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GLOBAL TRENDS IN SCIENCE: RESEARCH, INNOVATION AND DEVELOPMENT

ISSUE №109

eoss-conf.com



**October 12-14, 2026
Varna, Bulgaria**





**EUROPEAN OPEN
SCIENCE SPACE**

**Proceedings of the 4th International Scientific
and Practical Conference**

**"Global Trends in Science: Research,
Innovation and Development"**

October 12-14, 2026

Varna, Bulgaria

Collection of Scientific Papers

Bulgaria, 2026

UDC 01.1

Collection of Scientific Papers with the Proceedings of the 4th International Scientific and Practical Conference «Global Trends in Science: Research, Innovation and Development» (October 12-14, 2026, Varna, Bulgaria). European Open Science Space.

ISBN 979-8-89704-966-0 (series)

DOI 10.70286/EOSS-12.10.2026



The conference is included in the Academic Research Index ReserchBib International catalog of scientific conferences.



The conference is registered in the database of scientific and technical events of UkrISTEI to be held on the territory of Ukraine (Certificate №563 dated 28.07.2026).



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ISBN 979-8-89704-966-0

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Section: Information Technology, Cyber Security and Computer Engineering

REQUIREMENTS ENGINEERING FOR DATA ANALYTICS PROJECTS: A PRACTICAL FRAMEWORK FOR EARLY-STAGE PLANNING

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Abstract. Data analytics projects depend not only on analytical techniques but also on the quality of the requirements defined before data acquisition and analysis begin. Unclear goals, poorly specified data sources, and mismatched expectations about outputs can increase project complexity and undermine the usefulness of results. This paper examines how requirements engineering can support the early planning of data analytics projects. It synthesises literature on data analytics, data-driven decision-making, and requirements engineering, with particular attention to the generic requirements template proposed by Kumarasinghe and Kirikova for descriptive and diagnostic analytics. The paper organises key requirements around four phases—initiation, acquisition, analysis, and presentation—and develops a practical checklist for discussions between analysts and stakeholders. The checklist covers project objectives, data sources and properties, data preparation, analytical methods, tools, result validation, and reporting requirements. It is intended to improve completeness and communication at the project's outset, while recognising that detailed requirements must be refined for each project context.

Keywords: data analytics, requirements engineering, project planning, data quality, descriptive analytics, diagnostic analytics

Introduction. Data analytics has become an important means of understanding real-world systems and supporting evidence-informed decisions. By applying mathematical, statistical, and computational techniques to data, organisations can describe patterns, investigate events, and communicate insights to decision-makers [1, 4]. However, the availability of data and analytical software does not automatically yield useful results. An analytics project can fail to meet stakeholder expectations when its objective is vague, the intended users are not identified, the data are unsuitable, or the final deliverable is not clearly specified.

Requirements are not merely administrative documentation. They connect a stakeholder's need to the work analysts perform and the outputs users will ultimately

receive. Hussain, Mkpojiogu, and Kamal [2] discuss the role of requirements in software project success and failure, highlighting why requirements should be addressed systematically rather than treated as an informal conversation. The same principle applies to data analytics, where a project may involve several data sources, transformations, analytical choices, and forms of presentation.

ISO/IEC/IEEE 29148:2018 provides a standardised basis for requirements engineering across systems and software life cycles [3]. It frames requirements in relation to needs, constraints, and conditions. In analytics projects, these may include access permissions, dataset characteristics, rules for incomplete data, analytical methods, software tools, verification practices, and the expected format of results. Fawcett and Provost [4] connect data analysis to business decision-making, making the definition of the decision context an important part of project planning.

A particularly relevant contribution is the study by Kumarasinghe and Kirikova [6], which derives a generic requirements template from descriptive and diagnostic analytics cases. The authors structure analytics work into four phases: initiation, acquisition, analysis, and presentation. Their template is intended to reduce the complexity of identifying requirements from scratch and to serve as a starting point for stakeholder discussions. The present paper builds on that contribution by synthesising the main areas of requirement into a compact, practice-oriented framework.

Aim and objectives of the study. The aim of this paper is to explain how a structured requirements checklist can support the early planning of data analytics projects and improve communication between analysts and stakeholders.

The objectives are: (1) to identify the principal requirement areas reflected in the selected literature; (2) to organise these areas according to the four phases of an analytics project; (3) to formulate a concise checklist for initial requirements elicitation; and (4) to discuss the checklist's practical value and limitations.

Research approach. This paper uses a focused literature-based synthesis rather than reporting a new empirical experiment. The five sources supplied for the study address data analytics, business-oriented data science, and requirements engineering [1–5]. The analysis also draws on the attached paper by Kumarasinghe and Kirikova [6], which proposes and applies a generic requirements template. The requirement areas from that paper are grouped by project phase and presented as questions for use during an initial stakeholder meeting.

The resulting framework is a conceptual and practical synthesis. It does not claim to statistically validate a new model, nor does it report original data collected from organisations. Its value lies in translating the literature into a usable structure for early project planning.

Research results and discussion. A data analytics project can be understood as a sequence of interdependent activities. During initiation, stakeholders establish the goal and decide what kind of analysis is appropriate. During acquisition, the team identifies and obtains the data, including transformations needed to make them usable. During analysis, appropriate methods and tools are used, and the reliability of the results is considered. During the presentation, findings are communicated in forms that

suit the intended users. Requirements should anticipate all four phases at the beginning, even though some details may be refined as the project develops.

The distinction between descriptive and diagnostic analytics is important. Descriptive analytics addresses what happened or what is happening, while diagnostic analytics investigates why a particular event or pattern occurred [1, 6]. A descriptive project may focus on summarising observations through counts, distributions, or visualisations. A diagnostic project may require a defined system or object, evaluation metrics, analytical models, and explicit procedures for checking whether proposed explanations are supported. Accordingly, a general template needs shared requirements as well as conditional requirements that apply only to particular project types.

The proposed checklist consolidates these requirements into four phases. It is based on the generic template in [6] and informed by broader requirements engineering and data analytics sources [1–5].

Table 1 – Requirements checklist for initiating a data analytics project

Project phase	Questions to be answered	Requirements to specify
Initiation	What problem or opportunity is addressed? Who are the stakeholders and intended users? What does success mean? Is the task descriptive or diagnostic?	Goal and scope; target system or object; stakeholder knowledge level and key terminology; strategy; quantitative metrics where relevant; validation expectations where required.
Acquisition	Which datasets and sources will be used? How will data be accessed and collected? What data do datasets contain? Can incomplete data be used?	Data sources and access; dataset contents and properties; collection procedures; derived data; data preparation and ETL; data warehousing, where relevant; rules for incomplete datasets.
Analysis	Which approach, models, algorithms, and software are appropriate? What is each model used for? How will reliability be assessed?	Analytical approach and details; equations or algorithms where needed; model source and purpose; tools/software; procedures for reliability, verification, or validation.
Presentation	How should findings be communicated? Which visualisations and textual formats are required? How will users apply the results?	Required charts and visual outputs; report structure and format; categorisation of diagnostic causes where relevant; level of technical detail; intended use of findings.

Source: Authors' synthesis based on [1–6].

Initiation: defining the problem and success. The first phase should establish a clear goal and define the system or object to be analysed. A statement such as “analyse customer data” is too broad to guide project decisions. A more useful goal identifies the issue, the population or process concerned, and the decision the analysis is expected to support. Stakeholders should also agree on the type of analytics required and the level of technical detail appropriate for the intended audience.

For diagnostic projects, the initiation phase may also require quantitative metrics to evaluate the system and an explicit plan to verify or validate results [6]. These requirements help distinguish an informative description from an explanation that must be supported by evidence. The goal should be sufficiently precise to guide data selection and method choice, but flexible enough to be refined if early investigation reveals limitations.

Acquisition: specifying data and constraints. Data acquisition requirements should specify both the data source and its contents. Naming a database or file is not sufficient if the team has not agreed on which variables, records, time periods, or categories to use. The collection procedure and restrictions on access or reuse should also be documented. These details make the project more transparent and help stakeholders judge whether the proposed data can answer the research question.

Data preparation is another essential consideration. The generic template in [6] highlights the need to define derived data and, where relevant, ETL (Extract, Transform, Load) and data warehousing. Projects should specify how missing or incomplete datasets will be handled, rather than deferring this decision until analysis begins. Data limitations may constrain the scope of conclusions, so they should be communicated before findings are interpreted.

Analysis: methods, tools, and reliability. The analysis phase should specify the broad approach and the level of detail needed to reproduce or understand it. Depending on the project, this may include statistical techniques, visualisation approaches, diagnostic models, equations, algorithms, and an explanation of the role of each tool. Runkler [5] provides a general treatment of data analytics methods, while Fawcett and Provost [4] connect analytical work to business problems and decisions. The method should be selected based on the goal and the properties of the available data, not simply because a tool is familiar.

Requirements should also address the reliability of results. The appropriate checks depend on the analytical task, but the project should state how errors, assumptions, or alternative explanations will be considered. In diagnostic analytics, verification is particularly important because observed relationships do not automatically establish causation. A requirement should describe what will be checked and what evidence will be considered sufficient for the intended use of the result.

Presentation: communicating findings for use. Presentation requirements define how the results will be delivered and interpreted. Outputs may include tables, charts, dashboards, or a written report. The intended audience influences the choice of format and the amount of technical explanation. For example, a management dashboard may prioritise a small number of indicators and clear visual comparisons, whereas a technical report may need to document methods, assumptions, and limitations in greater detail.

The template in [6] also draws attention to the way diagnostic causes are categorised and to the intended use of analytical findings. These elements matter because a technically correct analysis can still be of limited value if users cannot interpret the result or connect it to a decision. Presentation requirements should therefore be discussed at the start, not postponed until the analysis is complete.

Practical application and limitations. A structured checklist can improve the first stakeholder conversation by making implicit assumptions visible. It gives the analyst a consistent sequence of prompts and helps identify gaps before significant time is invested in data processing or model development. The source study [6] reports applying its template to a real-estate analytics project, in which it supported the elicitation of 13 requirements during a stakeholder interaction lasting no more than 70 minutes. The template was also applied in a multidisciplinary student project involving a classification model for the human gut microbiome, supporting discussion of datasets, data sources, and analytical techniques.

These examples suggest that a generic template can be useful at the start of a project, but they do not imply that a checklist alone provides a complete specification. The real-estate stakeholder expected more specific requirements, underscoring the need for follow-up elicitation and refinement [6]. In practice, each requirement should be checked for clarity, feasibility, relevance, and verifiability. Where several stakeholders are involved, conflicting priorities may need to be resolved and documented.

The framework also has a defined scope. The source template focuses on descriptive and diagnostic analytics. Predictive analytics, which estimates future outcomes, and prescriptive analytics, which support the selection of actions, may require additional requirements concerning model performance, uncertainty, monitoring, and decision constraints. These aspects should be treated as guidance for adaptation and further investigation rather than as validated elements of the present checklist.

Conclusions. Requirements engineering provides a practical foundation for planning data analytics projects. A framework organised around initiation, acquisition, analysis, and presentation helps stakeholders consider the project goal, target system, data sources, data preparation, analytical methods, tools, reliability of results, and reporting expectations before implementation. This early structure can reduce ambiguity and improve communication between analysts and project users.

The checklist presented in this paper synthesises selected literature and the generic requirements template proposed by Kumarasinghe and Kirikova [6]. It is intended as an initial aid for descriptive and diagnostic analytics, not as a substitute for detailed stakeholder analysis or project-specific requirements. Further work should examine its application across additional domains and, with appropriate validation, extend it to predictive and prescriptive analytics.

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MODERN NEURAL NETWORK-BASED METHODS FOR STEGANOGRAPHY

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In the modern digital environment, images are an important part of information exchange and storage. At the same time, they can be used not only to transmit visual data but also as carriers of hidden information. For this purpose, steganography is used as a method of concealing a message so that the very existence of the hidden information remains unnoticed by an unauthorized observer. One promising direction in its development is neural network steganography, in which machine learning models are used to embed hidden information into images and subsequently extract it.

The basis of neural network steganography is the process of concealing secret information within a carrier image. During the embedding stage, the neural network model receives the carrier image and the message and then generates a stego image in which the hidden information should remain imperceptible to the human eye. During the extraction stage, another part of the model processes the received stego image and recovers the hidden message. Thus, the performance of the system is determined not only by its ability to conceal information but also by its ability to correctly recover it after the image has been transmitted or processed (Fig. 1) [1].



Figure 1. General scheme of neural network steganography

During transmission and subsequent processing, a stego image may undergo various distortions that affect the hidden information. These include JPEG compression, noise addition, resizing, blurring, image cropping, and, in some cases,

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