Self-Service Business Intelligence Adoption and Value Realization: A Mixed-Methods Analysis of Drivers, Barriers, and Governance Implications

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***Abstract*—Self-Service Business Intelligence (SSBI) is widely promoted as a means to accelerate decision-making and democratize analytics beyond centralized IT units, yet cross-industry empirical evidence on adoption mechanisms and governance constraints remains limited. This study investigates the conditions under which SSBI is sustainably adopted and how value is realized across sectors in an emerging market context. Grounded in the Technology Acceptance Model (TAM) and Diffusion of Innovations (DOI), the research examines adoption drivers, implementation challenges, measurable performance effects, and effective integration strategies. A convergent mixed-methods design combines a stratified survey (N=101) with qualitative case studies and thematic analysis. Results identify perceived usefulness, particularly improved agility and decision-making speed, as the primary adoption driver. However, diffusion intensity is shaped by governance maturity, legacy integration, and regulatory constraints. The findings extend TAM and DOI by embedding individual acceptance within governance-constrained BI environments and provide actionable guidance for structured enablement, semantic governance, and phased architectural rollout.**

Keywords-self-service business intelligence; data democratization; technology acceptance model; diffusion of innovations; data governance.

I. Introduction

In today's data-driven era, organizations increasingly rely on technology to foster innovation, improve efficiency, and sustain competitive advantage. Business Intelligence (BI), which emerged from early decision support and data processing systems, has evolved substantially over the past decades. A pivotal milestone in this evolution was the emergence of data warehousing, which established centralized data integration to enable systematic analysis of historical information for strategic decision-making [1]. By the 1990s, BI ecosystems matured further, but many implementations positioned IT departments as gatekeepers of data access, reporting, and dashboard development. While these centralized approaches improved robustness and standardization, they were also associated with delayed reporting cycles, limited accessibility for non-technical users, and organizational bottlenecks stemming from IT dependency [2]. As globalization and market dynamics intensified in the 2000s, organizations increasingly demanded more agile analytics capabilities. This demand contributed to the shift toward SSBI, which this study conceptualizes as a set of tools and practices enabling users, regardless of technical background, to access, visualize, and analyze data with reduced reliance on central IT functions. In contrast, self-service analytics can be viewed as a subset emphasizing advanced techniques, such as predictive analytics and interactive dashboards. From an architecture point of view, SSBI is the user-facing frontend part of an entire BI-solution and hides the technical backend containing especially database structures from the user and encapsulates technical functions in a good working user interface [3].

This distinction highlights that SSBI represents a broader organizational approach to democratizing data access and accelerating decision-making [4] [5].

The remainder of this paper is structured as follows. Section II articulates the research gap and positions the study within the existing body of SSBI and adoption literature. Section III develops the theoretical foundation by synthesizing the Technology Acceptance Model (TAM), Diffusion of Innovations (DOI), and the concept of data democratization. Section IV presents the research methodology, detailing the convergent mixed-methods design, data collection procedures, and analytical approach. Section V reports the empirical results across the four research questions. Section VI interprets the theoretical and practical findings, deriving implementation implications and a structured Strengths, Weaknesses, Opportunities, and Threats (SWOT) synthesis. Section VII discusses limitations and avenues for future research. Finally, Section VIII concludes the paper by summarizing the central contributions and outlining strategic directions for sustainable SSBI adoption.

II. Research Gap and Contribution

BI has long been shaped by centralized data warehousing and IT-mediated reporting, which provide standardization but often create bottlenecks, delayed information availability, and limited accessibility for non-technical users [1] [2]. In response, SSBI has gained traction as organizations seek faster decision cycles and broader access to insights, supported by platform trends, such as cloud delivery and AI-enabled analytics. However, the literature still shows relevant gaps because cross-industry comparative evidence remains limited. Socio-technical constraints, such as governance, security, training and legacy integration, are frequently discussed but not consistently connected to adoption mechanisms. Finally, the translation from adoption theory to actionable, validated implementation strategies is still underdeveloped [6] [7]. This

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paper addresses the overarching question: under which conditions is SSBI sustainably adopted, which benefits and barriers emerge across industries, and which design and implementation measures (e.g., training, governance, integration and change enablement) are required to realize value? Building on the TAM to explain individual acceptance and DOI to explain organizational diffusion, we structure the study around four research questions:

RQ1 What drivers influence SSBI adoption (individual and organizational)?
RQ2 Which benefits and implementation challenges dominate (e.g., governance, security, training, legacy integration)?
RQ3 Which measurable effects are associated with SSBI use in terms of decision-making and collaboration?
RQ4 Which strategies support effective implementation and integration across contexts?

The answers to these research questions are followed by the derivation of a SWOT analysis of SSBI implementation for practical application. Beyond traditional BI adoption research, SSBI adoption increasingly intersects with broader digital transformation and data governance debates. Recent literature emphasizes that democratized analytics environments require new governance mechanisms, including semantic standardization, stewardship roles, and controlled data access frameworks. Consequently, SSBI adoption cannot be interpreted solely as a technological diffusion process, but rather as part of a wider organizational transformation toward data-driven decision-making capabilities.

We employ a mixed-methods design to capture both cross-sectional patterns and context-dependent mechanisms of SSBI adoption [8]. The qualitative strand uses multiple case studies across industries and semi-structured interviews to elicit drivers, realized benefits, and barriers, followed by thematic analysis to derive recurring themes and explanatory mechanisms [9]. The quantitative strand uses an online survey with Likert-scale items to measure adoption, perceived impact (e.g., decision-making speed, cross-functional collaboration) and challenges. Respondents are selected via stratified random sampling to represent both technical and non-technical roles (as operationalized in the study). Survey data are analyzed using descriptive statistics and correlation analysis to identify relationships between adoption-related constructs and outcome proxies. The findings are validated through methodological triangulation by integrating convergent and divergent evidence across qualitative and quantitative results.

III. Foundations in TAM, DOI and Data Democratization

A. Technology Acceptance Model - TAM

To explain adoption mechanisms, we draw on two established perspectives. The TAM links usage to Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which is especially relevant for SSBI tools designed for non-technical users [6]. PU is defined as the extent to which a user believes that using a particular technology will enhance their job performance. In the context of self-service BI, this might encompass how users view tools, such as Power BI or Tableau, in terms of improving decision-making processes and streamlining complex analytical tasks. PEOU refers to the degree to which a user finds a technology easy to operate. Tools that boast intuitive interfaces, short learning curves, and seamless integration are typically more readily adopted. For example, Malatji et al. [10] emphasize that PEOU plays a crucial role in reducing adoption resistance, particularly for non-technical users.

B. Diffusion of Innovations - DOI

The DOI model explains how innovations spread within social systems over time and highlights attributes, such as relative advantage, compatibility, complexity, trialability, and observability, as key drivers [7]. Together, TAM and DOI support an integrated view that covers both individual acceptance and organization-level diffusion of SSBI initiatives.

SSBI value realization is frequently constrained by socio technical barriers. Data governance and data quality become more critical as analytical autonomy increases, because inconsistent definitions and uncontrolled data preparation can undermine trust in results. Security and compliance requirements can restrict access and require role-based controls and auditability. Training and data literacy remain prerequisites for meaningful self-service usage. Integration with heterogeneous application landscapes, especially legacy environments, can add technical friction that interacts with governance and capability constraints. These barrier categories are widely discussed in SSBI research and practice and they provide a structured lens to interpret adoption challenges and derive implementation strategies.

C. Data Democratization

Data democratization, describes the deliberate shift from centralized, IT controlled access to broader, role appropriate access to data and analytics across the organization [2]. Its purpose is to shorten the path from business question to actionable insight by enabling users to explore and visualize trusted data without constant IT mediation. This shift has been accelerated by modern BI platforms and delivery models that emphasize usability, scalability, and cloud enabled distribution of analytics capabilities. Democratization matters because centralized BI delivery can become a bottleneck when demand for insights grows faster than the capacity of central teams, which can slow decision cycles and reduce responsiveness.

The main benefits typically include higher flexibility in analysis and faster insight generation (see Figure 1), which can improve coordination across functions and support quicker operational decisions [11]. However, democratization also increases the need for stronger data governance, since broader autonomy can lead to inconsistent definitions, uncontrolled data preparation, and reduced trust in results if ownership and standards are unclear [12]. Security and compliance requirements can become more challenging because wider access expands the potential attack surface and increases the

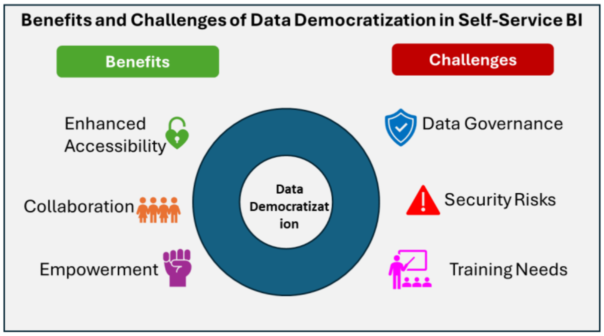

Figure 1. Benefits and Challenges of Data Democratization

importance of access control, auditing, and policy enforcement [13]. Another recurring challenge is capability building, since effective self-service depends on data literacy and tool proficiency, which often requires structured training and ongoing enablement [14]. Taken together, the findings suggest that SSBI implementation reshapes decision rights, accountability structures, and data ownership practices within organizations. Rather than functioning purely as a technological enhancement, SSBI alters how analytical responsibilities are distributed and governed across departments [12]. A practical way to frame the trade-off is that democratization increases speed and autonomy, but it must be paired with governance, security by design, and training to keep data valid, trusted, and compliant [14].

D. Operationalization of Technology Acceptance Model and Diffusion of Innovations Constructs

The study operationalized key constructs from TAM and DOI using multi-item Likert scales (1 = strongly disagree, 5 = strongly agree) to empirically ground the theoretical framework.

PU was measured using items assessing the extent to which SSBI improves decision-making speed, operational efficiency, and analytical effectiveness.

PEOU was operationalized through items measuring usability, learning effort, and interface intuitiveness.

From DOI, the following constructs were operationalized:

- Relative Advantage: perceived performance and agility improvements,
- Compatibility: alignment with existing workflows and data environments,
- Complexity: perceived integration and governance difficulty,
- Observability: visibility of benefits across departments.

All items were adapted from validated TAM and innovation diffusion scales and contextualized for SSBI environments. Composite scores were computed by averaging respective item groups.

IV. Research Methodology

We use a mixed methods design to study SSBI adoption because the topic involves both measurable adoption patterns and context-dependent organizational mechanisms [15]. Integration follows a convergent logic in which qualitative and quantitative evidence are compared and interpreted together to strengthen inference through triangulation [16].

The qualitative part consists of multiple case studies and semi-structured interviews with BI stakeholders to capture sector-specific drivers, benefits, and implementation barriers. Case study logic supports analytic generalization across contexts rather than statistical generalization [17]. Interview data and case notes are analyzed using thematic analysis, moving from familiarization to coding and theme development to produce cross-case patterns that map to the research questions. The semi-structured interviews lasted between 30 and 60 minutes and were conducted with BI managers, data analysts, and operational decision-makers. Thematic analysis followed the six-step procedure proposed by Braun and Clarke [9]: familiarization with the data, initial coding, theme identification, theme review, theme definition, and reporting. Two researchers independently coded a subset of transcripts to ensure interpretative consistency. Discrepancies were discussed and resolved to refine the coding scheme and strengthen analytic reliability. Cross-case comparison was then performed to identify recurring adoption patterns and sector-specific contextual mechanisms.

The quantitative strand uses an online survey with Likert-type items to measure adoption status, proxies for perceived usefulness and ease of use, perceived benefits, and barriers, such as governance, security, training, and legacy integration. Likert instruments are widely used for attitudinal measurement, though they can introduce information loss and bias that must be considered when interpreting the results [18]. To ensure coverage of diverse perspectives, participants are selected through stratified random sampling, ensuring representation of both technical and non-technical roles [19]. Data are analyzed using descriptive statistics and association analysis to identify patterns and relationships relevant to the research questions [20]. Participation is voluntary and based on informed consent. Data are anonymized and reported in aggregate form to protect participants and organizations, consistent with established qualitative research ethics practice [21].

Reliability and Validity Assessment: The internal consistency of the multi-item constructs was examined to ensure coherent measurement of the theoretical dimensions. The results indicate that the survey items demonstrated satisfactory consistency across constructs. Construct validity was assessed by evaluating whether items aligned clearly with their intended conceptual dimensions. The analysis confirmed that items were predominantly associated with their respective constructs, supporting the conceptual clarity of the measurement model. Given the exploratory design and the moderate sample size, the analysis emphasizes methodological transparency and robustness while avoiding unnecessary model complexity. In addition to descriptive statistics, exploratory correlation analysis was performed to examine relationships between TAM constructs (PU, PEOU) and perceived performance outcomes, such as decision-making speed and collaboration. The analysis

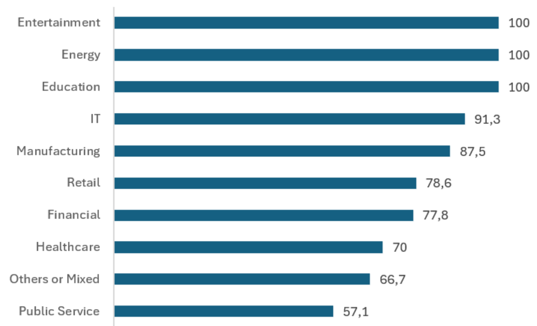

Figure 2. User Adoption Rate across Sectors

indicated positive associations between perceived usefulness and reported decision-making improvements, supporting the theoretical expectations derived from TAM.

V. Research Results

A. Sample and overall Adoption

The quantitative dataset includes 101 completed survey responses across multiple industries, including Fast-Moving Consumer Goods (FMCG), Healthcare, Manufacturing, IT, Financial Services, Retail, Public Service, Energy, and others. Sectoral differences were examined using descriptive comparisons of adoption rates and reported challenges across industry categories. This exploratory comparison approach allows identification of patterns and contextual differences, although the limited sample size prevents robust statistical testing of sector effects.

A large majority of respondents reported active use of self-service BI tools, with overall adoption exceeding 80% in the sample. Figure 2 illustrates the distribution of adoption rates across sectors, highlighting higher diffusion levels in IT and Manufacturing and comparatively lower adoption in Public Service and Healthcare.

B. Results for RQ1–Drivers of SSBI adoption

Respondents reported that the most important adoption driver was the need for agility, cited by 74%, followed by technological advancements at 68%, cost reduction at 53%, and competitive pressures at 37% (see Table I).

TABLE I
Drivers of SSBI Adoption

Driver	*Percentage of Mentions (%)*
Competitive Pressure	37
Cost Reduction	53
Technology Advancements	68
Need for Agility	74

These driver patterns are consistent with the high share of organizations reporting active SSBI use and with case based descriptions that emphasize operational agility and forecasting in FMCG and manufacturing settings.

C. Results for RQ2–Benefits and Implementation Challenges

A key reported benefit is faster decision-making after SSBI adoption, reflected in a strong shift in decision speed ratings from pre-adoption to post adoption. In addition, respondents reported operational improvements, including reductions in waste of 15-25% and a productivity increase of around 20% post-adoption, as summarized in the quantitative results. These performance improvements are based on self-reported managerial estimates comparing perceived pre- and post-adoption conditions. While indicative of operational gains, these figures should be interpreted cautiously due to potential response bias and the absence of audited financial validation.

TABLE II
Challenges in SSBI Adoption

Challenge	*Percentage of Mentions (%)*
Training Gaps	58
Legacy System Integration	45
Data Governance	41
Resistance to Change	32
Security Concerns	27

Regarding challenges among adopters (see Table II, respondents reported training gaps (58%), legacy system integration (45%), data governance (41%), resistance to change (32%), and security concerns (27%). The results also note sector differences in perceived severity, with lower challenge severity in FMCG and Retail contexts that reported structured onboarding, and greater difficulty in healthcare and financial services contexts that face tighter regulation and legacy constraints. In general, those findings correlate with the challenges of data democratization mentioned in Figure 1 and discussed by Achanta et al. [11].

D. Results for RQ3–Effects on decision-making and collaboration

The Decision-making speed improved significantly after SSBI adoption. Ratings of the decision quality category “Poor” decreased from 30% to 5%, and ratings of “Fair” decreased from 25% to 10%. Ratings of “Very Good” increased from 15% to 35%, and ratings of the category “Excellent” increased from 10% to 30%, while “Good” remained at 20%. The findings also report that 75% of users rated decision-making speed as “Very Good” or “Excellent” following adoption. The results indicate that the use of SSBI leads to a transition from poor decision quality to substantially improved decision quality.

E. Results for RQ4–Non-adoption factors

Among non-adopters, findings indicate that high initial costs at 36%, security and data governance concerns at 29%, and limited internal expertise at 24% are the leading barriers, followed by lack of executive buy-in at 20% and scalability concerns at 15%. A sector-specific breakdown of non-adoption reasons (see Figure 3) shows that high costs are the overall top factor for not introducing SSBI, especially in healthcare at 30% and retail at 25%, and that security concerns reach 28% in financial and public service contexts.

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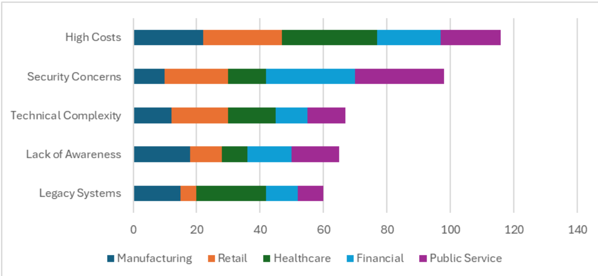

Figure 3. Factors for non-Adoption

VI. Discussion

1) Interpreting adoption drivers through TAM and DOI: The results indicate that SSBI adoption is primarily justified through agility, technology advancement, and cost-related expectations. From a TAM perspective, this pattern aligns with perceived usefulness as the dominant acceptance mechanism, as respondents associate SSBI with faster decision-making and operational improvements rather than with technical novelty. From a DOI perspective, agility and competitiveness map to relative advantage, while the sector differences in adoption suggest that compatibility with existing processes and data environments influences diffusion across industries. The sector view also indicates that diffusion is not only a tool decision, it is also shaped by organizational readiness and by how visible the benefits become to potential adopters, which relates to observability and trialability.

2) BI democratization as value promise and as operating model change: The findings support the view that BI democratization is pursued primarily to reduce analytical bottlenecks and enable faster decision-making closer to operational contexts [2]. However, democratization introduces governance challenges that must be addressed to maintain data trust and analytical consistency. This implies that strategic steering instruments, such as multidimensional controlling frameworks that integrate performance and cyber-risk perspectives, can support this governance shift and provide C-level transparency in democratized BI environments [22]. Increased autonomy requires clearly defined metric ownership, standardized semantic layers, and robust data stewardship mechanisms [12]. Thus, SSBI should not be interpreted merely as a technological capability but as an organizational operating model that redistributes analytical responsibilities across business units.

3) Barriers as socio technical constraints and how they explain sector differences: The most frequently reported implementation challenges cluster around training, legacy integration, and governance. These barriers align with the socio-technical nature of SSBI, where user experience and organizational environment jointly determine success. Training gaps directly limit perceived ease of use and reduce confidence in independent analysis, thereby weakening acceptance even when tools are intuitively designed. Legacy integration and governance complexity increase perceived complexity and reduce compatibility, slowing diffusion across units and creating uneven scaling within organizations. Security concerns, while not always the top barrier, remain structurally important because broader access increases exposure and the need for role-based controls and auditing to maintain compliance. Taken together, these constraints explain why some sectors show higher non-adoption rates despite the general attractiveness of SSBI: regulated contexts and legacy-heavy environments face a higher burden of governance and integration work before democratization becomes safe and trusted.

4) Practical implications for implementation and SWOT Analysis: The results suggest that implementation should focus on three linked workstreams. The first is enablement. Organizations should establish tiered training that starts with core data literacy and tool basics, then progresses to advanced analytics patterns for power users. This directly addresses training gaps and supports sustainable self-service usage. The second is governance. A pragmatic governance setup should define metric ownership, approved datasets, and standard semantic definitions, and support lightweight stewardship roles that enable democratization while protecting trust. The third is architecture and integration. Organizations should adopt a phased rollout that starts with a limited number of high-value use cases and expands once data pipelines and access controls are stable, thereby increasing trialability and observability and supporting faster diffusion. Where security and compliance constraints are strong, the governance workstream must include role-based access controls, logging, and auditability as baseline requirements for democratized analytics. Industry trend reports also indicate that modern platform capabilities, including cloud delivery and AI-enabled features, can lower friction, but they do not replace the need for governance and enablement as core success factors. The major findings are summarized in a SWOT Analysis chart in Figure 4, which helps to develop an SSBI approach in a company.

5) Theoretical Contribution: This study provides one of the first cross-industry empirical examinations of SSBI adoption in an emerging market context and embeds individual acceptance mechanisms within governance-constrained BI environments. While TAM explains adoption primarily through perceived usefulness, the results indicate that diffusion across sectors depends on structural conditions, such as governance arrangements, regulatory intensity, and legacy system compatibility.

Furthermore, in regulated industries, compatibility and complexity attributes from DOI appear more influential than relative advantage alone, contextualizing innovation diffusion within compliance-intensive environments.

VII. Limitations and Future Research

This study employs a cross-sectional mixed-methods design, limiting causal inference. While analysis identifies significant associations, longitudinal designs would be required to establish directionality. The quantitative data relies on self-reported measures, which may introduce response bias. Future research should incorporate objective performance metrics. Although the sample spans multiple industries, the empirical context is limited to Nigeria. Institutional and regulatory

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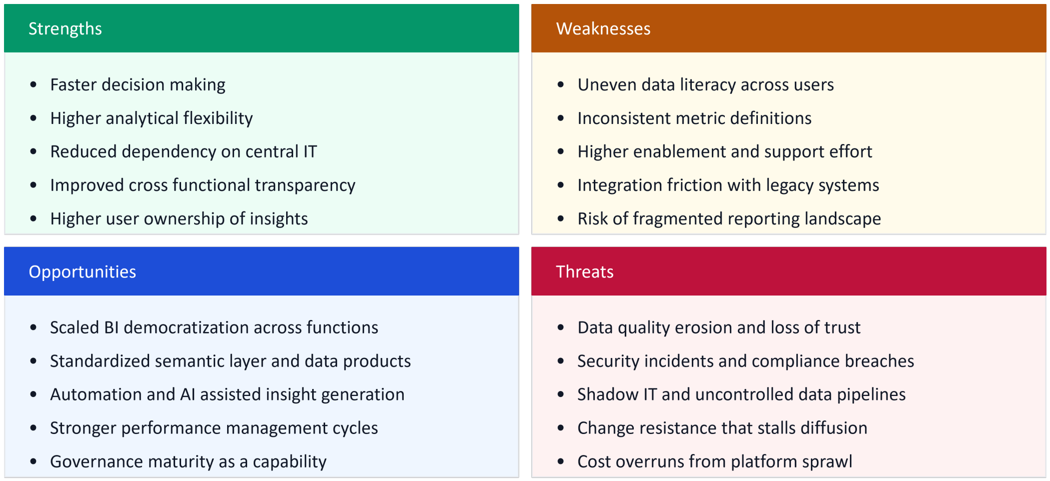

Figure 4. Final SWOT Analysis

differences may limit generalizability. This suggests several methodological and theoretical extensions. Future research should apply confirmatory factor analysis (CFA) and structural equation modeling (SEM) to validate theoretical relationships and explore governance maturity as a measurable moderating construct.

VIII. Conclusion

This study examined SSBI adoption and value realization across industries in an emerging market context using a convergent mixed-methods design (N = 101). The results demonstrate that perceived usefulness is the primary driver of adoption, while implementation challenges cluster around training, governance, and legacy integration constraints.

In synthesis, SSBI adoption represents a socio-technical transformation that reshapes how analytical responsibilities, decision authority, and governance mechanisms are distributed within organizations. While individual acceptance factors explain initial uptake, sustainable diffusion depends on structured enablement, consistent semantic governance, and security-by-design principles. The strategic challenge is therefore not whether to democratize analytics, but how to institutionalize controlled autonomy within a scalable governance architecture.

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