Proposal Success in a European Call for Digital Innovation Intermediaries: A Text Analysis of Applications

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Abstract

This study examines how document features influence grant proposal success in competitive research funding. Analyzing proposals submitted to the European call for digital innovation intermediaries, we investigate whether proposal success depends on content alignment with agency priorities and communication quality, measured through document structure, text readability, and linguistic tone. We find that proposals with greater emphasis on conceptual content, higher readability, and less constraining language achieve significantly higher evaluation scores and more favorable funding outcomes. Technological diversification reflecting applicants' capabilities and alignment with policy objectives affects expert scores but not final funding decisions, while visual elements show the opposite pattern, suggesting distinct cognitive stages in the evaluation process. Our findings indicate that how ideas are communicated matters as much as what is communicated, with practical implications for proposal preparation and evaluation design. Improvements in communication quality could yield substantial gains in proposal success.

JEL classification: O30; O38; D83, O32, C55

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1. Introduction

Business communication involves the creation of clear, strategic messages tailored to achieve defined business objectives. Start-up business plans are designed to attract potential investors, e.g., Venture Capitalists, by presenting a compelling case for the business idea they try to secure funding by demonstrating viability and growth potential. Initial Public Offering (IPO) prospectuses include detailed information about a company's financial health, business strategy, risks, and governance. They are intended to inform and reassure potential shareholders during the public listing process, ensuring transparency and regulatory compliance. Annual reports offer an overview of a company's performance, including financial results, strategic developments, and future outlook (Healy and Palepu 2001; Bloomfield 2002). Besides fulfilling legal reporting requirements, they are crucial for maintaining investor confidence, persuade and build credibility. At the same time, research on patent disclosure shows that textual quality may reflect strategic disclosure choices, whereby firms deliberately reduce clarity or increase vagueness to manage information asymmetries, as observed in corporate patenting (Kong et al. 2023). Each of the above types of business communication serves a specific function but shares a common objective: to support the organization's strategic goals through effective, purposeful messaging. It has been shown that the quality and clarity of business communication reflect the overall potential and performance of the business they represent (Li 2008; Subramanian et al. 1993; Eugene Baker and Kare 1992). Overall, high quality communication helps to reduce information asymmetry between the organization and its stakeholders (Brown and Hillegeist 2007; You and Zhang 2009).

Inspired by the evidence highlighting the importance of language quality and clarity for the success of business operations, we extend this perspective to study the proposals submitted to a call for research and innovation (R&I) grants. Like other forms of business communication mentioned above, applications for public funding represent a distinctive type of purposeful communication. They share fundamental similarities with business plans, IPO prospectuses, and annual reports in that they all aim to secure resources or support by persuading a specific audience through clear, credible, and strategically aligned communication. Grant proposals, like investment documents, must balance technical detail with accessibility, demonstrate feasibility and impact, and align with the objectives and expectations of the funding body, similar to how business documents align with investor or regulatory priorities (Connor and Upton 2004). Moreover, both rely on clarity, coherence, and persuasive structure to reduce uncertainty and foster trust in the organization's

competence and vision. These parallels underscore that successful grant writing, much like effective business communication, depends not only on the substantive quality of the content but also on its rhetorical effectiveness and alignment with stakeholder expectations. Thus, we are analyzing if proposal success depends on effectively aligning the proposal with the agency's strategic priorities and evaluation criteria.

To analyse this question empirically, we use a dataset of 328 proposals submitted to the 2021 two calls for EU action grants in the field of Deployment of Capacities and Interoperability under the Digital Europe Programme (EC 2021). These calls aimed to establish a network of European Digital Innovation Hubs (EDIHs), which act as intermediaries connecting research institutions, industry, and public sector organisations to support the digital transformation of companies and public administrations (De Nigris et al. 2023; Carpentier et al. 2025). The EDIH proposals follow a standardized structure used across EU funding programmes, available through the Funding and Tenders Portal. Each application includes Part A, containing administrative information, and Part B, a narrative description of the project. Our analysis focuses on the textual content of Part B, as it is the main vehicle through which applicants communicate the relevance, feasibility of implementation, alignment with policy objectives and expectations of the funding body, and expected impact of their projects. This corpus provides a consistent and representative basis for examining how linguistic quality, clarity, and rhetorical structure may influence evaluators' assessments and, ultimately, funding outcomes.

Although the success factors of proposals submitted for public subsidies have been widely studied, reflecting the growing role of the public sector in supporting R&I, an analysis of the actual text quality and alignment of these proposals appears to be missing in the literature. Existing studies typically rely on quantitative rather than qualitative measures to assess the determinants of proposal success. For example, they often use scientometric indicators to measure the research performance of applicants (Bornmann et al. 2010; Van Den Besselaar and Leydesdorff 2009), financial and innovation performance measures (Mina et al. 2021; Bellucci et al. 2025), or consortium characteristics (Wanzenböck et al. 2020; 2015; Lepori et al. 2015).

The inclusion of proposal texts in analyses of how language affects funding success is gradually gaining traction as new analytical tools enable large-scale text analysis. Initial studies indicate that, as in other forms of business communication, the quality, clarity, tone, and structure of proposal

texts play an important role in convincing funding bodies of their merit. Consequently, the wording and presentation of grant proposals influence evaluation scores and funding outcomes (van den Besselaar and Mom 2022). Moreover, longer texts that use fewer common words and convey greater verbal certainty tend to secure higher funding amounts (Markowitz 2019). Similarly, significant relationships have been found between linguistic features of proposals and grant productivity (Tohalino et al. 2021). Examining the quality of proposal texts is therefore justified, as written communication is the primary medium through which applicants convey the feasibility and significance of their ideas to evaluators.

Beyond offering new research insights, our study also has important practical implications for the development of efficient and scalable approaches to grant proposal evaluation, particularly using advanced text analysis tools. The growing reliance on public support for R&I has led to a rapid increase in the number of funding applications, a trend further amplified by the availability of modern generative tools that facilitate proposal preparation. This development is clearly illustrated by the sustained and substantial interest in the European Union's (EU) R&I programmes. Participation has expanded considerably over time, resulting in a very large volume of proposals requiring evaluation. For example, the EU's Seventh Framework Programme received 598,080 eligible applications, while Horizon 2020 and Horizon Europe attracted approximately 146,000 and 120,000 applications per year, respectively (EP 2016; RTD 2024). This scale places significant organizational and administrative demands on the evaluation process. Under Horizon 2020 alone, more than 22,000 independent experts from 114 countries evaluated over 850,000 proposals (RTD 2021).

As part of efforts to improve the evaluation process, the European Commission (EC) has explored various approaches to enhance efficiency without compromising quality and fairness. One such measure was the reduction of the application page limit from 70 pages in Horizon 2020 to 45 pages in Horizon Europe. While this change aimed to streamline the evaluation process and ease reviewers' workload, it does not fundamentally address the underlying challenge—the ever-increasing number and complexity of proposals to be assessed. Consequently, experts analysing the R&I evaluation system have highlighted the need for more transformative solutions. In particular, the adoption of advanced analytical and digital tools has been identified as a promising avenue to support and complement human evaluation. Such technologies could improve multiple aspects of the process, including reviewer selection, content analysis, and the overall consistency

and objectivity of assessments. By applying the same systematic approach to all proposals, they could also help mitigate variability and potential bias among reviewers (Pier et al. 2018).

Building on the discussion above, this study addresses both conceptual and practical gaps at the intersection of language use and research evaluation. While previous work has highlighted the importance of textual clarity and communicative quality in determining the success of business and funding proposals, systematic evidence on how these factors influence the outcomes of large-scale R&I grant application evaluations remains limited. At the same time, despite growing recognition of the administrative pressures placed on evaluators, the practical integration of advanced text analysis tools into the assessment process is still underexplored. This study therefore pursues a twofold objective. First, it examines the linguistic quality of submitted grant proposals and its correlation with evaluator assessments, seeking to identify how the content, structure, and clarity of written communication affect funding success. Second, by applying computational text analysis techniques focused on readability and textual quality, the research explores whether these tools can effectively support evaluators in their complex and time-constrained tasks. The goal is to determine how automated approaches can provide actionable insights that streamline the evaluation process, improve consistency and transparency in assessments, and alleviate administrative workload. Ultimately, the study contributes both theoretically and practically by assessing the feasibility and potential added value of integrating text analysis tools into the evaluation framework of the EU's R&I funding programmes, thereby addressing a critical need for efficiency, fairness, and scalability in an era of growing proposal volumes.

The remainder of the paper is structured as follows. Section 2 reviews the literature on business and research communication, emphasizing the role of language quality, clarity, and rhetorical structure in the success of proposals, and derives the hypotheses guiding our analysis. Section 3 describes the dataset of EDIH proposals and the standardized structure of EU grant applications. Section 4 outlines the text analysis methodology used to assess linguistic quality and readability. Section 5 presents the empirical results, examining the relationship between textual features and evaluators' assessments. Finally, Section 6 concludes by summarizing the key findings, discussing their implications for research funding practices, and highlighting the potential of advanced text analysis tools to support more efficient and consistent evaluation processes.

2. Literature Review and Hypotheses

Purposeful business communication involves the creation of clear, strategic messages tailored to achieve defined business objectives. These strategic communications are typically aimed at external stakeholders such as investors, shareholders, regulatory bodies, or the general public. Their purpose is not only to inform but also to persuade, build credibility, and support decision-making (Hallahan et al. 2007; Cornelissen 2000).

Examples of purposeful business communication include startup business plans, Initial Public Offering (IPO), annual reports, and applications for public grants. *Start-up business plans* that are designed to attract potential investors, such as venture capitalists and secure funding, by presenting a compelling case for the business idea— the company's vision, target market, product or service offering, competitive advantage, and financial viability (Honig and Karlsson 2004; Mason and Stark 2004). *Initial Public Offering (IPO)* prospectuses, on the other hand, serve to inform and reassure potential shareholders by providing comprehensive information about a company's financial health, business strategy, risk factors, and governance (e.g., Hanley and Hoberg 2010). *Annual reports*, issued once a year, offer an overview of a company's performance, including financial results, strategic developments, and future outlook, aiming to fulfill legal reporting requirements, ensure transparency, and maintain investor confidence (Brennan and Merkl-Davies 2018; Beattie 2014). Similarly, *applications for public grants*, such as R&I subsidies, represent another form of purposeful business communication, with the goal of presenting a compelling case to a public agency by clearly demonstrating the quality, relevance, and potential impact of the proposed research or innovation project in order to secure funding (Derrick and Samuel 2016; Van Den Besselaar and Leydesdorff 2009).

While these documents serve distinct objectives, they share a common strategic purpose: to persuade decision-makers through clear and credible communication. The signaling literature shows that observable attributes of messages or their presentation convey information about otherwise unobservable quality (Connelly et al. 2011; Spence 1973). Prior research indicates that the clarity and quality of business documents meaningfully can operate as signals of managerial competence, organizational credibility and project potential (e.g., Parhankangas and Ehrlich 2014; Hartley 2013; Karlsson and Honig 2009; Li 2008; Hall and Hofer 1993). Yet, despite numerous manuals on writing successful proposals (e.g., Liu et al. 2016; Koppelman and Holloway 2012; Liu et al. 2016), systematic empirical evidence directly linking document characteristics to

evaluation outcomes remains scarce. Existing studies show that the quality, clarity, tone, and structure of grant proposal texts significantly influence evaluation scores, funding outcomes, and subsequent research productivity (van den Besselaar and Mom 2022). Longer, more precise texts with fewer common words and greater verbal certainty tend to perform better, highlighting the importance of written communication as the main medium through which applicants convey the feasibility and significance of their projects (Markowitz 2019; Tohalino et al. 2021).

Based on existing research, we argue that the communicative effectiveness of project proposals in achieving a specific goal—in our case, successful proposal evaluation and securing project funding—depends not only on the project's content and purpose but also on how the information is presented and communicated. Specifically, drawing on the literature presented below, we distinguish between different document features that may influence various dimensions of purposeful communication and contribute to success: (1) document structure and design, (2) text readability and complexity, (3) tone and sentiment of the language used, and (4) content demonstrating the proposal's alignment with the funding guidelines.

Document Structure and Design

First, we presume that document structure and design—especially the space in the document dedicated to discussion of the conceptual project idea as well as graphical presentation—may facilitate understanding of the project idea, leading in turn to higher evaluation success. Extensive research shows that visual elements (figures, flow charts, conceptual diagrams) can facilitate comprehension and cognitive understanding due to their capacity to efficiently summarise and convey potentially complex information (Mayer 2024; Hartley 2013; Tractinsky and Meyer 1999; Meyer et al. 1997; Lorch and Lorch 1995; Larkin and Simon 1987) and help form a coherent mental model of a project idea (Stone and Lodhia 2019; Schnotz and Bannert 2003).

In the proposal context, both the inclusion of informative figures and the allocation of space to conceptual framing (versus operational details) can communicate the maturity of the project concept and the plan's coherence and feasibility; such cues may exert an impact on evaluator's impressions and judgements (Stone and Parker 2013; Hall and Hofer 1993). Hence, our first hypothesis is formulated as follows:

H1: The structure and design of a proposal document influence proposal evaluation success.

Readability

Second, the readability of the text influences the communicative efficacy of the document and its persuasiveness. Readability refers to the ease with which a reader can decode and comprehend a written text, encompassing factors such as sentence length and structure, vocabulary complexity, and overall document clarity (Hartley 2013; Gunning 1952; Flesch 1948). Cognitive load and multimedia learning theories predict that higher textual readability reduces cognitive effort required to construct a coherent mental model of the project idea, allowing evaluators to focus on substantive issues rather than struggling with form (Sweller 1988; Mayer 2024). Empirical work in related evaluative settings supports this mechanism: in the context of financial disclosures, more readable filings are associated with stronger market responses, greater perceived transparency, and a higher firm's bankruptcy risk (Yang et al. 2022; Taylor and Riley 2017; Li 2008; Graham et al. 2006). In investor and management research, dense or overly complex wording has been shown to reduce persuasive impact, increase perceived opportunism or obfuscation, and affect investor comprehension and market responses (Loughran and McDonald 2016; Tan et al. 2014; Bodnaruk et al. 2015; Loughran and McDonald 2011). Further, Boyack et al. (2018) revealed that the clarity and quality writing in research proposals are positively related to the proposal success in funding competition.

Given theoretical and empirical evidence, as well as the fact that reviewers typically evaluate many proposals under time pressure (Abdoul et al. 2012), we presume that less readable, more complex research proposals increase evaluators' cognitive burden, which can obscure a project's merits and reduce its chances of funding. Hence, our second hypothesis is as follows:

H2: The readability of the proposal text positively influences proposal evaluation success.

Linguistic Tone and Sentiment

Third, the tone or sentiment of the language used in funding proposals is a further important document feature that can influence evaluators' perceptions and decisions. Loughran and McDonald (2011; 2016) developed specialized dictionaries and sentiment measures for business and financial document analysis to quantify theses aspects and to link them to economic outcomes—identifying categories such as positive, negative, uncertain, litigious, constraining, and

modal language.[2] Their research demonstrated that these linguistic features from corporate filings and earnings announcements predict market reactions and relate to firm risk, litigation, and managerial behavior (Loughran & McDonald, 2011; Loughran & McDonald, 2016). For example, a higher frequency of negative words or uncertainty terms in 10-K filings tends to be associated with worse subsequent performance and stronger adverse market responses, while positive tone often reflects with optimistic (sometimes overly optimistic) managerial framing—indicating that textual tone conveys meaningful information to stakeholders beyond numerical data (Loughran and McDonald 2011).

Other scholars have extended these findings across various business communication contexts. For example, Davis et al. (2012) found that the tone of earnings press releases affects market reactions, with more positive language associated with stronger stock performance. Henry and Leone (2016) showed that the tone in financial disclosures adds information beyond the financial statement, with negative qualitative information having a greater effect on stock prices than positive information. Pouryousof et al. (2023) revealed a positive relationship between inconsistency in the use of positive and negative language in financial reporting and a company's future performance, and a negative relationship with its future risk. Parhankangas and Renko (2017) found that linguistic style, including the use of concrete and precise language, significantly influences crowdfunding success by allowing crowdfunders to develop a clearer mental representation of the campaign's purpose and expected outcomes. Davis et al. (2017) demonstrated that entrepreneurs' passionate language in crowdfunding pitches increase funders' positive reactions and investment likelihood. Allison et al. (2017) showed that persuasive communication strategies, including positive framing in pitch narratives, significantly increase funding success. Moreover, Hyland (1998) revealed that hedging in academic writing enables scholars to present claims cautiously; however, excessive hedging reduces perceived confidence.

Accordingly, we assume that the tone and sentiment of the proposal text can shape evaluators' impressions in two ways: positive language may signal project feasibility and team confidence—likely increasing perceived chances of success—while constraining and/or uncertain language may

[2] Loughran and McDonald (2016; 2011) showed that general sentiment dictionaries (developed for social science research like Harvard IV-4 word lists) perform poorly on business and financial documents because many common words have different connotations in finance/accounting.

rise concerns about project feasibility, diminishing the proposal's funding chances. Thus, our third hypothesis is as follows:

H3: The tone of the proposal text influences proposal evaluation success.

Proposal Content and Alignment

Finally, the proposal content itself—informing about the project and demonstrating alignment with the call and funding guidelines—fundamentally influences the proposal's evaluation success (Laudel 2006; Derrick and Samuel 2016; Langfeldt 2006). Content quality represents the core substance of a funding application and encompasses multiple interrelated dimensions that evaluators systematically assess during the evaluation process, including the relevance and novelty of the project idea or innovation, the soundness and feasibility of the proposed approach and methods, expected impact and fit with funder priorities and criteria (Abdoul et al. 2012; Boyack et al. 2018; Van Den Besselaar and Leydesdorff 2009; Laudel 2006; Marsh et al. 2008; Jayasinghe et al. 2003; Gallo et al. 2014). Hence, our fourth hypothesis is formulated as follows:

H4: The content and alignment with the funding guidelines positively influence proposal evaluation success.

Overall, however, we presume that excellent substantive content alone does not guarantee funding success; proposals must also effectively communicate that content. Where content is weak on critical dimensions such as novelty or alignment with funder priorities, favorable presentation alone is unlikely to secure funding. Conversely, proposals with excellent substantive merit can be undermined by poor alignment with the specific call requirements or by unclear, inaccessible exposition that obscures the project's strengths. Thus, proposal content and alignment represent necessary but not sufficient conditions for funding success.

3. Context and Data

3.1. The European Call for Digital Innovation Intermediaries

The European Union's Framework Programmes (FPs) for R&I were launched in 1984 to address a growing research gap between Europe and other regions, initially focusing on pre-competitive research to strengthen Europe's technological capabilities. Over time, the scope of the FPs expanded, integrating innovation alongside research, as highlighted in FP7 and FP8, reflecting a

shift towards a collaborative innovation ecosystem and the recognition of knowledge and innovation as key drivers of economic growth (EC 2015). More recently, EU support has extended across the full innovation value chain, exemplified by the Digital Europe Programme (DEP) and the EDIHs (De Nigris et al. 2023). The objective of EDIHs are to support the adoption and diffusion of digital technologies while enabling broader digital transformation of European economies (Colovic et al. 2025).

Launched in 2021, the EDIHs initiative adopts a bottom-up approach to organising digital innovation intermediaries at the regional level (EC 2021). Conceived as one-stop shops for digital innovation support, EDIHs aim to ensure that SMEs and public-sector organisations across Europe can easily access the expertise and guidance needed to adopt advanced digital technologies and leverage them to develop new or improved products, services, and processes. By initiating the programme through a call for proposals to self-organised consortia, the initiative sought to build on existing regional strengths while integrating these actors into a coordinated European network.

At the time of the call, EDIHs were expected to combine strong regional anchoring with the advantages of a pan-European structure. Their local presence was intended to ensure close engagement with regional industry and innovation ecosystems, offering support responsive to local needs. At the same time, the EU-wide network was meant to enable exchanges of best practices and provide access to specialised expertise when it was not available locally. In this dual capacity, EDIHs were expected to act as intermediaries that reduce fragmentation in innovation support, offer more coherent access to digital transformation resources, and accelerate the translation of digital technologies and research into market-ready applications.

A total of 328 applications were submitted to two EDIH calls, of which 151 were selected for funding (De Nigris et al. 2023). An additional 76 proposals received the Seal of Excellence (SoE) for national funding eligibility. The network became gradually operational from September 2022.

As established, the EDIH Network comprises 2,355 organisations, including universities, research institutes, private companies, primarily in ICT and professional services, and various associations. Each EDIH is regionally anchored and organised as a multi-partner collaboration that brings together research organisations, industry associations, incubators, accelerators, and vocational training providers. Through this configuration, EDIHs are expected to orchestrate regional digital innovation ecosystems, ensuring that SMEs and public sector actors can access the expertise,

services, and scalable digital solutions they need, while simultaneously fostering cooperation at regional, national, and European levels.

In practice, the network has taken shape as a diverse and flexible support infrastructure. As *one-stop shops* for digital innovation support, EDIHs innovation intermediaries providing access to testing facilities and technical expertise alongside innovation services such as training, access to finance, and skills development (Carpentier et al. 2025). They also assist organisations in deploying digital technologies to improve sustainability. On average, each EDIH supports nine technologies, spans seven sectors, and delivers eight types of services. This reflects the breadth of their activities and their capacity to adapt to differing regional and sectoral needs.

3.2. EDIH proposal submission and selection

In this paper, we focus on the question of whether the success of grant proposals depends on how effectively applicants align their submissions with the funding agency's strategic priorities and evaluation criteria. To investigate this, we analyse 328 proposals submitted to the first two calls for EU action grants described above.

The structure of EDIH proposal documents follows a standardized format of *application form* available at the EU Funding & Tenders Portal, which serves as the template for EU grants applications.[3] Each application is submitted through the portal and consists of two parts: Part A, which captures structured administrative information, and Part B, which provides the narrative technical description of the project.

In the current analysis, we use the Part B of the application forms that include technical description of the proposed projects. Proposals typically begin with *General Information* such as the project title, proposal number, and coordinating organization. The *Relevance* section outlines the objectives, innovation potential, and alignment with EU digital transformation priorities. The *Implementation* section describes the work plan, methodology, and roles of participating organizations, often structured into work packages with defined deliverables, timelines, and milestones. The *Impact* section highlights expected benefits for SMEs and the public sector, emphasizing scalability and long-term sustainability. The consortium description presents the expertise and responsibilities of each participating entity, demonstrating their capacity to execute

[3] https://ec.europa.eu/info/funding-tenders/opportunities/portal/screen/home

the project. Finally, the *Budget and Resources* section provides a detailed financial breakdown, justifying the requested funding. This structured format ensures that proposals communicate their strategic, technical, and financial viability clearly and effectively for EU evaluation.

After a proposal is submitted, the EC performs a formal check to verify its admissibility, i.e., whether it is complete and properly assembled, and eligibility, that is, if it meets all eligibility conditions. Proposals that pass these checks are evaluated through a one-step evaluation process carried out by an independent evaluation committee. This committee is usually composed of European Commission staff from the Granting Authority, in the case of the EDIH Network, the Directorate-General for Communications Networks, Content and Technology (DG CNECT), and is supported by external experts who carry out individual assessments and take part in consensus evaluations.

Eligible proposals are then assessed based on three award criteria: *Relevance*, *Implementation*, and *Impact*. *Relevance* considers alignment with EU objectives, contribution to long-term policy goals, and potential to facilitate the adoption of digital technologies among European firms. *Implementation* evaluates the project's maturity, feasibility, resource efficiency, and the applicants' capacity to execute the work. *Impact* measures the project's expected outcomes, societal and economic benefits, and contributions to environmental sustainability.

The evaluation covers both the award criteria and the operational capacity of the consortium and its members. Operational capacity is assessed on the basis of participants' competence, experience, and operational resources, e.g., human, technical, and other that are necessary to implement and execute the project.

Proposals are ranked based on their scores, with priority given to higher *Relevance* scores, followed by *Impact* and then *Implementation* in cases of ties. Each criterion is scored out of 5 points, with a minimum threshold of 3 points per criterion. The maximum total score is 15 points, and proposals must achieve at least 10 points overall to be considered for funding, subject to budget availability.

The evaluation and scoring process leads to three possible outcomes for proposals:

(1) *Below threshold* – Proposals that fail to meet the minimum required score for one or more of the three award criteria (*Relevance, Implementation, or Impact*) or fail to reach the overall threshold of 10 points. These proposals are rejected and will not be considered for funding.
(2) *Above threshold* – Proposals that achieve at least the minimum score for each individual criterion (at least 3/5) and reach the overall threshold of 10 points. While these proposals are eligible for funding, they may not receive it if the budget is insufficient.
(3) *Main list* – Proposals that pass all thresholds and rank high enough to receive funding within the available budget. These proposals are prioritised based on their final scores. In case of ties, priority is given first to higher scores in *Relevance*, then *Impact*, and finally *Implementation*.

These two dimensions of evaluation results, i.e., the proposal's score and its funding outcome, are subsequently used as dependent variables in our empirical models to analyse how linguistic quality and alignment with the call objectives relate to evaluation performance.

4. Empirical strategy

To examine how the quality and content of project proposals relate to their success, we extract a range of document features that capture writing and presentation characteristics, and we estimate different regression models on the proposal evaluation results.

First, we run a linear regression of the continuous evaluation score:

$$y_{score} = x\beta + \epsilon, \quad (1)$$

where y_{score} denotes the observed expert score, x is the vector of proposal quality and content measures, as well as control variables (discussed below). βs are the coefficients estimated by ordinary least squares (OLS), and ϵ is the error term.

Further, our second dependent variable is the project final status $y_c \in \{1,2,3\}$, with three evaluation outcomes: $c = 1$ (*below threshold*), $c = 2$ (*above threshold*), and $c = 3$ (*main list*). Because y_c is a categorical ordinal variable, we estimate an ordered logit regression model. In this framework, the observed ordinal variable y_c is derived from an unobserved continuous variable y^* with two threshold points, μ_1 and μ_2. The value of the observed variable y_c depends on whether y^* crosses these thresholds, as follows:

$$y_c = 1 \quad if\ y^* \leq \mu_1, \tag{2}$$

$$y_c = 2 \quad if\ \mu_1 < y^* \leq \mu_2, \tag{3}$$

$$y_c = 3 \quad if\ \mu_2 < y^*. \tag{4}$$

The continuous latent variable is modeled as:

$$y^* = x\beta + \epsilon, \tag{5}$$

where x is the same set of the independent variables as above (see Eq. 1). The unknown parameters βs and thresholds μs are estimated by the maximum likelihood (ML) method; ϵ captures unobserved factors affecting the evaluation outcome.

The explanatory variables x—summarized in Table 1 (variables descriptions and descriptive statistics for the whole sample; groups-specific statistics for *below threshold, above threshold* and *main list* proposals are shown in Table A 1 in the Appendix)—capture proposal quality and content through four dimensions of document characteristics: (i) structure and design, (ii) text readability and/or complexity, (iii) linguistic tone, and (iv) proposal content and alignment.[4] To measure document structure and design—fundamental aspects of the textual analysis for conveying information (Mayer 2024; Loughran and McDonald 2016; Hartley 2013)—we use three indicators: a dummy for long documents (more than 50 pages), which primarily reflects proposals submitted in the second call; the number of figures as a proxy of the maturity of development and communication of the project idea; and the share of pages devoted to conceptual section, indicating the space allocated to explaining ideas versus providing operational details.

We assess textual readability and complexity using three widely used, traditionally indices (Mayer 2024; Kong et al. 2023; Yang et al. 2022; Collins-Thompson 2014): Flesch Reading Ease, Flesch-Kincaid Grade Level, and the Gunning Fog Index. The formulas are as follows:

[4] The extraction of document features was performed using appropriate Python libraries on 328 proposals provided as PDF files. First, the documents were converted to Word (DOCX) files and the characteristics required to compute measures of document structure and design were extracted (number of pages, number of pages devoted to the conceptual section, and number of figures). The proposal texts were then extracted and preprocessed for subsequent analysis: in step 1, each document was tokenised; in step 2, the most frequent terms (the so-called stop words) were removed; subsequently, abbreviations, headings, and numbers (including decimals) were removed so that remaining full stops can be assumed to mark sentence terminations—an assumption required later to determine variables such as the number of sentences in a document. The processed proposal texts were saved as plain TXT files for the calculation of text metrics and features relating to readability, tone and sentiment, as well as proposal alignment with the call objectives, as described in Section 4.

$$Flesch\ Reading\ Ease = 206.835 - 1.015\left(\frac{total\ words}{total\ sentences}\right) - 84.6\left(\frac{toal\ syllables}{total\ words}\right), \quad (6)$$

$$Flesch - Kincaid\ Grade\ Level = 0.39\left(\frac{total\ words}{total\ sentences}\right) + 11.8\left(\frac{total\ syllables}{total\ words}\right) - 15.59, \quad (7)$$

$$Gunning\ Fog\ Index = 0.4\left[\left(\frac{total\ words}{total\ sentences}\right) + 100\left(\frac{complex\ words}{total\ words}\right)\right], \quad (8)$$

where complex (i.e., difficult-to-read) words are defined as those of more than three syllables. The Flesch Reading Ease score reflects the US education system and ranges from 0 (professional reading level) to 100 (5th-grade level). The Flesch–Kincaid Grade Level is equivalent to US grade levels; values of 16 or more indicate text that is difficult to read (postgraduate level). Similarly, the Gunning Fog Index reflects how difficult a text is to read, corresponding to the years of formal education typically required to understand the text at first reading; scores of 17 or more indicate a postgraduate level. Because these measures are typically highly correlated (see Table A 2 for the correlation matrix), we consider them separately and estimate alternative model specifications for each index.

To capture the tone and the sentiment of the language used in proposals, we compute the proportions of words signalling positive framing ($\%positive$), uncertainty ($\%uncertainty$) and constraining language ($\%constraining$) relative to the total word count in each proposal, using the sentiment word lists developed by Loughran and McDonald (2011; 2016).[5]

Since EDIHs were conceived as a network of one-stop shops for digital innovation support across advanced digital technologies, we assess the technological diversification of submitted proposals to evaluate their content and alignment with the call objectives. To this end, we mapped proposal text to digital domains using the Digital Techno-Economic ecosystem (DGTES) keyword dictionary (JRC 2022).[6] Based on counts of distinct keywords associated with 15 technological areas (n=15), we calculated the Normalised Herfindahl–Hirschman Index ($NHHI$) for each proposal, which quantifies the degree of concentration—that is, how evenly or unevenly keyword

[5] Further information on the sentiment dictionaries, as well as the Python module provided by McDonald that we use in our analysis is available at https://sraf.nd.edu/loughranmcdonald-master-dictionary/.

[6] This dictionary defines a structured semantic space of 15 digital technology areas, developed through a two-step expert-guided process: (i) document scanning and (ii) semantic identification of keywords associated with each digital area. In total, the dictionary includes nearly 500 keywords mapped to these 15 areas, allowing detailed coverage of the digital ecosystem while avoiding redundancies. Examples of these areas include Artificial Intelligence, 5G and beyond, Advanced Computing, 3D Printing and Additive Manufacturing, Internet of Things, Blockchain, and Extended Reality.

counts are distributed across technological domains—as follows (e.g., Brezina et al. 2016; Khurshid et al. 2009):

$$NHHI = \frac{HHI - 1/n}{1 - 1/n} = \frac{\sum_{i=1}^{n}\left(\frac{c_i}{C}\right)^2 - 1/n}{1 - 1/n}, \quad (9)$$

where c_i is the number of distinct keywords in technological area i, and C is the total number of distinct keywords across all technological domains. $NHHI$ takes values in $[0, 1]$; $NHHI = 1$ if all keywords are associated with a single technological domain, and $NHHI = 0$ if the keywords are equally distributed across the fifteen categories. Thus, a lower $NHHI$ indicates greater diversification of a proposal across technological areas, reflecting closer alignment with the funder's objectives—namely, the EDIHs' role as one-stop shops for digital technologies expertise.

Finally, we include control variables—the requested funding amount, the share of project partners in the private sector, the number of consortium members, and their experience in R&I FP projects—to account for project-related differences that may affect proposals' evaluation scores and outcomes, independently of writing quality (Wanzenböck et al. 2020).

[Table 1 about here]

5. Results

5.1. Descriptive analysis results

Of the 328 proposals, 151 reached the main list, whilst approximately 54% did not receive funding: 108 were *above threshold* and 69 *below threshold*. The average evaluation score was 11.3 points and, as expected, *main list* proposals achieved significantly higher expert scores (on average 12.9 points) than *below threshold* proposals (on average 8.2 points) (see Table 1 and Table A 1).

The average requested funding amount was 4.27 million euro, with no significant differences between proposal statuses. However, significant differences were observed in the proportion of private sector partners and consortium member numbers. The private partner proportion was lower for *main list* proposals (23%) compared to *below threshold* proposals (34%). Interestingly, proposals *below threshold* involved consortium members with the lowest number of prior FP participations, underscoring the importance of experience in publicly funded R&I schemes. Limited familiarity with administrative procedures and evaluation standards may reduce proposal

quality, whereas experienced consortia benefit from accumulated knowledge, coordination capabilities, and reputational advantages (Wanzenböck et al. 2020).

Regarding document structure, proposals differed significantly in their communication strength and focus on the planned conceptual orientation of EDIH. *Main list* proposals dedicated a higher proportion of pages to the conceptual part (average 52%) compared to *below threshold* proposals (44%). *Main list* proposals also relied more heavily on communicating content through figures than other proposal statuses. Additionally, the frequency of documents exceeding 50 pages (indicating second call submissions) was higher (22%) for *above threshold* proposals. Furthermore, the readability of *main list* proposals' texts—assessed via traditional measures Flesch Reading Ease and Flesch-Kincaid Grade Level—was significantly higher than other document groups. Significant differences were also observed in the linguistic tone. The proportion of positive and constraining words was similar for *main list* and *above threshold* proposals, but on average, there were more positive and fewer constraining words in these groups compared to *below threshold* proposals. Finally, on average, the concentration measure on specific digital areas appears to be comparable between the three proposal groups.

5.2. Regression results based on expert scores

Table 2 sets out the findings of the OLS regression results based on expert scores; models (1a) through (1d) show the findings for the stepwise introduced groups of independent variables, whereby Flesch Reading Ease is used as the readability measure in the first instance; models (2) and (3) each contain the complete set of explanatory variables, whereby Flesch-Kincaid Grade Level and Gunning Fog Index are used as readability/complexity indicators respectively.

Overall, the findings across all model variants remain robust. Regarding the structure of documents, interestingly, neither the length of the document nor the number of figures had a significant impact on the score, suggesting that simply adding more content or visual elements does not influence evaluators' assessments. However, the internal structure of the proposal—measured by the percentage of pages devoted to the conceptual content—showed a positive and significant effect. This suggests that better-structured and more elaborated proposals are likely to be scored more favourably, potentially because they demonstrate clarity and focus in addressing the call's objectives.

Readability measures also proved to be highly relevant. All three indices used—Flesch Reading Ease, Flesch-Kincaid Grade Level, and Gunning Fog Index—were significantly associated with higher evaluation scores. This result points to the importance of well-prepared and accessible language in grant proposals, reflecting the consortium's effort in producing high-quality documentation. Easier-to-read proposals may help evaluators better understand the project's value and implementation strategy.

Regarding tone, sentiment variables such as the share of positive words and those revealing uncertainty showed no significant effects. However, the presence of constraining language had a significantly negative effect on the score. Apparently, more confident language makes projects seem doable and more persuasive. Since language conveys commitment and confidence in execution plans, less constraining language could signal a higher degree of project maturity and feasibility, and could also translate into higher perceived credibility of the project team, thus leading to higher success chances for the projects.

With respect to the technological focus of proposals, we found that the stronger the concentration on specific digital domains, the lower the expert scores. This may reflect alignment with the programme's aim to support broad-based, one-stop-shop solutions through the EDIH network. Proposals covering a wider range of digital competencies were likely seen as more comprehensive and better suited to support diverse regional needs.

As for controls, we find that the requested budget is positively related to expert scores; however, the higher the share of private organisations in a consortium, the lower the achieved score of a proposal. Interestingly, after controlling for document and textual characteristics, the size of the consortium—measured via number of partners—has no significant effect on expert scores. Finally, this also applies to the experience of consortium members in R&I FP projects.

[Table 2 about here]

5.3. Regression results based on evaluation outcomes

Table 3 presents the estimation results of the ordered logistic regression models, which examine the likelihood of a proposal being classified into the three funding outcome categories defined as an ordinal variable; each of the three model variants includes a different measure of text readability.

As for document structure and design, we found that document length has no significant influence on the evaluation outcome, as with the OLS models. Interestingly, however, unlike the OLS models, the number of figures included in a proposal had a significant effect on the likelihood of being placed in a higher outcome category and thus enhancing success chances. This suggests that visual content might contribute to a more persuasive presentation, aiding comprehension and perceived professionalism. The percentage of conceptual content remained a strong and positive predictor of success, reinforcing the importance of clear and focused project design.

Readability measures again demonstrated a significant impact, confirming that clearer proposals are not only scored higher but also more likely to be funded. Furthermore, tone-related findings remained consistent: positive phrases and uncertainty measures were not significant, while the use of constraining language had a positive effect on funding outcomes.

However, a notable difference emerged regarding technological diversification. While it was a significant positive factor for evaluation scores in the OLS model, it became statistically insignificant in the logistic model. This discrepancy suggests that whilst technological breadth may help proposals earn higher scores, it is not a decisive factor in final funding decisions, which might depend more on other qualitative aspects or budget constraints.

Finally, only one control variable—the share of private consortium members—had a significant and negative effect on the likelihood of being assigned to a higher outcome category.

[Table 3 about here]

Since the evaluation outcome can, but does not necessarily have to, be considered as an ordinal variable—after all, the proposals in both the *above threshold* and *main list* categories were eligible for funding—we performed an additional robustness check by treating the dependent variable as nominally scaled and thus estimating Multinomial Logit Models (MLR) with the same set of independent variables as described in Section 4 (see Table A 3 in the Appendix).

The results confirmed the impact of the space devoted to conceptual information, the readability of the text, and constraining sentiment on the probability of funding the project, similarly to previous model estimation results. The coefficient of the dummy variable for documents longer than 50 pages is significantly positive for the *above threshold* outcome, compared to the *below threshold* proposals (the reference category), indicating a higher likelihood of the proposals from

the second call being in the *above threshold* group, which is in line with the descriptive analysis. Moreover, the *above threshold* proposals relied on a higher share of positive language—also using positive framing in the description of the project idea—than the *below threshold* category.

6. Discussion and conclusions

This study explores the cornerstones of purposeful written business communication for securing project funding by investigating the relationship between various document features of EU grant proposals submitted within the framework of the funding programme for European Digital Innovation Hubs, and their evaluation scores (continuous, ranging between 0 and 15) as well as evaluation outcomes (classified as *below threshold*, *above threshold*, and *main list*). To this end, we extracted various measures from the proposal documents concerning document structure and design, text readability, tone and sentiment of the language used to describe the submitted project, as well as the content and/or alignment of the project idea with the call and EU digital transformation priorities. Thus, in line with the literature, we argue that successful and effective business communication relies not only on the substantive content quality and alignment with funders' expectations and priorities but also on the proposal's effectiveness in terms of rhetoric and content presentation (e.g., van den Besselaar and Mom 2022, Tohalino et al. 2021, Connor and Upton 2004).

Our findings revealed that the internal organisation of the proposal document, readability and complexity of the text, as well as the tone and sentiment of the language used to depict the project idea, are key factors that correlate not only with the expert scores but also with evaluation outcomes. Specifically, a stronger emphasis on the conceptual section, higher readability, and less constraining language are positively related not only to the expert scores but also to favourable evaluation outcomes. These characteristics likely enhance the evaluators' ability to assess the proposals' strategic and technical merits quickly and efficiently (Mayer 2024; Hartley 2013). Further, clarity and a pronounced persuasive structure may reduce uncertainty and foster trust in the organisation's competence and vision (Boyack et al. 2018; Loughran and McDonald 2016).

However, the content and alignment with the EDIHs call and EU digital transformation priorities—here EDIHs' objective as a one-stop shop with a wide range of expertise and services across different digital areas—was a crucial factor behind expert scores only. On the other hand, a higher number of figures enhances the chances of proposal success and funding, but including

visuals appears to exert no significant impact on expert scores. We interpret this pattern as reflecting how evaluators work during outcome assignment: after detailed review of the proposals and scoring individual criteria, they must efficiently recall an overall mental picture of each proposal and compare the proposals with each other. In that process, the way information is presented—for example, clear conceptual sections and helpful figures—makes it easier and quicker for reviewers to grasp and recall a proposal's strengths and its strategic and technical merits, which, in turn, can influence the final outcome.

Overall, the alignment with the funder's objectives and call, the utilisation of figures, a strong focus on conceptual content, text readability, and less constraining language were distinguishing features of successful proposals. These elements likely facilitate a clearer understanding of the project's potential impact and feasibility, signalling otherwise unobservable characteristics of the project and project team (Parhankangas and Renko 2017; Connelly et al. 2011; Li 2008).

The results of this study allow us to formulate several policy implications for those defining the call for proposals, the candidates, and the evaluation process design. Integrating advanced text analysis tools into the proposal evaluation framework could automate initial assessments of readability and tone, streamlining the process and reducing the evaluators' administrative burden. Agencies might also provide more explicit guidance on effective proposal preparation beyond technical requirements, including readability guidelines, writing workshops, or AI-powered writing assistance. Given the influence of linguistic tone on evaluation outcomes, initiatives that help applicants present their ideas positively and confidently could be beneficial, potentially including training on conveying optimism and assurance.

For applicants, our results underscore the importance of investing in proposal preparation beyond technical content. The significant effects of conceptual content emphasis, readability, and linguistic tone indicate that how ideas are communicated matters as much as what is communicated. Applicants should allocate sufficient time for iterative drafting, editing for clarity, and careful structuring to highlight conceptual foundations. Visual elements should be considered strategic tools for enhancing comprehension and recall.

From a broader policy perspective, improving communication quality in grant proposals benefits the entire funding ecosystem. Better-prepared proposals enable more efficient and accurate evaluation, allowing funding agencies to identify and support the most promising projects more

effectively. This efficiency gain becomes increasingly valuable as EU research and innovation programmes grow in scale and complexity.

As with other studies, this paper suffers from several limitations. Our analysis is based on relatively straightforward text-specific metrics and a deterministic approach—the use of pre-existing word dictionaries to capture the content and alignment of proposals with the funder's objectives. More sophisticated natural language processing techniques, including topic modeling or machine learning approaches, could reveal additional nuances in how successful proposals communicate ideas and align with funder priorities. Furthermore, the dataset comprises proposals from a single programme, which may limit generalizability. Future research should consider other funding programmes and include more document-specific and text-related metrics and additional text analysis to capture more specifically the communicative abilities of the business documents, especially in terms of the content and project idea. A particularly promising avenue for future research would be linking proposal characteristics to post-award project performance. Do features predicting funding success also predict successful implementation and research impact? Or might some communication characteristics that enhance evaluation success correlate negatively with implementation performance? Investigating these relationships could inform both proposal evaluation design and broader questions about optimizing research funding allocation to maximize societal benefit.

In conclusion, this study provides empirical evidence that effective grant proposals require careful attention to both what is communicated and how it is communicated. Strategic alignment with funder priorities, clear document structure, accessible language, confident tone, and effective use of visual elements collectively distinguish successful proposals. While substantive quality remains fundamental, the ability to communicate that quality clearly and persuasively significantly influences evaluation outcomes. Our findings suggest that relatively straightforward improvements in proposal preparation practices and evaluation processes could yield substantial gains in both funding efficiency and research impact, helping ensure that the most promising research receives the support it deserves.

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Tables

Table 1 Descriptive statistics of the dependent and independent variables

Variable	Description	Mean	SD	Min	Max
Dependent variables					
Esrscore	Expert score (range from 0 to 15)	11.34	2.24	0.00	15.00
Final Status	Categorical variable according to project status: 1 = '*below threshold*', 2 = '*above threshold*', 3 = '*main list*'	-	-	1	3
Structure of the document					
Long doc	Document exceeding 50 pages (dummy variable)	0.15	0.36	0.00	1.00
Figures no.	No. of figures (count)	18.22	21.03	0.00	170.00
%conceptual	Percentage of pages in conceptual section (%)	49.79	12.04	0.00	78.00
Traditional readability measures					
Flesch Reading Ease	Flesch Reading Ease Score (0-100, higher is easier)	42.15	6.01	22.53	61.93
Flesch Kincaid Grade Level	Flesch-Kincaid Grade Level (lower is easier, 16+ postgraduate)	13.34	1.47	8.33	18.85
Gunning Fog Index	Gunning Fog Index Score (lower is easier, 17+ postgraduate)	20.77	1.40	17.42	25.70
Tone of project proposal					
%positive	Positive words (%)	1.90	0.37	0.99	3.56
%uncertainty	Uncertainty words (%)	0.44	0.11	0.19	0.88
%constraining	Constraining words (%)	0.21	0.06	0.06	0.55
Content / Specialization in digital areas (DA)					
HHI digital areas	Normalized HHI based on distinct counts of DA	0.07	0.04	0.02	0.28
Controls					
Budget	Requested funding amount in the project proposal (in K€)	4,269	1,289	276	7,433
Private share	Share of project partners assigned to the private sector (%)	0.27	0.21	0.00	1.00
Partner no.	No. of consortium (project proposal) members (count)	11.52	7.38	1.00	38.00
FP participation	No. of participations of project partners in FP projects per member (count)	70.20	104.69	0.00	623.40
No. of observations (project proposals) N = 328					

Table 2 Results of the OLS regression models based on expert scores

	(1a)		(1b)		(1c)		(1d)		(2)		(3)	
Structure of the document												
Long doc	0.096	(0.378)	0.145	(0.367)	0.084	(0.353)	0.019	(0.352)	0.060	(0.35)	0.064	(0.351)
Figures no.	0.006	(0.005)	0.005	(0.005)	0.004	(0.005)	0.003	(0.005)	0.003	(0.005)	0.005	(0.005)
%conceptual	0.048 ***	(0.013)	0.051 ***	(0.013)	0.039 ***	(0.014)	0.038 ***	(0.013)	0.037 ***	(0.013)	0.036 ***	(0.013)
Traditional readability measures												
Flesch Reading Ease			0.043 **	(0.022)	0.043 **	(0.021)	0.048 **	(0.02)	-		-	
Flesch Kincaid Grade Level			-		-		-		-0.212 ***	(0.08)	-	-
Gunning Fog Index			-		-		-		-		-0.242 ***	(0.076)
Tone of project proposal												
%positive					0.318	(0.312)	0.259	(0.316)	0.243	(0.314)	0.298	(0.315)
%uncertainty					1.298	(1.117)	1.499	(1.122)	1.357	(1.108)	1.328	(1.103)
%constraining					-7.542 ***	(2.714)	-7.067 ***	(2.438)	-7.364 ***	(2.419)	-7.541 ***	(2.427)
Content												
HHI digital areas							-8.122 **	(3.992)	-7.657 *	(3.91)	-8.163 **	(3.924)
Controls												
Budget (in M€)	0.327 ***	(0.107)	0.332 ***	(0.107)	0.343 ***	(0.101)	0.345 ***	(0.098)	0.349 ***	(0.098)	0.353 ***	(0.097)
Private share	-2.102 ***	(0.707)	-2.191 ***	(0.704)	-2.139 ***	(0.65)	-2.009 ***	(0.64)	-2.070 ***	(0.639)	-1.980 ***	(0.646)
Partner no.	0.048 ***	(0.017)	0.045 **	(0.017)	0.034 **	(0.017)	0.026	(0.018)	0.027	(0.017)	0.033 *	(0.017)
FP participation	0.000	(0.001)	-0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)
Constant	7.441 ***	(0.804)	5.563 ***	(1.23)	6.632 ***	(1.519)	7.110 ***	(1.479)	12.084 ***	(1.688)	14.167 ***	(2.004)
Adjusted R^2	0.188		0.198		0.232		0.247		0.250		0.253	

Note: OLS regression coefficients and robust (HC3) standard errors in parentheses; * p < 0.1, ** p < 0.05, and *** p < 0.01.

Table 3 Results of the ordered logistic regression models

	(1)		(2)		(3)	
Structure of the document						
Long doc	0.082	(0.307)	0.116	(0.309)	0.097	(0.308)
Figures no.	0.013 **	(0.006)	0.013 **	(0.007)	0.015 **	(0.007)
%conceptual	0.030 ***	(0.01)	0.028 ***	(0.01)	0.027 ***	(0.01)
Traditional readability measures						
Flesch Reading Ease	0.061 ***	(0.019)	-		-	
Flesch Kincaid Grade Level	-		-0.240 ***	(0.077)	-	
Gunning Fog Index	-		-		-0.210 ***	(0.081)
Tone of project proposal						
%positive	0.209	(0.329)	0.202	(0.328)	0.238	(0.329)
%uncertainty	0.077	(1.103)	-0.059	(1.102)	-0.113	(1.097)
%constraining	-4.331 **	(1.994)	-4.749 **	(1.998)	-4.775 **	(1.99)
Content						
HHI digital areas	-4.439	(3.062)	-3.974	(3.051)	-4.335	(3.058)
Controls						
Budget (in M€)	0.137	(0.09)	0.138	(0.09)	0.136	(0.09)
Private share	-1.393 **	(0.546)	-1.440 ***	(0.548)	-1.332 **	(0.544)
Partner no.	0.000	(0.016)	0.003	(0.016)	0.008	(0.016)
FP participation	-0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)
Threshold						
[FinalStatus_num = 1]	2.185	(1.392)	-3.760 **	(1.502)	-4.853 **	(1.983)
[FinalStatus_num = 2]	3.882 ***	(1.405)	-2.065	(1.491)	-3.169	(1.972)
McFadden's R^2	0.082		0.081		0.077	
Chi^2	56.712 ***		56.148 ***		53.005 ***	
Test of parallel lines Chi^2	13.959 (p=0.303)		17.059 (p=0.147)		15.858 (p=0.198)	

Note: Standard errors in parentheses; * p < 0.1, ** p < 0.05, and *** p < 0.01.

Appendix

Table A 1 Descriptive statistics and Kruskal-Wallis test results for comparing central tendency of the variables across three project proposal statuses

Variable	(1) Below threshold		(2) Above threshold		(3) Main list		H-statistic
	Mean	SD	Mean	SD	Mean	SD	
Esrscore	8.16	1.98	11.21	1.07	12.87	1.14	218.28 ***
Structure of the document							
Long doc	0.12	0.32	0.22	0.42	0.11	0.32	6.71 **
Figures no.	13.52	18.49	15.71	16.79	22.17	24.04	27.45 ***
%conceptual	44.25	11.71	49.89	11.70	52.25	11.68	31.45 ***
Traditional readability measures							
Flesch Reading Ease	40.95	6.06	41.67	5.97	43.05	5.91	6.62 **
Flesch Kincaid Grade Level	13.60	1.47	13.47	1.47	13.14	1.46	7.1 **
Gunning Fog Index	20.89	1.31	20.84	1.45	20.66	1.40	1.83
Tone of project proposal							
%positive	1.75	0.34	1.94	0.37	1.95	0.37	14.03 ***
%uncertainty	0.45	0.11	0.45	0.11	0.42	0.10	4.3
%constraining	0.23	0.07	0.20	0.05	0.20	0.06	17.02 ***
Content / Specialization in digital areas (DA)							
HHI digital areas	0.08	0.05	0.07	0.04	0.07	0.03	4.65 *
Controls							
Budget (in K€)	4,035	1,415	4,256	1,270	4,385	1,234	2.23
Private share	0.34	0.25	0.28	0.21	0.23	0.20	9.99 ***
Partner no.	9.78	8.23	12.43	7.19	11.68	7.02	11.79 ***
FP participation	68.42	121.37	59.31	78.38	78.80	112.56	4.72 *
No. of project proposals	69		108		151		

Note: * p < 0.1, ** p < 0.05, and *** p < 0.01.

Table A 2 Correlation table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Esrscore	--															
(2) Final Status	0.789*	--														
(3) Long doc	-0.072	-0.036	--													
(4) Figures no.	0.142*	0.171*	-0.069	--												
(5) %conceptual	0.308*	0.245*	-0.157*	0.163*	--											
(6) Flesch Reading Ease	0.095	0.142*	-0.055	0.096	-0.099	--										
(7) Flesch Kincaid Grade Level	-0.094	-0.129*	0.092	-0.083	0.075	-0.917*	--									
(8) Gunning Fog Index	-0.049	-0.069	0.075	0.068	0.090	-0.769*	0.852*	--								
(9) %positive	0.207*	0.179*	-0.032	0.180*	0.329*	-0.075	0.072	0.144*	--							
(10) %uncertainty	-0.099	-0.125*	0.026	-0.181*	-0.073	-0.014	-0.050	-0.113*	-0.230*	--						
(11) %constraining	-0.300*	-0.209*	0.011	-0.114*	-0.249*	-0.020	-0.044	-0.126*	-0.237*	0.287*	--					
(12) HHI d.a.	-0.240*	-0.154*	-0.046	-0.118*	-0.140*	0.085	-0.051	-0.150*	-0.163*	0.174*	0.201*	--				
(13) Budget	0.234*	0.102	-0.152*	0.118*	0.025	0.033	-0.013	0.050	0.089	-0.053	-0.015	-0.046	--			
(14) Private share	-0.219*	-0.187*	0.006	-0.074	-0.143*	0.061	-0.100	-0.043	-0.202*	0.199*	0.071	0.116*	0.005	--		
(15) Partner no.	0.192*	0.076	-0.084	0.037	0.059	0.090	-0.050	0.101	0.003	-0.138*	-0.207*	-0.212*	0.232*	0.135*	--	
(16) FP participation	0.067	0.053	0.006	0.168*	0.035	0.159*	-0.107	-0.099	0.172*	-0.032	-0.054	-0.024	0.113*	-0.208*	-0.049	--

Note: No. of observations (project proposals) = 328; * $p < 0.5$

Table A 3 Results of the MLR models

	(1)				(2)				(3)			
	Main list		Above threshold		Main list		Above threshold		Main list		Above threshold	
Structure of the document												
Long doc	0.442	(0.511)	1.177 **	(0.49)	0.535	(0.514)	1.247 **	(0.494)	0.522	(0.513)	1.251 **	(0.494)
Figures no.	0.017	(0.01)	0.006	(0.011)	0.018 *	(0.01)	0.007	(0.011)	0.020 *	(0.01)	0.008	(0.011)
%conceptual	0.040 ***	(0.015)	0.025 *	(0.015)	0.039 ***	(0.014)	0.026 *	(0.015)	0.036 **	(0.014)	0.024	(0.015)
Traditional readability measures												
Flesch Reading Ease	0.092 ***	(0.029)	0.053 *	(0.029)	-		-		-		-	
Flesch Kincaid Grade Level	-		-		-0.382 ***	(0.118)	-0.227 *	(0.119)	-		-	
Gunning Fog Index	-		-		-		-		-0.367 ***	(0.125)	-0.258 **	(0.127)
Tone of project proposal												
%positive	0.653	(0.531)	1.083 **	(0.539)	0.623	(0.528)	1.066 **	(0.537)	0.716	(0.531)	1.145 **	(0.542)
%uncertainty	0.433	(1.644)	2.391	(1.661)	0.199	(1.645)	2.268	(1.666)	0.131	(1.635)	2.224	(1.659)
%constraining	-6.084 **	(2.964)	-6.140 **	(3.088)	-6.628 **	(2.966)	-6.430 **	(3.097)	-6.947 **	(2.955)	-6.708 **	(3.099)
Content												
HHI digital areas	-6.967	(4.419)	-3.213	(4.455)	-6.338	(4.395)	-2.979	(4.453)	-6.835	(4.386)	-3.299	(4.463)
Controls												
Budget (in M€)	0.185	(0.137)	0.128	(0.14)	0.195	(0.137)	0.136	(0.141)	0.192	(0.137)	0.132	(0.142)
Private share	-2.216 ***	(0.81)	-1.522 *	(0.814)	-2.393 ***	(0.818)	-1.667 **	(0.823)	-2.200 ***	(0.806)	-1.566 *	(0.813)
Partner no.	0.009	(0.025)	0.037	(0.026)	0.013	(0.025)	0.041	(0.026)	0.022	(0.025)	0.047 *	(0.026)
FP participation	-0.002	(0.002)	-0.003 *	(0.002)	-0.002	(0.002)	-0.004 **	(0.002)	-0.002	(0.002)	-0.004 *	(0.002)
Constant	-4.982 **	(2.115)	-4.982 **	(2.177)	4.181 *	(2.226)	0.348	(2.296)	6.604 **	(2.982)	2.624	(3.061)
McFadden's R^2	0.113				0.114				0.110			

Notes: Multinomial logistic regression models with *below threshold* (1) being the reference category. Standard errors in parentheses;
* p < 0.1, ** p < 0.05, and *** p < 0.01.