transformation, fostering a more agile and evidence-based decision-making environment. However, this transition is fraught with inherent challenges that temper its idealistic vision. Daradkeh (2019) ^[24] further cautions that the decentralization of analytical capabilities introduces significant risks related to data governance, including issues of data quality, security, consistency, and the potential for inconsistent interpretation across the enterprise. Furthermore, a critical skills gap often exists; equipping users with powerful tools does not automatically confer the necessary data literacy or statistical reasoning to avoid erroneous conclusions, leading to what could be termed "the paradox of democratization"—increased access without commensurate understanding can potentially lead to more widespread misinterpretation.

Within the ecosystem of SSA platforms, Oracle Analytics has established itself as a prominent enterprise-grade solution, distinguished by its comprehensive and integrated feature set. The platform's architecture is designed to cater to the dual demands of ease-of-use and advanced functionality. Its intuitive visualization interface, predicated on drag-and-drop mechanics, lowers the initial barrier to entry for novice users (Oracle Corporation, 2021) ^[30]. More significantly, Oracle has heavily invested in embedding artificial intelligence and machine learning directly into its workflow, offering features like automated pattern detection and natural language querying to guide users towards insights they might otherwise have missed. This suite of AI-driven capabilities aims to act as an intelligent copilot for the business analyst. Nevertheless, this power and complexity come with a trade-off. As comparative studies have indicated, while Oracle Analytics excels in areas like predictive analytics and handling large, complex datasets, it can present a steeper learning curve compared to more consumer-oriented tools like Microsoft Power BI, which often prioritize immediate user-friendliness over advanced feature depth (Richardson *et al.*, 2020) ^[31]. This dichotomy underscores a critical market tension between simplicity for the casual user and sophistication for the power user.

The broader self-service analytics landscape includes widely adopted platforms such as Tableau and Microsoft Power BI, each offering distinct strengths in usability, visualization capabilities, and enterprise integration.

Tableau is frequently recognized for its advanced visualization functionality and user-centered design, while Power BI is often favored for its accessibility, cost effectiveness, and integration with the Microsoft ecosystem. Oracle Analytics differentiates itself through its strong enterprise architecture, embedded artificial intelligence capabilities, and advanced analytical functions. Understanding these distinctions is important because the effectiveness of training interventions may be influenced by platform complexity, feature richness, and user experience design.

This study is conceptually grounded in Kolb's Experiential Learning Theory (ELT) and the Technology Acceptance Model (TAM). Kolb's Experiential Learning Theory posits that effective learning occurs through a cyclical process involving concrete experience, reflective observation, abstract conceptualization, and active experimentation (Kolb, 2014) ^[29]. This framework is particularly relevant to self-service data visualization training because users must move beyond passive instruction and actively engage with analytical tools to develop practical competency. The structured training intervention employed in this study was therefore designed to facilitate experiential learning through guided tutorials, hands-on exercises, and real-world dashboard development tasks. In addition, the Technology Acceptance Model provides a useful lens for understanding user adoption of self-service analytics platforms. According to TAM, perceived usefulness and perceived ease of use are primary determinants of technology acceptance and continued utilization. For non-technical users, confidence, usability, and perceived value are critical factors influencing whether analytical tools become integrated into routine decision-making processes. By combining experiential learning principles with technology adoption theory, this study examines not only whether training improves technical proficiency, but also how it influences user confidence, engagement, and willingness to leverage self-service analytics for organizational decision-making. Furthermore, the study aligns with broader principles of data democratization, which emphasize empowering business users to independently access, analyze, and interpret data while maintaining organizational governance, data quality, and responsible decision-making practices. This theoretical foundation provides a framework for evaluating how structured training can bridge the gap between technological capability and effective organizational use of self-service analytics platforms.

Recent studies have demonstrated the expanding role of artificial intelligence, analytics, and data-driven governance across multiple domains including recruitment, software engineering, healthcare, cybersecurity, digital transformation, sustainability, and public-sector innovation. Research on the HITHIRE framework and the HitHire governance model established the importance of explainable, ethical, and bias-resilient decision-making systems, particularly in recruitment and human-resource analytics environments (Albaroudi *et al.*, 2026; Albaroudi *et al.*, 2026; Albaroudi *et al.*, 2025; Albaroudi *et al.*, 2025; Albaroudi *et al.*, 2024) ^[10, 14, 11, 12, 8]. Complementary work has highlighted the growing influence of generative AI on software engineering, organizational innovation, and workforce

transformation, emphasizing the need for governance structures that balance technological advancement with responsible deployment (Albaroudi *et al.*, 2025; Albaroudi *et al.*, 2025) ^[13, 15]. Similarly, collaborative artificial intelligence architectures such as COLLAB-LLM have demonstrated the potential of role-based multi-agent systems to enhance communication, coordination, and decision-support capabilities in complex analytical environments (Albaroudi *et al.*, 2026) ^[6].

Beyond organizational analytics, recent studies have explored data sovereignty in healthcare systems, sustainable smart energy frameworks, AI-enabled water management, IoT-based compliance monitoring, and cybersecurity applications for intrusion detection, collectively illustrating the importance of accessible analytics, trustworthy data governance, and informed decision-making across diverse sectors (Albaroudi *et al.*, 2025; Albaroudi *et al.*, 2025; Albaroudi *et al.*, 2025; Albaroudi *et al.*, 2025; Hejazi *et al.*, 2025) ^[3, 4, 5, 7, 27]. Furthermore, investigations into algorithmic bias in hiring and the application of generative AI in healthcare underscore the broader societal implications of democratizing analytical capabilities while maintaining transparency, accountability, and ethical safeguards (Albaroudi *et al.*, 2024; Albaroudi *et al.*, 2024) ^[8, 9].

Collectively, these studies reinforce the argument that successful self-service analytics initiatives require not only technical accessibility but also robust governance, ethical oversight, and continuous user empowerment. While technological capabilities are important, the success of self-service analytics initiatives ultimately depends on the ability of end users to effectively adopt, understand, and utilize these tools within their daily decision-making activities.

The challenges inherent in both SSA adoption and the complexity of powerful platforms like Oracle Analytics bring the critical role of training into sharp focus. The provision of software is a necessary but insufficient condition for success; effective training is the essential catalyst that bridges the gap between potential and proficiency. As visualization expert Stephen Few (2009) ^[26] has long argued, effective data communication is a teachable skill, and training must go beyond simple software instruction to foster genuine data literacy, encompassing principles of visual perception, logical reasoning, and ethical representation of information. This involves educating users on which chart types are most effective for specific data types and messages, how to avoid common misrepresentations, and how to construct a coherent analytical narrative. Moreover, the learning process is not a single event but a continuous journey. Kolb's (2014) ^[29] experiential learning theory provides a robust framework for understanding this, suggesting that effective training must be an iterative process involving concrete experience, reflective observation, abstract conceptualization, and active experimentation. Therefore, sustained adoption of SSA tools requires not just initial onboarding but a culture of continuous support, including advanced workshops, community forums, and accessible expert help, to reinforce skills and build user confidence over time. This body of literature collectively points to a clear conclusion: the ultimate return on investment in a sophisticated SSA platform is contingent upon a parallel and strategic investment in a comprehensive, principled, and ongoing training regimen.

Despite the growing body of literature on self-service analytics, data democratization, AI-enabled decision support, and organizational learning, a significant research gap remains regarding the effectiveness of structured training interventions for non-technical users operating within enterprise-grade analytics platforms. Existing studies primarily focus on technological capabilities, governance considerations, or adoption factors, while comparatively limited empirical evidence exists concerning how specific training methodologies influence dashboard quality, analytical proficiency, user confidence, and decision-making effectiveness. Furthermore, few studies have examined these relationships within Oracle Analytics environments. This study seeks to address this gap by providing a comprehensive evaluation of structured training outcomes among non-technical business users.

3. Methodology

This study was designed to rigorously evaluate the impact of structured training on the proficiency of non-technical users in a self-service data visualization (SSDV) environment. To capture the multifaceted nature of this impact—encompassing skill acquisition, practical output quality, and subjective experience—a mixed-methods research design was employed. This approach integrates quantitative data, which provides measurable, statistical evidence of change, with qualitative data, which offers rich, contextual insights into the user experience, thereby yielding a more comprehensive and valid understanding of the research problem than either method could achieve in isolation (Creswell & Plano Clark, 2017) ^[23].

The quantitative component was anchored by pre- and post-training surveys designed to measure participants' self-reported confidence across a range of SSDV competencies using a Likert scale. This instrument allowed for the statistical analysis of changes in perceived skill levels immediately following the training intervention. The qualitative component consisted of semi-structured interviews conducted after the practical evaluation phase and a thematic analysis of open-ended feedback provided on the training materials themselves. This dual-pronged qualitative approach was essential for identifying the nuanced barriers, facilitators, and unexpected challenges encountered by users, providing depth and explanation for the quantitative findings.

3.1. Participant Selection and Recruitment

A purposive sampling strategy was used to identify ten participants who genuinely represented the target demographic for SSDV tools: non-technical business users in data-dependent roles. Participants were recruited from three key departments—Sales, Human Resources, and Marketing—to ensure a diversity of analytical use cases and perspectives. The inclusion criteria mandated that all participants had limited to no prior experience with formal data analytics tools like Oracle Analytics, Tableau, or Power BI, though they were required to have a foundational familiarity with data interpretation from spreadsheets or standard reports. Crucially, the exclusion criteria screened out individuals with technical backgrounds in IT, data science, or data analytics to maintain the integrity of the "non-technical" user profile. All participants provided informed

consent, and ethical considerations regarding data anonymity and voluntary participation were strictly adhered to throughout the study. Although the sample size was intentionally limited to ten participants, this is consistent with exploratory mixed-methods and usability-oriented research designs that prioritize depth of observation and detailed user feedback over statistical generalization. The selected sample size allowed for close monitoring of participant interactions, detailed dashboard evaluation, and in-depth qualitative

interviews while remaining manageable within the study's scope and resources.

3.2. Implementation Phases

The research was executed in three sequential phases to ensure a controlled and structured evaluation. The process is visually summarized in the following research workflow diagram:

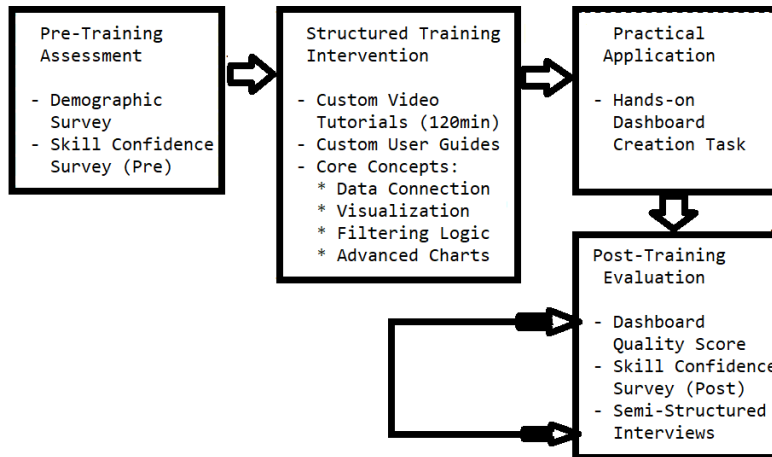


Fig 1: Research Workflow Diagram

Phase 1: Dataset Preparation: A curated, open-source HR dataset from Kaggle (2023) [28] was selected for its relevance to a common business function and its contained complexity, featuring multiple related tables (e.g., employee demographics, performance ratings, salary history, department records). This dataset was rigorously cleaned to remove inconsistencies and missing values, and then uploaded into a dedicated Oracle Analytics Cloud instance. A semantic model was built to define table relationships, calculated measures (e.g., employee turnover rate, average tenure), and logical hierarchies, replicating a realistic enterprise analytics environment.

Phase 2: Structured Training Intervention: Participants received a standardized training package totaling 120 minutes of instruction. This was not a simple software demo but a

pedagogical curriculum built on principles of experiential learning (Kolb, 2014) [29]. Customized video tutorials and illustrated user guides were developed to cover fundamental concepts: connecting to a data source, the principles of effective visual encoding, dashboard creation, and the application of data filters. Crucially, the training also introduced more advanced visualizations such as Trellis (small multiple) charts and Heat Matrices, moving beyond basic bar and pie charts to assess the transfer of more complex analytical concepts.

Phase 3: Evaluation and Analysis: The evaluation phase, detailed in the diagram below, involved both objective and subjective measures. Participants were given a practical task: to create a dashboard answering specific business questions with the prepared HR dataset.

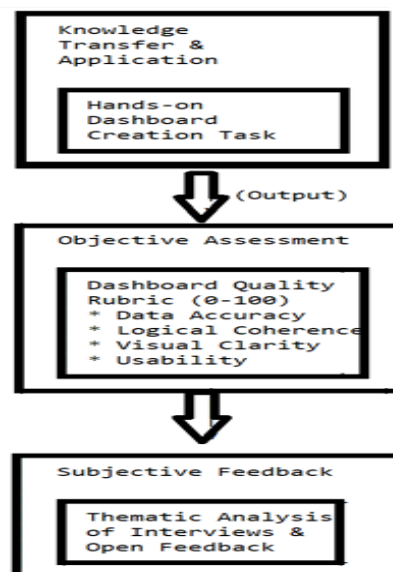


Fig 2: Training & Evaluation Cycle

The quality of each resulting dashboard was objectively scored by a panel of two experts using a validated rubric across ten criteria, including data accuracy, logical coherence, narrative clarity, visual effectiveness, and usability, yielding a composite score out of 100. Subsequently, semi-structured interviews were conducted to explore the participants' experiences, challenges, and perceptions of the tool's utility, with transcripts analyzed using thematic analysis to identify common patterns and insights.

To enhance evaluation reliability, both experts independently assessed each dashboard before discussing any scoring discrepancies. Minor differences were resolved through consensus, ensuring consistency in the final dashboard quality scores and reducing the potential influence of individual evaluator bias.

3.3. Research Instruments

To ensure a comprehensive evaluation of the training intervention, three complementary research instruments were utilized: a survey questionnaire, a dashboard evaluation rubric, and a semi-structured interview protocol.

Survey Questionnaire: A pre- and post-training questionnaire was developed to assess participants' self-reported confidence, perceived competency, and familiarity with self-service data visualization concepts. Responses were collected using a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Survey items focused on participants' confidence in creating visualizations, interpreting data, applying filters, selecting appropriate chart types, and using Oracle Analytics independently.

Dashboard Evaluation Rubric: The quality of participant-generated dashboards was assessed using a structured evaluation rubric consisting of ten criteria: data accuracy, chart appropriateness, visual clarity, consistency of design, usability, analytical depth, narrative coherence, effective use of filters, interactivity, and overall decision-support value. Each criterion was scored on a scale of 0–10, resulting in a maximum composite score of 100. The rubric was adapted from established principles of dashboard design and data visualization evaluation reported in the literature.

Semi-Structured Interviews: Following the practical dashboard development exercise, semi-structured interviews were conducted with all participants to explore their experiences using Oracle Analytics, perceptions of the training materials, challenges encountered during dashboard creation, and perceived value of self-service analytics in their professional roles. The interview format allowed participants to provide detailed feedback while ensuring consistency across all sessions.

The use of multiple research instruments enabled methodological triangulation by capturing quantitative measures of learning outcomes alongside qualitative insights into user experiences, perceptions, and challenges. This approach enhanced the reliability and validity of the study findings.

3.4. Data Analysis Procedures

The collected data were analyzed using both quantitative and qualitative techniques consistent with the study's mixed-methods research design. Quantitative data obtained from the

pre- and post-training surveys were analyzed using descriptive statistics, including frequencies, percentages, means, and score comparisons, to assess changes in participants' confidence and perceived competency levels following the training intervention. Dashboard evaluation scores were similarly summarized using descriptive statistical measures to identify overall performance patterns and variations among participants.

The dashboard quality assessment was conducted using a structured evaluation rubric, with each dashboard receiving scores across ten predefined criteria. Individual criterion scores were aggregated to generate a composite score out of 100, enabling objective comparison of dashboard quality and analytical effectiveness across participants.

Qualitative data obtained from semi-structured interviews and open-ended participant feedback were analyzed using thematic analysis. Interview transcripts and written responses were reviewed iteratively, coded, and grouped into recurring themes related to user experience, learning outcomes, usability challenges, confidence development, and perceived organizational value. This process enabled the identification of common patterns and insights regarding the effectiveness of the training intervention and the adoption of self-service analytics practices.

To enhance the credibility and validity of the findings, quantitative and qualitative results were triangulated during the interpretation phase. The integration of multiple data sources provided a more comprehensive understanding of participant experiences and allowed quantitative performance outcomes to be interpreted within their broader organizational and behavioral context.

4. Results

The findings from this mixed-methods study reveal a nuanced and multi-layered impact of structured training on the adoption and efficacy of self-service data visualization (SSDV) among non-technical users. The results are presented across four key domains: the perceived effectiveness of the training intervention, the objective quality of the analytical outputs produced, the subjective user experience, and the anticipated organizational impact.

4.1. Quantitative and Qualitative Assessment of Training Effectiveness

The initial assessment of the customized training materials yielded strongly positive feedback, indicating a successful foundation for skill development. On a 10-point Likert scale assessing clarity, relevance, and pacing, 90% of participants rated the guides and video tutorials an 8 or higher, with a mean satisfaction score of 8.9. Furthermore, 70% of participants assigned ratings of 9 or 10, indicating a high level of satisfaction with the training materials.

This high level of user satisfaction, visualized in Figure 1, demonstrates that the pedagogical approach was well-suited to the target audience. However, qualitative data from post-session interviews provided crucial depth to these numbers, revealing a clear desire for more applied learning. A common thematic insight was that while the foundational concepts were clear, users craved additional, context-rich practical examples directly mirroring their real-world tasks. In a responsive and agile implementation, the research team

incorporated these feedback points iteratively between sessions, adding new video segments that walked through complex scenarios like blending HR data with performance metrics. This adaptive

process itself became a key finding, underscoring that effective SSDV training is not a static product but a dynamic, evolving practice that must respond to user needs in real-time.

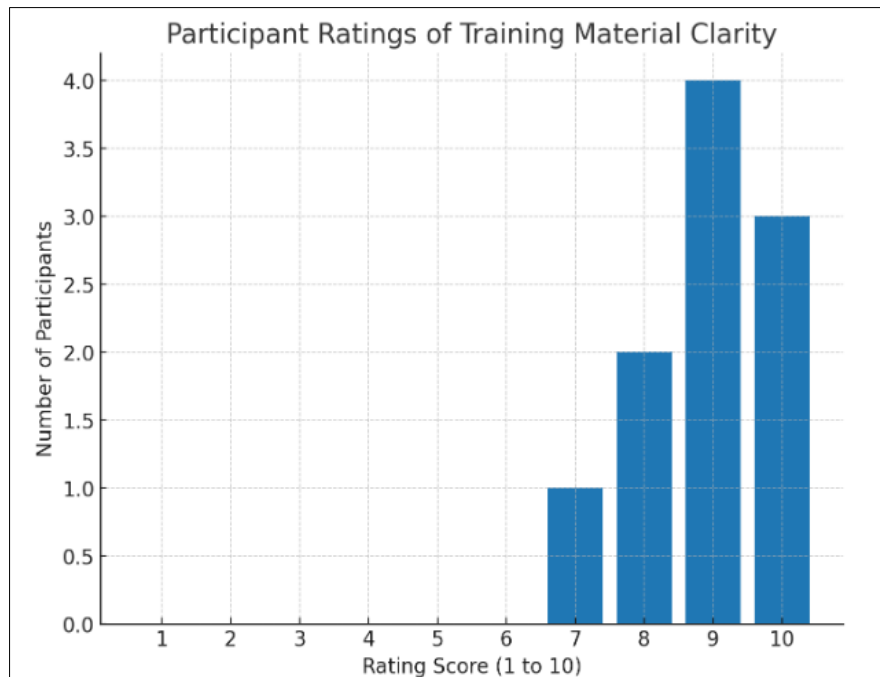


Fig 3: Distribution of Participant Ratings for Training Material Clarity (n=10)

Comparison of the pre- and post-training survey results indicated a substantial increase in participant confidence across all assessed competencies. Average self-reported confidence scores increased from 2.8 to 4.2 on a 5-point Likert scale, representing a 50% improvement following the training intervention. The greatest improvements were observed in dashboard creation, data filtering, and visualization selection, suggesting that the training effectively enhanced participants' practical analytical capabilities.

These findings suggest that the training intervention was effective not only in improving participant satisfaction but also in enhancing perceived analytical self-efficacy and readiness to engage with self-service analytics tools.

4.2. Objective Evaluation of Dashboard Quality and Analytical Output

The most significant measure of the training's effectiveness was the quality of the dashboards produced by participants. As presented in Table 1, performance varied significantly, with scores on a 100-point rubric ranging from a high of 90 to a low of 60. A detailed analysis of the evaluation criteria,

as illustrated in Figure 2, reveals the specific strengths and weaknesses in the participants' outputs. The highest-performing dashboards, such as those for "Recruitment Source" and "Employee Demographics," were characterized by their logical layout, judicious use of color, appropriate chart types for the intended message, and the effective implementation of interactive filters that allowed for meaningful data exploration. In contrast, lower-scoring dashboards, such as the "Employee Performance" example, suffered from critical flaws that severely limited their utility. These included chart clutter, where an overabundance of visual elements created cognitive overload; misaligned metrics, where a chosen visualization type distorted the underlying data relationship (e.g., using a pie chart for time-series data); and in one case, a fundamental error in filter logic that isolated data points incorrectly, leading to potentially misleading conclusions. This disparity highlights that while training can effectively convey the mechanics of the tool, the higher-order skills of visual storytelling and rigorous analytical reasoning require more sustained practice and support.

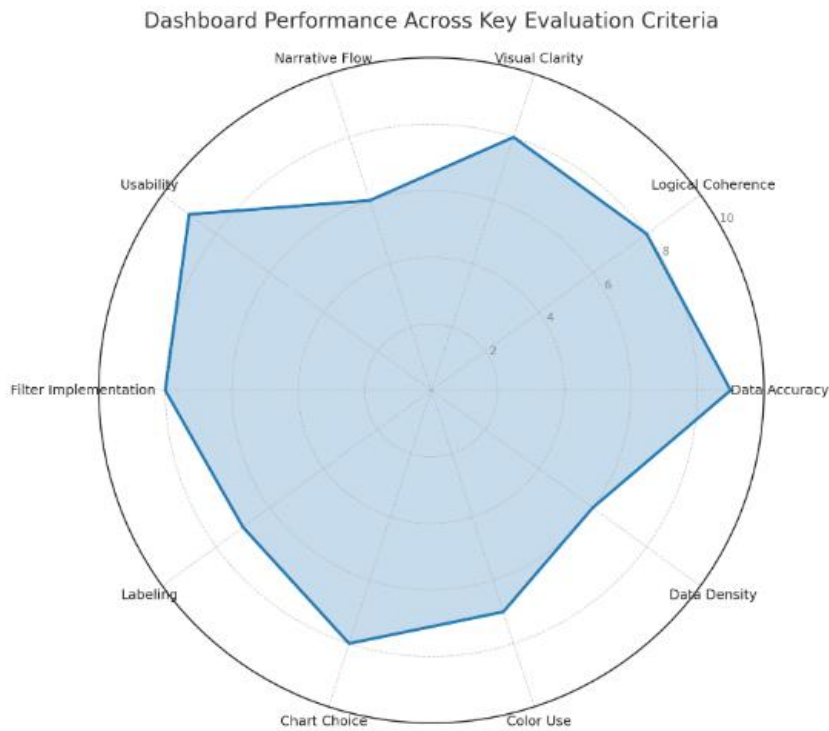


Fig 4: Radar Chart of Average Dashboard Scores by Evaluation Criterion

The radar chart reveals a clear distinction between technical proficiency and advanced analytical communication skills. Participants performed particularly well in data accuracy and usability, both receiving average scores of 9 out of 10, indicating a strong ability to construct technically correct and functional dashboards. Similarly, visual clarity, logical coherence, chart selection, and filter implementation achieved average scores of 8, demonstrating successful application of core visualization principles. However, lower

scores for narrative flow and data density (both averaging 6) suggest that participants experienced greater difficulty transforming analytical findings into coherent data stories and managing information complexity. These findings indicate that while structured training effectively develops foundational dashboard creation skills, additional support may be required to strengthen higher-order analytical communication competencies.

Table 1: Dashboard Evaluation Scores

Dashboard Title	Score (/100)	Key Strengths	Key Weaknesses
Recruitment Source	90	Clear narrative, excellent filter use	Minor labeling issues
Employee Demographics	89	Intuitive design, strong visual clarity	Limited depth of analysis
Employee Performance	60	Attempted complex analysis	Cluttered layout, misaligned data

Overall dashboard performance was encouraging, with an average evaluation score of 79.4 out of 100. Eight of the ten participants achieved scores above 75, indicating that the majority successfully applied the concepts introduced during training. The results suggest that structured instruction can enable non-technical users to produce dashboards that meet acceptable standards of analytical quality, usability, and visual effectiveness.

4.3. User Experience: Empowerment Tempered by Technical Hurdles

The thematic analysis of post-training interviews painted a vivid picture of the user journey, characterized by a powerful sense of empowerment alongside clear, persistent challenges. Participants overwhelmingly reported a newfound confidence in their ability to engage directly with data. As

Participant 3 from Sales eloquently stated, "I now create my own reports to track regional sales trends instead of waiting weeks for a ticket to be processed by IT. It feels like I've been given a new lens to see my own work." This sentiment was echoed across departments, indicating a successful shift towards data democratization. However, this empowerment was not absolute. A significant minority, 40% of users, reported hitting a "complexity wall" when attempting to utilize advanced features such as multi-measure prompts, custom calculated fields, or setting up specific data hierarchies. These features, which are essential for moving beyond basic descriptive analytics, represented a significant cognitive leap that the initial 120-minute training could not fully bridge for all users, pointing to a clear need for tiered or advanced follow-up training modules.

Table 2: Summary of Themes Identified Through Thematic Analysis

Theme	Frequency (%)	Representative Insight
Increased confidence	90%	Users reported greater independence in data analysis
Improved decision-making	80%	Participants indicated faster access to actionable insights
Need for advanced training	40%	Users struggled with advanced analytics features
Greater data literacy	70%	Participants demonstrated improved understanding of visualization principles
Organizational value	70%	Users perceived benefits for team performance and reporting efficiency

4.4. Perceived Organizational Impact and Skill Integration

Beyond individual capability, participants perceived a substantial positive impact on their teams and wider organization. Seventy percent reported they had already integrated, or had concrete plans to integrate, SSDV techniques into their daily and weekly workflows for tasks such as analyzing marketing campaign funnels, monitoring HR recruitment pipelines, and tracking sales performance against targets. This represents a tangible acceleration in decision-making cycles. Furthermore, users consistently framed their new skills not just as an immediate tactical advantage but as a critical investment in their long-term professional growth and marketability, citing data literacy as an indispensable skill for the modern business professional. This suggests that investing in SSDV training offers a dual return: improving immediate operational efficiency while simultaneously building a more valuable and future-ready workforce.

The findings also provide preliminary support for the study's theoretical foundations. Improvements in user confidence and competency align with the principles of Experiential Learning Theory, suggesting that hands-on engagement with analytical tools facilitates meaningful skill development. Similarly, participants' positive perceptions of Oracle Analytics support key assumptions of the Technology Acceptance Model, whereby perceived usefulness and ease of use contribute to greater willingness to adopt and utilize technology in professional settings.

5. Discussion

The findings of this study illuminate the complex interplay between technology, training, and human factors in the successful adoption of self-service data visualization (SSDV) tools within an enterprise context. While the promise of data democratization is powerfully alluring, this research demonstrates that its realization is neither automatic nor guaranteed by the mere provision of sophisticated software. Instead, our results affirm that structured training acts as the critical catalyst, transforming a powerful application like Oracle Analytics from a potential source of frustration into a genuine engine of empowerment and insight for the non-technical user. This discussion synthesizes the key findings, places them within the broader academic conversation, acknowledges the study's limitations, and proposes actionable directions for both practice and future research.

The central finding of this research is the unequivocal confirmation that SSDV tools, while designed for ease of use, present significant initial barriers that can only be overcome through tailored pedagogical intervention. The high ratings for training clarity and the notable improvement in self-reported confidence scores from pre- to post-training surveys

provide quantitative evidence for this claim. Qualitatively, the user feedback underscores a desire not for less training, but for more—specifically, for training that is deeply contextual and rich with practical, role-specific examples. This directly challenges any organizational strategy that views training as a one-time cost rather than a continuous investment. Furthermore, the wide variation in dashboard quality scores offers a nuanced perspective on this empowerment. The high-performing dashboards, characterized by logical coherence and effective visual encoding, were almost exclusively produced by participants who engaged most deeply with the practical examples in the training materials. Conversely, the lower scores, plagued by clutter and misaligned data, were linked to a more superficial engagement or a struggle to translate abstract concepts into applied practice. This suggests that the effectiveness of training is not just a function of its content but also of its ability to foster active, experiential learning, directly supporting Kolb's (2014) ^[29] model and indicating that dashboard quality is less an innate skill and more a direct correlate of training comprehensiveness and user engagement.

The findings also provide support for the Technology Acceptance Model (TAM). Participants consistently reported increased confidence, perceived usefulness, and willingness to incorporate Oracle Analytics into their routine workflows following the training intervention. These outcomes suggest that structured training can positively influence both perceived ease of use and perceived usefulness, which are widely recognized as key determinants of technology acceptance and continued utilization. Consequently, effective training may serve not only as a mechanism for skill development but also as a catalyst for sustained adoption of self-service analytics technologies.

When placed within the existing body of literature, these findings both corroborate and extend previous work. Our results strongly align with the principles long advocated by visualization experts like Stephen Few (2009) ^[26], confirming that effective visualizations—those that are clear, accurate, and narratively coherent—are indeed a teachable skill set that enhances decision-making fluency. However, this study moves beyond simply validating established principles by identifying specific, unmet needs in the current ecosystem of SSDV support. While vendors like Oracle focus on adding increasingly powerful features, our research reveals a critical gap: the user experience for advanced functionality remains daunting for the non-technical majority. Participants' struggles with multi-measure prompts and calculated fields are not a failure of the user but a design and support challenge. This points to a pressing need for software developers to invest in simplifying interfaces for complex features and for organizations to abandon the concept of a

single training course in favor of continuous learning paths. This could include micro-learning modules on specific advanced features, curated communities of practice for peer support, and access to expert consultation, creating a scaffolded support system that grows with the user's proficiency.

Beyond technical competency, the findings underscore the growing importance of responsible analytics practices. As organizations increasingly empower non-technical users to create and interpret analytical outputs, governance mechanisms become essential for maintaining transparency, fairness, and accountability. Prior studies on ethical AI decision-making and recruitment governance have demonstrated that explainability and bias mitigation frameworks significantly improve user trust and adoption while reducing risks associated with algorithmic decision support systems (Albaroudi *et al.*, 2025; Albaroudi *et al.*, 2026) ^[12, 14]. Consequently, future self-service analytics initiatives should integrate governance principles alongside technical training to ensure that democratized analytics remains both effective and responsible.

It is crucial to interpret these findings within the context of the study's limitations. The primary limitations of this study include the relatively small sample size of ten participants and the condensed evaluation period of ten days. While this sample was sufficient to generate rich, qualitative insights and identify clear trends, it limits the generalizability (external validity) of the quantitative findings. A larger, longitudinal study is needed to see how these skills decay or improve over months of daily use and to understand the long-term organizational impact on decision quality and efficiency. The short time frame captured the initial learning curve and immediate reaction to training but could not observe the full journey from novice to competent practitioner, which likely involves periods of frustration and discovery that extend well beyond a single week. Furthermore, the use of a single, clean HR dataset controlled for data quality issues but may have presented an idealized scenario that fails to represent the messy, complex, and often contradictory data landscapes users face in their actual roles. From a scholarly perspective, this study contributes to the growing body of knowledge on self-service analytics adoption by demonstrating the critical role of structured training in bridging the gap between technological capability and practical user competence. Unlike studies that focus primarily on platform functionality or adoption intentions, this research provides empirical evidence linking training interventions to improvements in confidence, dashboard quality, analytical effectiveness, and perceived organizational value. The findings therefore extend existing research by highlighting training as a central mechanism through which data democratization initiatives can achieve sustainable success.

Despite these limitations, this study offers clear implications for practice and a roadmap for future research. For organizations, the mandate is clear: strategic investment in SSDV must include a parallel and substantial investment in ongoing, adaptive, and role-specific training programs. For researchers, this work opens several avenues: a large-scale replication to validate these findings, a longitudinal study to

track skill development over time, and deeper investigation into the specific design principles that make advanced features more intuitive for non-technical users. Ultimately, this research concludes that the path to true data democratization is not paved with software licenses alone, but with a sustained commitment to building human capability, ensuring that the power of data visualization is placed effectively and responsibly into the hands of those who drive the business forward.

6. Conclusion & Recommendations

In conclusion, this study demonstrates that structured training plays a critical role in enabling non-technical users to effectively utilize self-service data visualization platforms such as Oracle Analytics. While modern analytics tools are designed to democratize access to data, the findings reveal that meaningful adoption depends on users developing the confidence, skills, and analytical understanding necessary to transform data into actionable insights. The results showed substantial improvements in participant confidence, dashboard quality, and perceived decision-making capability following the training intervention. By integrating quantitative performance measures with qualitative user experiences, this study contributes empirical evidence that training serves as a key enabler of successful data democratization initiatives.

To maximize the impact and return on investment of self-service analytics initiatives, organizations should adopt a holistic implementation strategy that extends beyond software deployment. It is recommended that organizations develop structured, tiered training programs that cater to varying skill levels, guiding users from foundational concepts to advanced analytical techniques. Furthermore, organizations should establish ongoing support mechanisms, including communities of practice, refresher workshops, and role-specific learning resources, to reinforce user competency over time. Software vendors should likewise prioritize user-centered design by simplifying complex analytical features and reducing cognitive barriers that hinder adoption. Sustainable success ultimately requires the cultivation of a strong data-driven culture supported by leadership commitment, continuous learning, and responsible analytics governance.

Future research should explore the integration of generative artificial intelligence and collaborative multi-agent systems within self-service analytics environments. Recent studies have demonstrated the potential of role-based multi-agent frameworks to support complex analytical workflows, automate insight generation, and improve decision support for non-technical users (Albaroudi *et al.*, 2026) ^[6]. Furthermore, research on Generative AI adoption in Saudi Arabia highlights opportunities for enhancing software engineering practices, governance, and organizational innovation through intelligent assistants and AI-enabled decision support systems (Albaroudi *et al.*, 2025; Albaroudi *et al.*, 2025) ^[13, 15]. Incorporating such capabilities into self-service analytics platforms may further reduce barriers to data exploration while improving analytical effectiveness and organizational agility.

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How to Cite This Article

Ahmed I, Moustafa AA, Hatamleh M, Albaroudi E. Empowering non-technical users through self-service data visualization in Oracle Analytics. *Int J Future Eng Innov*. 2026;3(3):132-143. doi:10.54660/IJFEI.2026.3.3.132-143.

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