Case studies of subjective data dimensions in business intelligence based on literature

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Abstract: *Data quality is widely recognized as a decisive factor for the success of business intelligence systems, as it directly influences the reliability of insights, the effectiveness of decision-making, and the level of trust placed in analytical outcomes. Traditional approaches have emphasized technical aspects such as accuracy, completeness, and consistency. Recently, attention has shifted toward subjective, user-related dimensions of data quality, influenced by perception, trust, and understanding. This study responds to this development by defining and categorizing subjective dimensions of data quality and identifying the organizational and technical conditions affecting user perception and trust in business intelligence environments. A mixed-methods approach was employed, combining a structured literature review with five case studies conducted in financial and non-financial organizations. Data from the case studies were gathered through semi-structured interviews with practitioners responsible for designing and managing data solutions. The findings revealed four distinct categories of subjective data quality (data access, usability, processing, and evaluation), which together capture the ways in which users assess the relevance, interpretability, and value of data. Six critical success factors were identified as essential in shaping these perceptions: data governance, metadata management, knowledge and competence development, organizational culture, technological infrastructure, and stakeholder relationships. From these insights, five best practices were derived that support the enhancement of subjective data quality, such as developing business glossaries, comprehensive metadata catalogues, and transparent documentation of data lineage. The study concludes that subjective data quality is co-produced by technological infrastructures and human factors, and it proposes a multi-layered model that integrates these dimensions to guide the design of business intelligence systems that foster trust, understanding, and greater decision-making value.*

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Introduction

In recent years, the role of data quality has become increasingly prominent in the domains of business intelligence (BI). High-quality data is recognized as a strategic asset that underpins effective decision-making, operational efficiency, and organizational trust (Al-Eisawi et al., 2020; Hartl & Jacob, 2016). Existing literature has developed a variety of frameworks and methodologies for data quality management, addressing dimensions such as accuracy, completeness, consistency, and timeliness (Eppler & Helfert, 2004; Woodall et al., 2013). These objective or intrinsic aspects of data quality are often complemented by regulatory demands that emphasize transparency, traceability, and relevance (Al-Okaily & Teoh, 2023).

However, a growing body of research has begun highlighting the importance of subjective data quality dimensions, those shaped by users' perceptions, contextual factors, and domain-specific expectations (Bouchana & Janati Idrissi, 2015; del Pilar Angeles & García-Ugalde, 2012). Despite these insights, the literature lacks a comprehensive synthesis and systematic analysis of how subjective data quality is defined, measured, and influenced by technological and human factors in business intelligence (BI) systems. While some typologies differentiate between declarative and utilitarian quality dimensions (Jayawardene et al., 2015) or suggest user-centred categorizations (Abdullah & Arshah, 2018), there remains limited empirical validation of these frameworks, especially in real-world organizational settings. In parallel, the landscape of business intelligence has been rapidly transformed by AI-driven and self-service analytics solutions (e.g., Fu et al., 2024; Liang et al., 2022). While automation and generative analytics tools increasingly influence data preparation and interpretation, the role of human users as active evaluators and contextual interpreters of data remains essential for ensuring subjective data quality and organizational trust in BI outputs.

This study addresses this gap by combining a structured literature review with case study research to explore the concept of subjective data quality in BI environments. The aim is to define and categorize user-influenced quality dimensions and to identify critical success factors that support their improvement. The study also seeks to inform the design of BI systems by outlining key organizational and infrastructural conditions that foster trust, usability, and data interpretability from the end-user perspective. Doing so contributes to a deeper theoretical understanding and provides actionable insights for data quality practice in complex organizational contexts.

1 Theoretical background

As stated in the study by Cai and Zhu (2015), there is currently a lack of comprehensive analysis and research on quality standards and quality assessment methods for big data. The article's authors used the Prisma method for the literature search, asking keywords in the Web of Science: subjective data quality business intelligence. A total of 20 publications were found. The following articles were selected from them (Tab. 1).

Based on the provided sources, data quality management (DQM) can be understood as a set of processes, methodologies, and strategies to ensure and maintain a high standard of data quality within an organization. Data quality is widely recognised as an asset, especially in business intelligence and analytics (BI&A), where it is considered BI's most valuable asset, along with data provisioning. Low data quality can lead to significant financial losses and erode user trust in BI systems, resulting in insufficient or decreasing usage. Ensuring data quality is considered the initial step for successful BI.

The literature includes various frameworks and methodologies for data quality management, which differ in the definition, assessment, and improvement of data quality. Requirements for data and their quality vary between organizations, making the selection of suitable

Tab. 1: Key aspects of data quality management according to the sources – Part 1

Key aspects	Issues	Authors
Definition and dimensions of data quality	Data quality dimensions are attributes that can be measured to indicate the overall level of data quality. There are several classifications of dimensions, for example, into categories such as intrinsic, accessibility, contextual, and representational. The most common dimensions are completeness, timeliness, and accuracy, followed by consistency and accessibility. The definition of data quality is fundamentally associated with the degree to which the products of an information system convey meaning.	Al-Eisawi et al. (2020)

Tab. 1: Key aspects of data quality management according to the sources – Part 2

Key aspects	Issues	Authors
Data quality assessment	The data sources suggest a new perspective for assessment through the five attributes: data, source, system, task, and human. Each attribute presents its own challenges and opportunities.	Mohammed et al. (2024)
Cost aspects	Costs are an important factor in DQM. They arise from poor data quality (e.g., costs of lost opportunities, process failures, higher maintenance costs) and costs for improvement (e.g., training costs, infrastructure costs). Data quality improvement projects must benefit the organization. DQM frameworks offer different approaches to assessing costs and benefits, including cost-benefit analysis, ROI, or cost classification.	Eppler and Helfert (2004)
Data quality improvement	DQM includes methods for improving data quality. Decision strategies for improvement should be established and often depend on costs. Technologies such as master data management (MDM) can help improve the overall data quality within an organization. MDM is considered a challenging, time-consuming, and expensive task. Traceability of BI master data changes is an ongoing challenge in master data management.	Torres and Sidorova (2019)
Organizational and human factors	The success of DQM, and thus BI projects, depends on collaboration between departments and IT. Different perceptions of data quality between departments (e.g., controlling and IT) can stem from poor communication. Addressing these communication problems can contribute to improving data quality. Knowledgeable BI&A users can also compensate for the limitations of the system interface. Furthermore, BI&A producer expertise is critical for enabling access to system representations and positively relates to actionability, suggesting that they help filter irrelevant or unactionable representations. Investing in BI&A personnel is reaffirmed as necessary.	Del Pilar Angeles and García-Ugalde (2012)
Documentation and metadata	Quality data requires good data documentation, including structured metadata (schema, statistics, provenance) and textual descriptions. Metadata is key to understanding the meaning and concepts of data and reducing the risk of misuse. Ensuring data provenance traceability is a significant challenge and requires documentation.	Woodall et al. (2013)
Relationship with information quality and BI&A success	Data quality is fundamental for ensuring transparent interaction, representational fidelity, and actionability, which are components of practical use. Empirical findings show that data quality was a strong predictor of both perceived benefit and user satisfaction, and these factors positively affect organizational benefits.	Hartl and Jacob (2016)
Regulatory requirements	Regulations, such as GDPR and the EU AI Act, underscore the growing importance of data quality. They explicitly mention data quality dimensions like accuracy, completeness, and relevance and require their assessment.	Al-Okaily and Teoh (2023)

Source: stated in the table

methods challenging. Overviews of methodologies for assessing and improving data quality for different data types exist, comparing criteria such as data and system types, costs, and data quality dimensions.

Data quality management can thus be described as a multifaceted discipline encompassing technical, process, organizational, and strategic aspects. It aims to ensure that data is trustworthy, fit for its intended use, and contributes to organizational success.

2 Research methodology

This research employs a mixed-method approach, utilizing literature to comprehensively investigate subjective dimensions of data quality and case studies to link these dimensions with critical success factors influencing subjective dimension of data quality and best practice to increase them. Literature research was chosen as it provides a framework for identifying existing theoretical insights in defining subjective data quality dimensions. Results of literature research were used in case studies as the interviews were based on identified data quality dimensions. This was needed as we could not use a ready-to-use framework (it was not identified in the literature).

There were three research questions stated:

RQ1: What are the user-related (i.e., subjective) dimensions of data quality identified in the literature? (Method: systematic literature review)

RQ2: What are the critical success factors of business intelligence (BI) solutions from the perspective of subjective data quality? (Method: case studies)

RQ3: To what extent, and through which approaches, do organizations seek to improve data quality to support more effective BI processes? (Method: case studies)

A combined approach in literature review was adopted to define the concept of subjective data quality, incorporating classical, preliminary, and systematic literature reviews. The final procedure was as follows:

i) A classical review to define the basic concept of data quality (theoretical backround);
ii) A preliminary exploration of dimensions using Google Scholar (discovery that systematic review already exists);
iii) Adoption of the systematic approach by Cichy and Rass (2019);
iv) Targeted search for studies linking data quality dimensions with the data-processing subject (see following paragraph);
v) Selection of works offering alternative conceptualizations of data quality dimensions;
vi) Systematic categorization and synthesis of the identified dimensions.

In the step focused on identifying dimensions with links to the subject (i.e., the user or data processor), the original search query – “data quality” and “dimension” and “framework” (limited to the period 2015–2023, sorted by relevance) – was extended with additional keywords: “user,” “human factor,” “subjective,” and “satisfaction.” The first two pages of results were screened. Only studies offering original conceptual frameworks that consider the user’s role were considered. This aligns with the fitness-for-use principle (Watts et al., 2009), which posits that data quality is determined not only by its use but also by the user’s specific needs within a given context. Such a perspective corresponds with early context-sensitive approaches to data quality (Strong et al., 1997), and it enables the definition of subjective dimensions, those shaped, at least in part, by the user’s perspective.

Case studies were selected to gain in-depth, real-world insights into how organizations practically implement and manage subjective data quality within their BI solutions. The case studies were focused on detailed examination and contextual analysis of interactions between human factors and technical infrastructures. The research focused particularly on companies within the financial sector, such as banks and insurance companies. These organisations were selected due to their expected maturity on advanced BI systems, as the data quality plays a critical role in their operational and strategic processes for many years (Bany Mohammad et al., 2022). In addition to their BI maturity, the selected organizations represent industries with varying data governance challenges and user cultures (financial, manufacturing, retail, and multinational banking) allowing for comparison across both regulated and competitive environments (Tab. 2). The inclusion of medium-to-large enterprises was deliberate, as these organizations typically possess established BI infrastructures and formalized data management roles necessary to explore subjective dimensions of data quality in depth. Furthermore, one of the authors had

Tab. 2: Overview of case studies

Case	Turnover/insured category	Employees category	Region
A-insurance	EUR 0.4–2 billion	500–999	CZ
B-electrotechnics	EUR 0.4–2 billion	5,000–9,999	CEE
C-retail	>EUR 2 billion	>10,000	CEE
D-bank	EUR 0.4–2 billion	5,000–9,999	CZ
E-banking group	>EUR 2 billion	>10,000	EU

Source: own

previously conducted related research within three of the participating organizations, which facilitated access, ensured informed interpretation of context-specific practices, and enhanced data validity through established trust with respondents.

Companies were based in the Czech Republic or Belgium (for the E-case) but some of the data solutions were covering larger region in Central and Eastern Europe (CEE).

Each case study was based primarily on one in-depth semi-structured interview with the person responsible for BI solution within the organization, typically the head of BI or an equivalent managerial role. The interviews lasted approximately 90 minutes. In four of the five cases (A, B, C, and E), an additional short follow-up discussion was held with another team member occupying a different role to verify or clarify selected information. Data collection occurred between May and July 2023 via Microsoft Teams, where interviews were both recorded and transcribed automatically. The interview protocol consisted of two parts: the first focused on understanding the data environment and context of the participating enterprise, and the second addressed issues related to subjective data quality and knowledge management. To ensure accuracy and clarify ambiguities, follow-up questions were addressed through email or phone communication. Respondents were guaranteed anonymity to encourage open and candid responses.

3 Results and discussion

3.1 Subjective data quality definition

There is no unified theory for grouping data quality dimensions. Our findings are summarized in Tab. 3. Jayawardene et al. (2015) propose a division into declarative and utilitarian dimensions from a usage perspective. Declarative dimensions can be assessed without reference to context, whereas utilitarian ones depend on specific use cases and situational factors. Their framework comprises 127 dimensions grouped into eight clusters and spread along a continuum from fully declarative to fully utilitarian. Building on this, Abdullah and Arshah (2018) focus on usage-related dimensions, which they organize into four overlapping areas: internal (data-specific), subject-related, perception-based, and expectation-related. This typology supports the conceptualization of subjective data quality by emphasizing the user's role in evaluating the usefulness and relevance of data, whether direct or indirect.

Additional distinctions arise from the domain of data processing. Baldassarre et al. (2018) highlight the importance of operational data quality, particularly in big data contexts where efficiency and source integration directly influence outcomes. Their categorization into operational, contextual, and temporal dimensions reflects practical needs in complex systems. Firmani et al. (2016) extend this perspective to data processed through automated models and machine learning, introducing dimensions that apply to human and artificial users. These user-relevant dimensions further support the inclusion of subjective factors in data quality assessment.

Bouchana and Janati Idrissi (2015) distinguish between data quality dimensions, performance indicators, and user satisfaction factors in the BI context. While these often overlap, the authors argue that factors such as ease of use, content usefulness, and representational clarity are key contributors to perceived data quality. These perspectives collectively emphasize the importance of subjective dimensions

Tab. 3: Data dimension overview

Dimension	Jayawardene et al. (2015)	Abdullah and Arshah (2018)	Baldassarre et al. (2018)	Firmani et al. (2016)	Bouchana and Janati Idrissi (2015)
Accessibility/ findability	X	X	O	X	
Accuracy	/		/		
Appropriate amount	X				
Believability	X	X	/	X	
Completeness	O		/		
Concise representation	X				
Consistency	O		/		
Consistent representation	X			X	X
Currency	O		O		
Free-of-error	O				
Interpretability	X	X			X
Objectivity	X	X			X
Precision	X		O		
Relevancy	X	X	/		
Reputation	X	X	/	X	
Security	X		O		
Timeliness	/		O		
Understandability	X	X	/	X	X
Validity	O				
Value-added	X	X		X	X

Note: X – fully subjective; / – party subjective; O – technical dimension.

Source: own based on sources stated in the table

and reinforce the view that quality is shaped not only by intrinsic data properties but also by user expectations, the context of use, and the interpretability of the information.

After finishing our research, study by Ridzuan and Zainon (2024) was published. Their study added to the comprehensive taxonomy of data quality dimensions relevant to big data also subjective characteristics. Subjective, or user-oriented, dimensions are highlighted as increasingly critical due to the contextual and interpretative nature of big data usage. These dimensions include credibility, reputation, believability, relevance, and understandability. The study emphasizes that subjective dimensions are often underrepresented in technical data quality frameworks yet play a decisive role in how data is trusted and acted upon by end users. Accordingly, the authors advocate for incorporating user-centric metrics in future data quality models.

Similarly (despite not focusing on user), authors Miller et al. (2024) also added to common data quality dimensions represented by ISO 25012 those connected to the human factor. In their extension of the ISO 25012 data

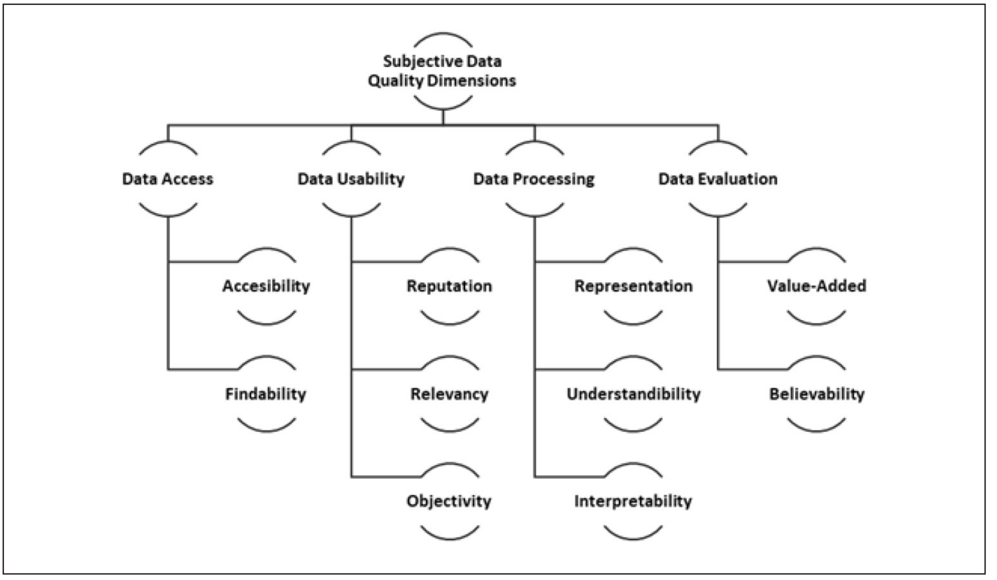

Fig. 1: Grouped subjective data quality dimensions

Source: own

quality model, the authors propose the inclusion of several user-oriented dimensions that reflect the growing importance of subjective and contextual factors in data evaluation. These added dimensions include usefulness, reputation, believability, and understandability, each emphasizing the user's perception and experience when interacting with data. The authors argue that these dimensions capture aspects of data quality that are not strictly technical but are nonetheless critical for effective data use in decision-making.

Based on the identified dimension we grouped these into four categories (Fig. 1). Data access concerns users' perceptions of the ease and efficiency with which they can obtain necessary data within their workflows, emphasizing availability, good access and easy to be searched. Data usability relates to how directly applicable the data are to specific user tasks, with a focus on reputation and objectivity assessment. Data processing reflects users' experiences with transforming raw data into actionable insights, including the understandability and interpretability. Lastly, data evaluation encompasses users' assessments of the believability and value-added assessment of data produced by BI systems, highlighting the importance of clear validation mechanisms and consistent standards that enable confident, data-driven decision-making.

3.2 Critical success factors for subjective data quality

In the context of this study, critical success factors are defined as the essential organizational, technical, and cultural conditions that must be present for subjective data quality to emerge and be sustained. The research identified six critical success factors influencing subjective data quality in BI solutions based on findings from case studies (Tab. 4). Architecture and infrastructure form the foundation, encompassing technological platforms, tools, and integration capabilities essential for efficient data storage, retrieval, and analysis. Organizations with scalable and well-structured architectures reported improved data access, system performance, and reliability, which enhanced users' perceptions of data quality.

Data culture refers to the organizational attitudes and behaviours toward data use. A mature data culture, marked by collaboration, open communication about data issues, and

Tab. 4: Critical success factors in subjective data quality area

Factor	A-insurance	B-electrotechnics	C-retail	D-bank	E-bank group
Architecture/ infrastructure	X	X		X	
Data culture	X	X	X	X	X
Data governance		X	X	X	
Knowledge			X	X	X
Metadata	X	X	X	X	X
Relations	X			X	X
Documentation	X	X	X	X	X

Source: own

commitment to data-driven decision-making, consistently aligned with higher subjective data quality. Such environments foster user engagement and improve usability, trust, and processing efficiency. Knowledge represents user competencies, training, and awareness of data practices. Organizations investing in education and knowledge-sharing reported greater data understanding and usability, improving processing and evaluation outcomes through enhanced data literacy.

Data governance includes the structures, policies, and accountability mechanisms for managing data. Clear governance (defined roles, responsibilities, and ownership) ensures transparency in data sources and lineage, leading to increased trust and more effective data evaluation.

Metadata and documentation were also key, as comprehensive and accessible metadata improve transparency and interpretability across the data lifecycle. Strong metadata management was linked to greater user confidence and more consistent data evaluation. Finally, relationships (collaboration and communication among BI stakeholders) emerged as essential. Effective cross-functional interactions enhance contextual understanding, streamline problem-solving, and support coordinated governance. Organizations fostering strong stakeholder relationships reported higher user satisfaction and perceived quality across all subjective dimensions.

3.3 Critical success factors for subjective data quality

Best practices refer to the specific actions, tools, or managerial interventions derived from the identified critical success factors. The case studies revealed several best practices adopted

Tab. 5: Best practices in subjective data quality area

Factor	A-insurance	B-electrotechnics	C-retail	D-bank	E-bank group
Business glossary	X	X		X	X
Data catalog	X	X	X	X	X
Data lineage	X	X		X	X
Business lineage	X	X		X	X
DQ tool	X		X		X
BI excellence centrum	X	X	X	X	X
Business glossary	X	X		X	X

Source: own

by organizations to enhance subjective data quality across BI systems (Tab. 5). One widely implemented practice was the development of a business glossary, which standardizes terminology and clearly defines key business concepts and data elements. Organizations utilizing comprehensive glossaries reported notable improvements in data usability and evaluation. These tools reduced ambiguity, facilitated communication between business and technical stakeholders, and increased user confidence in interpreting analytical outputs.

Another frequently cited practice was the use of a data catalogue, a centralized repository of metadata and documentation that improves data access and usability. By offering searchable, structured information about data sources, relationships, and availability, data catalogues enable more efficient data discovery and greater user autonomy. Furthermore, documenting data lineage and business lineage emerge as a critical measure for enhancing transparency and interpretability of data flows. Organizations that track both technical and business-level transformations reported improved understanding of data processes, greater trust in analytical results, and more effective troubleshooting.

The adoption of data quality management tools was also found to be instrumental in proactively identifying and resolving data issues before they reached end-users This leads to strengthening data evaluation and increasing overall user trust. Finally, establishing a BI Centre of Excellence was recognized as a strategic initiative that consolidated expertise, standardized methodologies, and fostered a strong data culture. These centres played a key role in improving user knowledge, supporting governance efforts, and aligning data practices with organizational goals and contributed to higher perceived data quality within BI environments.

3.4 Discussion

Critical factors influencing subjective data quality identified through this research include architectural or technical factors. Integration includes not only the data side, but also the metadata side, since proper integration requires an understanding of individual data sources. However, in a company where key processes are not sufficiently managed and under control, integration is much more difficult and may not meet its goals (Popovič et al., 2012). Lopes et al. (2020) suggest adding a knowledge module and an adaptation model as part of the BI solution in the access layer, which will help with an iterative approach for applications and models using data from the BI solution.

Other critical factors identified in this research were rather human factors: data governance, user-centric digital competencies and a well-established data culture. Effective data governance mechanisms, characterized by clear data ownership, accountability, and transparency, are widely recognized as foundational to maintaining data integrity and trust (Alhassan et al., 2016; Jahnke & Otto, 2023). Data governance can have a positive impact on data quality, as it can contribute to sharing conclusions from data processing or sharing pre-prepared data sources (Saltz & Shamshurin, 2016). Some authors even add governance as special data quality dimension (Miller et al., 2024). The governance dimension introduced in the extended ISO model refers to the internal organisational structures, policies, and processes that guide data management practices. Governance ensures consistent and accountable data handling aligned with organisational goals. It encompasses elements such as authority, authorisation, accountability, alignment, and auditability, each contributing to oversight, access control, and traceability.

The implementation of best practices such as comprehensive business glossaries, centralized data catalogues, and meticulous documentation of data and business lineage was identified as particularly beneficial for subjective data quality. These tools standardize and clarify terminology and facilitate efficient communication among technical and business stakeholders, substantially enhancing data usability and interpretability (Koltay, 2016).

Metadata enables users to locate data in organization, understand its content, and optimize their time and analytical efficiency (Kumar et al., 2025). Descriptive metadata is essential for identifying and retrieving data; in its absence, data may effectively lose its utility (Aljumaili et al., 2016). Structural metadata describes the organization, storage, and relationships of data entities and types, supporting data analysis and reporting by clarifying inter-table connections rather than technical specifics (Kumar et al., 2025).

Maintaining a business glossary standardizes terminology and fosters consistent interpretation, reducing misunderstandings across technical and business domains (Mosha & Ngulube, 2023). Similarly, centralised data governance tools such as data catalogues enhance data discovery and strengthen user trust by providing accessible and reliable metadata (Bernardo et al., 2024). A user-centric data catalogue significantly enhances data quality by improving discoverability, context, and usability of data assets. Petrik et al. (2023) identify key features such as automated metadata extraction, semantic search, and integration with user workflows as essential for fostering trust and effective data use in self-service BI contexts (Petrik et al., 2023).

Documenting both data and business lineage increases transparency, allowing users to trace data origins and transformations, thus improving interpretability and auditability (Backes et al., 2015; Loyens, 2023). Guitton et al. (2024) highlights that lineage tracking when integrated with metadata management platforms and supported by trustworthy policy enforcement – enables more accurate data flow documentation, supports regulatory compliance, and improves users' trust in analytics outcomes (Guitton et al., 2024).

The establishment of BI Centres of Excellence emerged as a strategic approach to promote systematic knowledge sharing, enhance user confidence, and align data practices with organizational goals (Pugna & Boldeanu, 2013). Fostering digital competencies is crucial for empowering users to accurately interpret and effectively utilize data, thus significantly improving subjective perceptions of data quality (Wang et al., 2021). The study of Ghalavand and Nabiolahi (2024) advocates for increased involvement of domain experts in content creation and quality assurance, as well as educational initiatives to raise user awareness (Ghalavand & Nabiolahi, 2024). Namely commonly acknowledge the FAIR principles (findable, accessible, interoperable, reusable) are advised to be part of employees' knowledge (Gonzalez Soltero et al., 2024),

From a managerial perspective, the study extends prior literature by translating data quality constructs into organizational levers that leaders can actively shape. Strengthening data governance, deploying documentation tools (business glossary, data catalog and data lineage), implementing data quality tools and investing in user training emerge as strategic interventions that enhance not only perceived data quality but also the consistency and accountability of managerial decisions based on BI outputs.

3.5 Limitations

Despite these contributions, the research has certain limitations. The empirical validation was conducted through five case studies, which, while diverse, may not capture the full variability of BI implementations across different industries, organizational sizes, or cultural contexts. The organizations are primarily located in the Czech Republic with Central and Eastern European region scope, with one case representing a broader EU banking group. The focus on subjective perceptions of data quality also means that some objective technical measures were outside the study's scope. This geographic and sectoral concentration may limit the generalizability of findings to other institutional contexts.

The findings are influenced by the specific technological and organizational environments in which the case studies took place, which may affect their direct applicability elsewhere. Consequently, cultural, regulatory, and organizational specifics may influence the applicability of the identified success factors and best practices in other regions or industries.

Conclusions

This research defined and systematically categorized subjective data quality dimensions, emphasizing their critical role in user-centred BI environments. Empirical analysis identified key organizational and technical factors (such as data governance, metadata management, digital competencies, and data culture) that significantly affect subjective data quality perceptions. Based on these insights, a four-layer BI environment model was proposed (Fig. 2), integrating best practices. The outer layers represent the enabling environment, where organizational culture, governance policies, and tacit knowledge establish the conditions under which data quality is created and maintained. The intermediate layers highlight metadata management and codified organizational knowledge as the connective tissue between technical artefacts and end-user interaction. At the core, user competencies and interpretive practices determine how available data is accessed, understood, and evaluated for decision-making. The model's architecture emphasizes that improvements in perceived data quality emerge not from isolated interventions but from coordinated action across layers, ensuring that technical, informational, and human factors mutually reinforce one another. This systemic perspective positions the framework as both a conceptual lens for understanding subjective data quality and a diagnostic tool for practitioners aiming to align BI investments with user-centred quality outcomes.

The diagram (Fig. 2) synthesizes insights from the case studies, illustrating how identified critical success factors correspond to and interact across the organizational, metadata, infrastructural, and user layers of BI environments. These interactions capture how enablers such as governance, data culture, competence, and metadata management collectively shape users' perception of data quality. While the depicted relations are grounded in the empirical findings, their precise causal form and strength should be examined in future research to confirm and refine the proposed conceptual model.

Case studies offered showed some examples of link from subjective data quality dimensions to organization outcomes. In case D (a banking institution), insufficient understanding of customer 360° data by marketing teams led to poorly parameterized campaigns, resulting in low conversion rates and misallocated budgets despite technically accurate data. In case A (an insurance company) limited data reputation, caused by missing data lineage, resulted in the creation of data silos and higher operational costs. Similarly, in case E (a banking group) low data findability and understandability contributed to a 1.5-year prolongation of the common data layer implementation and a 25% cost overrun, amounting to several hundreds of EUR. In case B (an electrotechnical manufacturer) operational costs were also affected due to low perceived data trust and accessibility. Finally, in case C (a retail company) low perceived relevance of customer segmentation data led sales teams to disregard analytics-based recommendations, reducing campaign efficiency and cross-sell performance.

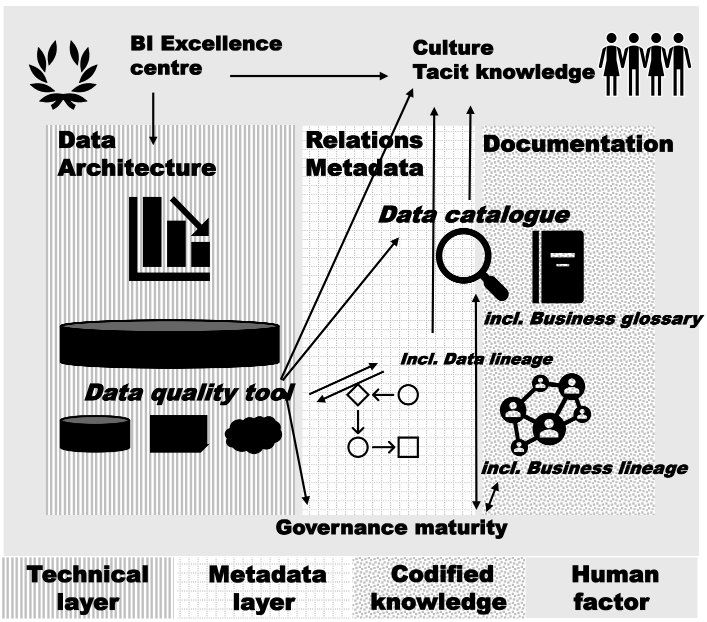

Fig. 2: **Four layers BI environment model with best-practice (cursive) for subjective data quality**

Source: own

This paper advances recent data-quality models by explicitly operationalizing user-oriented (subjective) dimensions inside BI solutions and validating them with empirical cases. Whereas Miller et al. (2024) extend ISO 25012 with new dimensions such as governance and usefulness, they stop short of detailing how these interact with users' competencies and organizational context inside BI; our four user-oriented dimensions (access, usability, processing, evaluation) and four-layer BI model fill that gap by specifying mechanisms that connect technical artefacts to perceived quality and knowledge creation. Likewise, industry-context reviews still emphasize design-time and system-level assurances (e.g., Fu et al., 2024) more than user perception; our findings integrate those assurances with user-centred determinants and show how they co-produce "fitness-for-use" in BI. In addition, our results align with and concretize the DQ dimension definitions and models proposed in recent cross-domain DQ syntheses (Wang et al., 2023) by mapping them to concrete BI critical success factors. Finally, we connect perceived data quality to BI usage depth, complementing evidence that perceptions of quality disproportionately drive advanced (vs. routine) analytics use (Mudau et al., 2024).

Beyond theoretical contribution, the results highlight the managerial importance of treating subjective data quality as an organizational capability. Relative to the emerging playbooks on data catalogues (Petrik et al., 2023), lineage, and governance, our contribution specifies which capabilities matter most for user-perceived quality and why. We translate data catalogue into actionable levers–business glossaries, searchable metadata, data lineage and business lineage. that demonstrably improve access, interpretation, and trust for BI users. We strengthen the lineage-to-governance link with evidence that end-to-end (technical + business) lineage most strongly affects interpretability and evaluation perceptions, extending recent governance/lineage treatments beyond. We also position BI Centres of Excellence not just as operating models but as quality enablers that coordinate governance, shared definitions, and competency building, an angle only briefly treated in current guidance. Finally, our best-practice set complements surveys of DQ tooling by showing how tools produce value when embedded in culture, roles, and knowledge flows, turning monitoring/checks into perceived usefulness and adoption in BI.

Future research should extend validation across sectors and geographies, employ longitudinal designs to capture temporal dynamics, and test the framework's applicability in diverse technological and cultural settings. Particular attention should be given to integrating subjective data-quality dimensions into AI-driven BI environments, where interpretability, trust, and user-centred quality are pivotal for adoption and responsible use (Bertossi & Geerts, 2020; Liang et al., 2022).

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Appendix

Structured interview protocol

Semi-structured interview conducted with a data management professional in team leader role.

I. Data importance in the organization

A. Do you consider data a key driver for decision-making in your company? Are there any exceptions?
B. Is data mainly leveraged in marketing processes (e.g., from product development to distribution)? If not, which areas are the most data-intensive?
C. Where do you see the main value-added use of data across the organization?

II. Data architecture

A. Is your current data architecture aligned with the strategic importance of data in your company?
B. Can you describe the architecture? Does it include a central component (e.g., data warehouse, data lake, marketplace, or platform)?
C. Is the solution fully centralized, or do you also maintain decentralized ("siloed") systems?

III. Roles, processes, and responsibilities

A. How is the operation of your data solution organized? Do you have specialized units?
B. Which roles are responsible for managing or supporting the data solution?
C. Are there any specific roles dedicated to data analysis or related functions?
D. Have you implemented data governance? What is its scope?
E. What tools or platforms support your data governance processes?

IV. Data quality management

A. Is data quality actively managed in your organization? On which levels and in what scope?
B. Does the current level of data quality reflect your organizational ambitions in terms of data use?
C. Who is accountable for ensuring data quality?

V. Selected data quality dimensions

a) Data accessibility

A. Is data in your organization easily findable and accessible?
B. What technological, documentation, or organizational tools do you use to improve data accessibility?
C. What could help further improve this area?

b) Data usability

A. Are your data considered relevant, objective, and trustworthy for key uses?
B. What tools or practices enhance data reputation and ensure relevance and objectivity?
C. Do you monitor the objectivity of data or derived products (e.g., reports, analyses)? What could improve this?

c) Data interpretability

A. Are your data understandable and interpretable? Is the storage format suitable for use in terms of structure, content, and units?
B. What supports user comprehension and correct interpretation of the data?
C. What could improve this area further?

d) Value assessment

A. Do you assess the added value generated from data?
B. If yes, what tools or processes do you use to support such assessment?

VI. Knowledge management in the data domain

A. Do you manage knowledge related to data? How and by whom?
B. How is data-related knowledge captured and stored?
C. Is there a collaboration platform supporting knowledge exchange?
D. Do you maintain a data catalog?
E. Do you apply consistent terminology, definitions, and taxonomies?
F. Do you share business-oriented reference lists (e.g., product types)?
G. Do you use advanced techniques (e.g., text mining) to extract knowledge from existing documentation?
H. How accessible is data-related knowledge across different roles?
I. What types of knowledge are currently inaccessible (e.g., tacit knowledge)? Are there plans to improve this?

VII. Additional best practices

A. Is there anything else you would highlight as a best practice that contributes to better data utilization in your organization?