Expert-Driven Criteria for Assessing SME Readiness for Open Data: Insights from an AI-Supported Brainstorming Workshop

Andrej Škraba,[1] Andreja Pucihar,[1] Staša Blatnik,[1] Nejc Čelik,[1] Franc Lavrič,[1] Radovan Stojanović,[2] Mirjana Kljajić Borštnar[1]

[1] University of Maribor, Faculty of Organizational Sciences, Cybernetics & Decision Support Systems Laboratory, Kranj, Slovenia
andrej.skraba@um.si, andreja.pucihar@um.si, stasa.blatnik1@um.si, nejc.celik1@um.si, franc.lavric@student.um.si, mirjana.kljajic@um.si
[2] University of Montenegro, Faculty of Electrical Engineering, Podgorica, Montenegro
stox@ucg.ac.me

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The growing importance of open data ecosystems highlights the need for SMEs to assess their maturity for open data use. This study presents findings from an expert workshop aimed at identifying the factors that drive or hinder SME open data maturity. The workshop, conducted at the 37th Bled eConference, involved 17 experts in a structured brainstorming session supported by the Kresilnik digital tool. A total of 260 ideas were generated through a two-phase process combining traditional ideation and AI-supported suggestion generation. The results indicate that AI assistance can mitigate the typical decline in brainstorming productivity by shifting participant roles toward evaluation and refinement of generated ideas. In addition to methodological insights into human–AI collaborative ideation, the study proposes a structured set of expert-derived criteria for assessing SME maturity for open data. The findings demonstrate the potential of hybrid brainstorming approaches for rapid knowledge generation in emerging digital transformation domains.

Keywords:
open data,
brainstorming,
AI,
LLM,
kresilnik

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1 Introduction

Open data (OD) is increasingly recognized as a key enabler of transparency, innovation, and data-driven decision-making across public and private sector ecosystems (Janssen et al., 2012; Page et al., 2023; Zuiderwijk et al., 2014). The concept of OD is commonly defined as data that can be freely used, reused and redistributed by anyone, subject to no proprietary restrictions and with at most requirements for attribution and share-alike (OPSI, 2016). Open data policies have become an important instrument for fostering transparent, accountable, and participatory governance while supporting innovation and economic development (European Commission, 2020; Publications Office of the European Union, 2024; Zuiderwijk et al., 2014). From an economic perspective OD create new opportunities for enterprises by lowering barriers to accessing valuable databases, that would otherwise be costly or unavailable (Jetzek et al., 2019; Magalhaes & Roseira, 2020). Studies estimate that the economic value of OD in the EU reaches billions of euros annually, driven by innovation, efficiency gains and the creation of new products and services (European Commission, 2020). This is particularly important for SMEs, which frequently face resource, capability, and data access constraints, positioning open data as a potentially valuable strategic resource (Janssen et al., 2012).

However, despite its potential the adoption of OD in SMEs remains underutilized. Prior research highlights several barriers among which include problems with OD standardization, quality and usability, security, availability, knowledge management, cooperation with stakeholders, and regulatory (Çaldağ & Gökalp, 2023; Crusoe & Melin, 2018; Ferencek & Kljajić Borštnar, 2025; Huber et al., 2020; Janssen et al., 2012; Wang, 2020; Wieczorkowski, 2019). Jetzek et al. (2019) further explore organizational barriers such as management support and data culture that influences the enterprises' ability to effectively use OD. As a result, understanding and assessing SME maturity to use OD is a critical step toward enabling broader adoption and value creation.

The concept of OD maturity refers to the extent to which organizations possess the capabilities to effectively discover, access, integrate, and exploit OD for value creation. Existing sources suggest that OD maturity is a multidimensional construct encompassing technological, organizational and strategic dimensions (Page et al., 2023; Zuiderwijk et al., 2015). Maturity includes the technological context, such as availability of appropriate IT infrastructure, data management tools and mechanisms that enable interoperability and integration of external datasets (OECD, 2019). Organizational context, on the other hand, relates to internal processes, employee skills and knowledge management, and its culture. This includes the ability to interpret data, identify relevant use cases and translate insights from data into business value. Management support and strategic alignment are also important factors, as they influence resource allocation and prioritization of OD initiatives (D'Addario et al., 2025; Jetzek et al., 2014; OECD, 2019; Zuiderwijk et al., 2014). Companies that integrate OD into their core strategies are more likely to create new products and services, improve operational efficiency and enhance customer relationships (Magalhaes & Roseira, 2020).

Despite these insights, there is still a lack of standardized and empirically validated methods for assessing OD maturity in SMEs. Most existing models are designed for public sector organizations, which differ significantly from SMEs in terms of resources, capabilities and strategic priorities (European Commission, 2020). This gap highlights the importance of developing context-specific criteria that reflect the unique characteristics and needs of SMEs. To address this gap an expert group was convened to systematically identify and refine relevant criteria for assessing OD maturity in SMEs through a structured brainstorming session supported by the "Kresilnik" tool (Lavrič & Škraba, 2023).

The integration of artificial intelligence (AI) into collaborative ideation processes is redefining traditional brainstorming methodologies. This study investigates the impact of AI-assisted brainstorming within the context of open data maturity for SMEs, as explored during a workshop "Open Data Maturity – Readiness of SMEs" at the 37th Bled eConference in June 2024. The "Kresilnik" tool (Lavrič & Škraba, 2023a) employed at the workshop is a digital platform designed to facilitate structured brainstorming sessions (Lavrič & Škraba, 2023b; Škraba et al., 2025; Škraba et al, 2022).

Recent research increasingly examines how collaboration between humans and AI reshapes teamwork, productivity, and collective problem solving. Field experiments show that integrating AI agents into collaborative work environments can significantly improve team performance and productivity by complementing human capabilities and facilitating information processing (Ju & Aral, 2025). At the same time, studies of knowledge workers indicate that the use of generative AI may influence cognitive processes during task performance, including reductions in perceived cognitive effort and changes in confidence when evaluating results (Lee et al., 2025). These findings highlight the importance of carefully designing human–AI collaboration so that AI systems augment rather than replace human reasoning and creativity. In group-based problem-solving contexts such as brainstorming, the structure of interaction among participants also plays a critical role, as decentralized collaboration and collective performance have been shown to enhance learning and idea development in multidisciplinary environments (Meluso & Hébert-Dufresne, 2023). Together, these insights provide an important theoretical background (Škraba et al., 2003) for examining hybrid brainstorming processes where human participants interact with AI systems to generate, refine, and evaluate ideas.

This paper analyses idea-generation dynamics in hybrid brainstorming sessions by examining the interaction between human creativity and AI support in the identification of OD maturity criteria. By comparing AI-assisted and traditional brainstorming approaches, the study explores how AI can enhance collaborative ideation for assessing SME open data readiness.

2 Methodology

The overall research goal was to design a multi-criteria decision model for evaluating SME open data maturity. To support the systematic development of the model, we adopted the Design Science Research approach focusing specifically on the exploratory criteria identification phase (Hevner et al., 2004). In the design phase, we applied the DEX (Decision EXpert) methodology, which is suitable for modelling complex multi-criteria decision models using qualitative scales (Bohanec & Rajkovič, 1990). The model development process includes problem definition, criteria identification, hierarchical structuring of criteria, definition of domain values and utility functions, as well as model verification and refinement. Since criteria identification represents a key phase of the modelling process, we first conducted a systematic literature review to identify factors that drive or hinder open data use in SMEs. We then organized an expert workshop to independently identify and validate the criteria against the factors identified in the literature. This paper focuses on that workshop phase.

Eight participants were from Slovenia and nine from other countries. The group included representatives from governmental institutions (2), companies (3), and academic institutions, all with professional or research interests in open data. An additional three participants assisted in conducting the workshop. A structured brainstorming session was conducted in 2024 using the custom-developed "Kresilnik" digital brainstorming tool, which lasted 30 minutes. Participants initially engaged in conventional idea generation. After 1080 seconds, AI support was introduced through an AI-assisted interface that enabled participants to generate, edit, and submit AI-generated ideas they considered valuable. During the 30-minute session, 17 participants collectively generated 260 ideas. Figure 1 presents the initial brainstorming question together with the prompt used to initiate the ideation process and its tokenized representation generated by the OpenAI tokenizer. Each coloured segment represents an individual token identified by the tokenizer, illustrating how the natural language prompt is decomposed into smaller computational units that are processed by the AI model. This visualization highlights the underlying mechanism through which the AI system interprets the brainstorming prompt before generating suggestions or supporting idea generation during the session.

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Please provide viable criteria and indicators for determining the readiness of
 SMEs in relation to open data maturity. State only one, short criterion or
 indicator at a time.
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Figure 1: Tokenized representation of the initial brainstorming prompt
Source: Created by the authors

The brainstorming session was divided into two distinct phases: Phase 1) A traditional brainstorming format and Phase 2) An enhanced mode incorporating real-time support from artificial intelligence. Within the session the following activities were conducted: a) Topic presentation, b) Collecting of ideas (in the first part of the session, the session followed a classical format, while in the second part, it was enhanced with the application of artificial intelligence), c) Categorization, d) Voting about the importance of the categories, and e) Voting about the importance of ideas in the first category.

Figure 2 presents an extended hybrid brainstorming workflow that integrates AI into the classical brainstorming process and expands the concept proposed by Lavrič and Škraba (2023a). After the initial call for ideas, the participants start with ideation process. If human ideas are available, they proceed directly into the traditional group brainstorming flow. When no ideas are produced, the participants can activate an AI-assisted pathway that generates ideas using OpenAI. Important technical addition is a database of previously generated AI ideas which reduces the redundancy of generated ideas by AI. The generated ideas are then reviewed by participants, who may check, modify, or correct them before evaluating whether they are unique and appropriate. Approved ideas are subsequently introduced into the group brainstorming process, while non-unique or inappropriate ideas trigger a new AI generation cycle. The key extension compared to the earlier model is the introduction of the AI-generated ideas database, which enables reuse, accumulation, and refinement of ideas across brainstorming sessions.

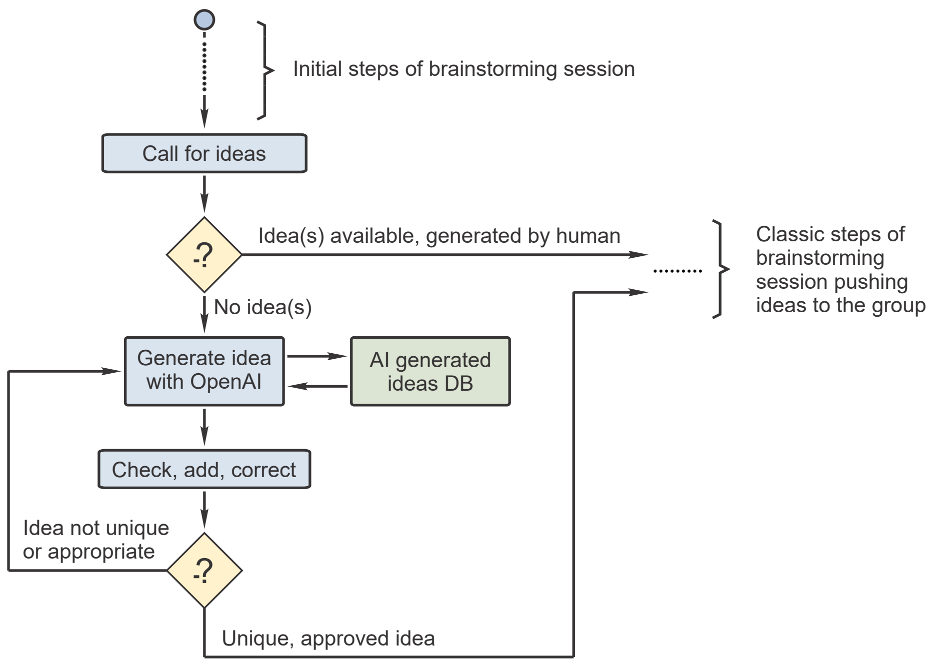

Figure 2: Extended hybrid brainstorming process integrating AI-generated ideas and an AI idea database

Source: Created by the authors

3 Results

A total of 30,759 interaction logs were recorded in a millisecond-resolution JSON database, capturing user input (keystrokes etc.) and interface interactions. These data form the foundation for analysing the dynamics and intensity of participation throughout the session.

Notably, among the 260 generated ideas, the one ranked third—'Use of open data to create innovative products or services addressing specific market needs'—was generated by the AI system, demonstrating that AI-supported idea generation can produce highly relevant contributions that are evaluated by expert groups as comparable to, and competitive with, human-generated ideas in the context of assessing SME open data readiness.

Figure 3 shows a word cloud generated from the collected ideas, highlighting the most frequent terms and concepts identified by the experts. Here the following stopwords were used at the generation of the word cloud: **`open data|SME|SMEs|within|s`**.

Figure 3: Word cloud of the Bled2024 brainstorming session

Source: Created by the authors

To gain a deeper understanding of participant engagement during the brainstorming session, we generated a visualization based on precisely timestamped keyboard interactions. Each interaction-such as a keystroke or idea entry-was recorded with millisecond accuracy and represented as a vertical line on a time axis. This approach captures the rhythm and intensity of the creative process in a way that is both intuitive and revealing.

The resulting Figure 4 can be seen as a spectral fingerprint of the brainstorming session-an abstract, high-resolution imprint of cognitive and collaborative energy unfolding over time. Time is mapped along the horizontal axis, covering the full 30-minute session (1800 seconds), while the vertical axis is used purely for plotting purposes, with each black line extending from 0 to 1. Every vertical line marks a precise moment of user interaction, and the collective density of these lines reflects the dynamic flow of ideation and engagement.

The visualization distinctly reveals two behavioural phases. In the first phase-spanning approximately the first 1080 seconds- Figure 4 displays a dense cluster of vertical lines, indicative of frequent and sustained keyboard input. This suggests a period of heightened cognitive effort and active idea generation, as participants were fully immersed in the creative process. The second phase begins after the 1080-second mark, coinciding with the introduction of AI assistance. From this point on, a visible reduction in line density occurs, signalling a decline in manual input. This shift may reflect participants transitioning from active ideators to evaluators, curators, or facilitators of AI-generated suggestions. It could also suggest the onset of cognitive fatigue, changes in group dynamics, or increased reliance on the AI's output.

Overall, this visual encoding of timestamped activity serves as an elegant and powerful method for uncovering the hidden temporal patterns of group brainstorming. It not only highlights key transitions in engagement but also provides a compact, interpretable snapshot of the human-machine creative interplay as it evolved during the session.

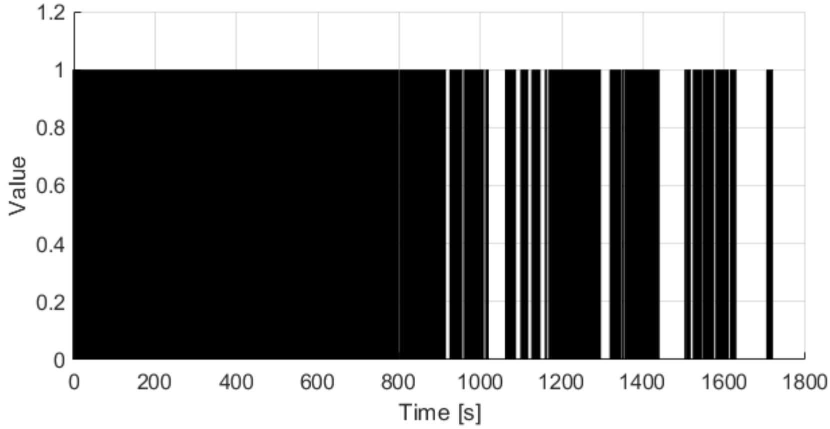

Figure 4: Spectral fingerprint of the brainstorming session
Source: Created by the authors

These results provide an indicator, that the AI support introduced at 1080s fundamentally changed the group's ideation dynamics, not just in level but in direction of growth.

Table 1 presents the final thematic categories derived from the expert brainstorming workshop together with their ranking scores assigned by participants. The categories were obtained through clustering and consolidation of the 260 generated ideas into broader conceptual dimensions representing SME readiness for open data. The ranking results indicate that experts considered business-related and data-related aspects to be the most critical determinants of SME readiness, while legal and regulatory aspects received comparatively lower, though still relevant, importance scores. The relatively low coefficient of variation (CV) values across most categories indicate a moderate to high level of agreement among participants regarding the importance of the identified dimensions.

Table 1: Ranked categories for assessing SME readiness for open data

Rank	Category	Example Criteria	Mean Score	Std. Dev.	CV
1	Business Potential	Value, innovation, competitiveness	8.41	1.68	0.2
2	Data Quality	Governance, metadata, consistency	8.12	1.41	0.17
3	Capabilities	Analytics, expertise, visualization	7.59	2.12	0.28
4	Innovation	Culture, agility, prototyping	7.35	2.08	0.28
5	IT Infrastructure	Platforms, dashboards, cybersecurity	6.82	2.15	0.32
6	Internal Strategy	Leadership, strategy, alignment	6.82	1.89	0.28
7	Business Environment	Ecosystems, funding, collaboration	6.59	2	0.3
8	Data Integration	Repositories, accessibility, interoperability	6.59	2	0.3
9	Training and Education	Literacy, workshops, learning	6.29	2.44	0.39
10	Regulations and Legal Compliance	GDPR, compliance, privacy	5.88	1.91	0.32

The results suggest that experts perceive SME readiness for open data primarily as a strategic and business-oriented capability rather than solely a technological issue. The highest-ranked category, Business Potential, emphasizes that SMEs must recognize and operationalize the business value of open data through its integration into products, services, and decision-making processes. The detailed ranking within this category further reinforces this interpretation, as the two highest-ranked ideas, “see value in open data” and “reliability of open data sources”, both achieved the highest average score (8.50), highlighting that perceived business value and trust in data quality are considered fundamental prerequisites for successful open data adoption. Particularly noteworthy is the third-ranked idea, “Use of open data to create innovative products or services that address specific market needs”, which was generated by the AI-supported brainstorming system and achieved an average score of 8.42. Its high ranking demonstrates that AI-generated contributions can be evaluated by experts as highly relevant and comparable to human-generated ideas in the context of open data readiness assessment. At the same time, the slightly higher coefficient of variation for this idea suggests somewhat greater disagreement among participants regarding the role of innovation-driven value creation as an immediate readiness factor.

The second-ranked category, Data Quality, further highlights the importance of governance, metadata quality, consistency, accessibility, and reliability of open data sources as prerequisites for effective data utilization within SMEs. Similarly, the highly ranked Capabilities category emphasizes the importance of analytical competencies, data literacy, visualization skills, and the ability to derive actionable knowledge from data. The categories Innovation and Internal Strategy additionally underline the importance of organizational culture, agility, leadership support, and strategic alignment in fostering open data adoption. Interestingly, more purely technical dimensions such as IT Infrastructure and Data Integration received lower rankings than business and strategic factors, indicating that experts perceive organizational readiness and value creation as more important determinants of open data maturity than technology alone. Overall, the findings support the view that SME readiness for open data is a multidimensional construct combining technological, organizational, strategic, cultural, and governance-related dimensions.

Figure 5 shows the evolution of average idea length over time during the 30-minute brainstorming session, with time divided into equal bins (60 seconds) along the horizontal axis and average idea length displayed on the vertical axis. The dashed red vertical line at 1080 seconds marks the point at which AI assistance was introduced, separating the session into a pre-AI phase (blue bars) and an AI-supported phase (orange bars). In the initial phase, idea length remains relatively moderate and variable, generally ranging between about 25 and 70 characters with occasional peaks, reflecting concise, human-driven idea generation. After the introduction of AI, a clear shift is observed, as average idea length increases substantially and stabilizes at higher values, typically exceeding 100 characters and reaching up to around 140–145 characters. This indicates that ideas in the AI-supported phase are more elaborated and detailed, suggesting a transition from rapid idea generation toward more reflective refinement and expansion of ideas, likely influenced by AI-generated suggestions.

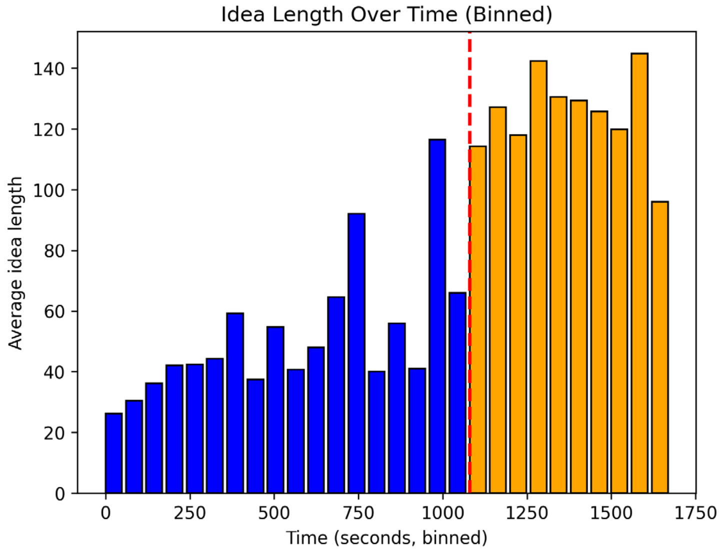

Figure 5: Average idea length (characters) before and after introduction of AI

Table 2 presents the ten most semantically unique ideas generated after the introduction of AI support, identified based on their lowest cosine similarity scores to any idea produced in the pre-AI phase. Idea similarity was computed using sentence embeddings generated with the SentenceTransformer model (Hugging Face Community, 2026), where lower similarity scores indicate greater semantic distance and therefore possible higher novelty. For each idea, the table lists its closest matching counterpart from the pre-AI phase along with the corresponding similarity score. The similarity scores indicate varying degrees of novelty among ideas generated in the AI-supported phase. A small number of ideas exhibit very low similarity scores (below 0.3), representing strong semantic divergence from previously generated ideas; however, these correspond to outliers or contextually irrelevant contributions by participants (e.g., "good coffee"), suggesting that low similarity alone does not guarantee conceptual relevance. More substantively, several ideas with similarity scores between 0.3 and 0.45 introduce genuinely new thematic dimensions, such as risk assessment and compliance, indicating meaningful expansion of the problem space; based on their style, phrasing, and level of contextual grounding, these ideas were most likely contributed by human participants rather than generated by the AI system. Ideas generated with support of AI fall within the range with similarity score of 0.5 and above, reflecting moderate novelty mostly in the form of elaborations or refinements of existing concepts rather than entirely new directions. Overall, the results suggest that the AI-supported phase contributed to both the emergence of new conceptual areas and the extension of previously identified themes, highlighting a combination of radical and incremental innovation. Based on stylistic characteristics, it is likely that most, if not all, human-generated ideas produced after the introduction of AI are represented among the top ten most unique contributions, indicating that human participants remained the primary source of conceptual novelty in the later phase of the session.

Table 2: Top 10 most unique ideas after AI introduction by similarity score to any idea from before AI introduction

Idea	Most similar	Similarity score
;-- SELECT * FROM users WHERE 1;	Easy to find data	0.230109721
Good coffee	Strategy	0.240747333
Doing a proper risk assessment	Use of the data to aid decision making	0.362663835
Understanding the challenge of compliance	Understanding the regulation governing open data	0.454871476
Culture - employees coming from different multicultural background - how do they accept changes?	Organizational culture	0.509587228
Clear communication channels and collaborative platforms are in place to facilitate seamless data sharing and collaboration across teams. --> I agree with this AI :-)	Taking part in data sharing ecosystems	0.513242185
Digital capability (such as technology use - especially data analytics, investment in IT department, what data (or digital) strategy they have as an organisation)	Technological capabilities	0.535972476
Evaluation of the SME's capability to leverage machine learning algorithms for extracting actionable insights from large open data sets.	Does the model/ prediction generated from open data have impact on real life business	0.537490427
Engagement in continuous learning and professional development programs focused on the latest advancements in open data technology and methodologies.	Open data being sufficient and insightful to the development process	0.541098237
Development of a disaster recovery plan to ensure continuity of open data initiatives in the event of a system failure or data breach.	Reliability of open data sources	0.554412842

5 Limitations

A limitation of present study is that the findings are based on a single expert workshop conducted within the context of the Bled 2024 eConference, which limits the generalizability of the results. Although the workshop involved participants from different countries and professional backgrounds, the sample size remained relatively small and may not fully represent the broader population of SMEs, policymakers, or open data practitioners. The study should therefore be considered exploratory in nature, primarily intended to identify and structure potentially relevant criteria for assessing SME readiness for open data. In addition, the brainstorming outcomes may have been influenced by the specific expertise, experiences, and perspectives of the participating experts, introducing a degree of expert-selection bias. While the integration of AI support contributed to increased ideation and idea elaboration, the quality and relevance of AI-generated suggestions were not independently validated outside the workshop context. Furthermore, the proposed criteria structure has not yet undergone longitudinal or large-scale empirical validation in real organizational settings. Future research should therefore include broader and more diverse participant groups, repeated workshops, and empirical testing of the resulting DEX-based assessment model across different SME environments and industries.

6 Discussion and Conclusion

The results of this study offer compelling evidence that the integration of artificial intelligence (AI) into group brainstorming sessions can significantly reshape both the trajectory and intensity of ideation processes. Through timestamped interaction data, sliding-window activity analysis, and linear trend comparisons, a nuanced and paradoxical behavioural pattern emerges—one that challenges traditional assumptions about group creativity over time.

Before the AI intervention, the group followed a classical brainstorming dynamic: high initial engagement, followed by a gradual decline in both interaction intensity and idea generation, reflecting expected cognitive fatigue and diminishing returns.

The integration of AI into group ideation appears to reverse the typical pattern of creative decline. It compensates for physical fatigue, sustains and even amplifies ideational output, and reconfigures participants' roles from individual contributors to collaborative co-curators. The findings suggest that AI has the potential to reshape collaborative brainstorming processes by supporting ideation continuity and refinement.

This study addresses the research gap related to the lack of standardized and empirically validated approaches for assessing OD maturity in SMEs by focusing on the identification of relevant evaluation criteria. Through an expert-driven brainstorming workshop using the "Kresilnik" tool, a comprehensive set of criteria reflecting technological, organizational and strategic dimensions of OD maturity was generated. It highlights that SME maturity to use open data extends beyond technical infrastructure and includes critical organizational factors such as data culture, skills, management support, and the ability to translate data into business value, which corroborates the findings of the systematic literature review (Blatnik et al., 2024). A smaller group of experts used the generated criteria for consequent modelling phases (Kljajić Borštnar et al., 2026). The findings demonstrate that the integration of AI into the ideation process significantly alters brainstorming dynamics, shifting participants from primary idea generators to evaluators and curators, while sustaining productivity and enhancing idea elaboration. The hybrid human–AI approach proved effective in rapidly generating diverse and structured knowledge in a complex and emerging domain. Overall, this study contributes both methodologically, by demonstrating the potential of AI-supported collaborative ideation, and substantively, by providing a foundation for the development of SME-specific OD maturity assessment model.

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Appendix

Figure 6 shows the mechanism used for dynamic prompt construction in iterative AI-supported brainstorming. During the first API call, the prompt consists only of the initial brainstorming question (`initialQuestion`) and additional instructions (`promptExtension`) that guide the model to generate a single concise idea.

For subsequent API calls, the prompt is extended by appending a list of previously generated ideas (`previouslyGeneratedIdeas`). These ideas are introduced in the prompt with the instruction "Please note that the following ideas have already been suggested:". This mechanism provides contextual information to the model and encourages the generation of novel, non-redundant ideas in later iterations. As a result, the system supports a structured and iterative AI-assisted brainstorming process.

```
// Prompt construction for iterative AI-supported brainstorming
let promptString = "";

if (numberOfChatGPTCalls === 1) {
    promptString =
        initialQuestion +
        promptExtension;
} else {
    promptString =
        initialQuestion +
        promptExtension +
        " Please note that the following ideas have already been suggested: " +
        previouslyGeneratedIdeas;
}
```

Figure 6: Dynamic prompt construction for iterative AI-supported brainstorming, where previously generated ideas are appended to the prompt to encourage the generation of novel and non-redundant ideas