Working with AI: A Practice-based Study of Knowledge Sharing in a Multinational Enterprise (MNE)

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Abstract: Knowledge sharing is central to intraorganisational collaboration in multinational enterprises (MNEs), where employees work across functions, locations and linguistic contexts. Existing research has highlighted the potential of AI to enhance knowledge management and organisational performance, but there is still limited understanding of how employees use AI in their everyday knowledge sharing practices in MNEs. This study therefore examines how AI influences these practices within an anonymised MNE, referred to as GlobalMFG. The study adopts a qualitative single-case study design and draws on six semi-structured interviews with managers and knowledge workers from different organisational functions. The findings demonstrate that AI supports knowledge sharing by improving access to information, assisting communication across geographically dispersed teams and supporting meeting follow-up. Its effectiveness remained dependent on employees' ability to formulate appropriate prompts and assess how AI-generated outputs could be applied within specific organisational contexts. AI was primarily used before and after interpersonal interactions. Experienced colleagues continued to be the preferred source of specialist and contextual knowledge. Although organisational documents reflected a strong strategic commitment to AI adoption, interview data revealed inconsistencies in access to AI tools, system integration, and governance, resulting in uneven implementation across the organisation. These findings highlight the need to connect AI investment with clear governance, consistent access to approved tools and task-specific employee support. Establishing ongoing employee feedback mechanisms can further support the responsible, effective, and contextually appropriate adoption of AI-enabled knowledge sharing practices within such MNEs.

Keywords: Knowledge sharing, Artificial intelligence (AI), Multinational enterprises (MNEs), Knowledge management, Practice-based perspective

1. Introduction

Knowledge sharing is a central process through which MNEs integrate dispersed expertise, coordinate work across subsidiaries and convert individually held knowledge into broader organisational capabilities (Grant, 1996; Gupta and Govindarajan, 2000; Gaur, Ma and Ge, 2019). In MNEs, geographically distributed units operate across different institutional, cultural and linguistic contexts, making knowledge sharing strategically important but difficult (Gupta and Govindarajan, 2000; Noorderhaven and Harzing, 2009; Gaur, Ma and Ge, 2019). Existing knowledge sharing practices have long relied on governance structures, social interaction and technology-enabled repositories. However, barriers remain. Studies have repeatedly identified cultural and cognitive distance, weak trust, limited incentives and tacit knowledge as persistent challenges in knowledge sharing (Riege, 2005; Wang and Noe, 2010).

Recent advances in AI, particularly GenAI systems built on advances in NLP, introduce new possibilities for organisational knowledge sharing. Earlier knowledge management systems (KMS) placed substantial emphasis on the codification, storage and retrieval of organisational knowledge (Alavi and Leidner, 2001). More recent AI-enabled systems extend these functions through conversational search, recommendation tools, translation support and content generation (Jarrahi et al., 2023; Alavi, Leidner and Mousavi, 2024; Benbya, Strich and Tamm, 2024). In this sense, GenAI and NLP-based tools may help employees access dispersed knowledge, reduce certain language-related barriers and prepare for cross-boundary interaction (Malik et al., 2021; Benbya, Strich and Tamm, 2024). These technologies also raise questions about whether employees can trust AI outputs, how they should verify them, how organisations govern data quality, and how far AI can support tacit, situated and relational knowledge sharing (Jarrahi et al., 2023; Alavi, Leidner and Mousavi, 2024; Ritala et al., 2024).

Existing research links AI with knowledge sharing and organisational performance, although the empirical base remains uneven and concentrated in particular sectors or applications (Malik et al., 2021; Olan et al., 2022). For instance, Lee et al. (2023) observe that "*there remains a lack of complete and comprehensive understanding of the use of AI, specifically its impact, influence, and critical success factors in organizations*" (pg.2). Their review identifies a broad implementation gap. This paper focuses on employees' knowledge sharing practices within an MNE. A practice-based perspective directs attention to the routines and interactions through which employees seek, interpret and use knowledge in their work (Orlikowski, 2002). The study therefore examines how AI is integrated within these practices through a shared organisational setting. The paper addresses the following research question: How does AI influence knowledge sharing practices within an MNE?

2. Knowledge Sharing

This paper positions knowledge sharing as the core social process that connects individual insight with organisational capability. Wang and Noe (2010) define knowledge sharing as the process by which individuals or organisations provide one another with task information, expertise and advice to help others solve problems, develop new ideas or implement procedures. Van den Hooff and de Ridder (2004) consider knowledge sharing to be a bidirectional process that includes bringing or 'donating' knowledge and getting or 'collecting' knowledge. This paper therefore defines knowledge sharing as a bidirectional process through which individuals and teams provide, receive and use task-related knowledge.

Knowledge sharing is central to the realisation of value from knowledge management. In this paper, knowledge management refers to the broader organisational processes through which knowledge is created, stored, shared and applied (Alavi and Leidner, 2001). Grant (1996) argues that the fundamental purpose of enterprise knowledge management is to transform the scattered knowledge held by individuals into the collective capabilities and strategic assets of the organisation. Al-Busaidi and Olfman (2017) describe knowledge sharing as one of the major processes of knowledge management. Its frequent appearance across knowledge management frameworks indicates its central place in organisational knowledge processes.

More recent research, such as Castaneda and Cuellar (2020) and Nguyen, Siri and Malik (2021), examines knowledge sharing in relation to organisational innovation and employee participation. For instance, Castaneda and Cuellar (2020) review the development of research on knowledge sharing and innovation, identifying collaboration as a central theme and connecting knowledge sharing with absorptive capacity, understood as the organisational ability to recognise, assimilate and apply relevant knowledge.

Wang and Noe (2010) review studies showing how knowledge sharing helps employees solve work-related problems and develop new ideas. Ahmad and Karim (2019) identify workplace learning as an important outcome, suggesting that knowledge sharing helps employees assimilate and apply knowledge in their work. These studies locate the effects of knowledge sharing in employees' everyday learning and problem-solving. With the increasing digitisation in the current era, this provides a basis for examining how digital technologies influence the practices of current organisations through which knowledge is shared.

3. AI-enabled Knowledge Sharing in MNE

The development of knowledge sharing technologies has moved from repository-based KMS to Web 2.0 platforms[1], and then to AI-enabled systems. Jarrahi et al. (2023) explain that AI is relevant to knowledge management because it supports how organisations organise, access, share and apply knowledge. For knowledge sharing, the shift is that technology does more than store codified knowledge after employees have entered it into a system. AI-driven tools may help locate knowledge sources, identify bottlenecks in knowledge flows and connect employees working on related projects or technical problems (Jarrahi et al., 2023). Alavi, Leidner and Mousavi (2024) further argue that GenAI changes employees' interaction with KMS by making large knowledge bases easier to access and by supporting the analysis and use of organisational knowledge. In MNEs, projects are coordinated across geographically dispersed units operating in different institutional settings. Subsidiaries develop knowledge shaped by their local operating contexts and organisational roles. Knowledge moves from headquarters to subsidiaries and from subsidiaries back to headquarters. It also circulates among subsidiaries (Yang, Mudambi and Meyer, 2008; Gaur, Ma and Ge, 2019). This distributed pattern gives knowledge flows strategic importance and creates coordination difficulties. Gaur, Ma and Ge (2019) show that these flows depend on relationships between organisational units and the employees who enact them.

Haas and Cummings (2015) find that geographic and structural differences create stronger barriers to knowledge seeking than differences associated with nationality or demographic characteristics. Employees working in different business units or functions may use specialised terminology and assess the relevance of knowledge differently. Ford and Chan (2003) identify language differences as a source of knowledge blocks in a multicultural subsidiary. Their case also shows that culturally shaped advice-seeking affects the direction of knowledge flows.

[1] Web 2.0 platforms are understood here as participatory digital platforms that allow employees to contribute, interact and share knowledge through collaborative functions (Paroutis and Al Saleh, 2009).

Cross-boundary knowledge sharing therefore depends on employees' ability to recognise the relevance of colleagues' expertise and on familiarity developed through prior interaction.

Jarrahi et al. (2023) explain that AI-enabled KMS can make dispersed expertise more visible and connect employees facing related technical problems. Mikalef and Gupta (2021) move the discussion from technical functionality to organisational capability. Their empirical study of senior technology managers links AI capability to organisational creativity and firm performance. Their capability construct gives technical resources a central place and considers the skills and coordination needed for deployment. Ritala et al. (2024) examine how such capability develops in industrial enterprises. Their analysis shows that AI-enabled exploration and exploitation can reinforce one another as enterprises adapt established operations and investigate emerging business opportunities. Learning accumulated during implementation shapes subsequent AI initiatives.

Barriers emerge when employees interpret and act on AI outputs. Jarrahi et al. (2023) identify continuously generated and unstructured data as an obstacle to timely AI-supported analysis. The study also warns that excessive reliance on AI may produce cognitive complacency, reducing employees' scrutiny of system outputs. Benbya, Davenport and Pachidi (2020) discuss limited explainability as a source of weak trust in AI-assisted decisions. Algorithmic bias can make problematic outputs appear authoritative. Responsibility for harmful or incorrect outcomes also becomes harder to assign as AI assumes a larger role in organisational processes. The MNE context adds a further layer because AI outputs are interpreted across units whose vocabularies and local working arrangements differ. Existing research identifies potential organisational value and recurring barriers. However, there is still limited understanding of how individual employees and project teams use, question, and adapt AI-enabled tools in their everyday knowledge sharing practices.

4. Research gap

Based on the literature review, there are several gaps related to AI-enabled knowledge sharing in practice. Yeboah (2023) shows that knowledge sharing studies give greater attention to enabling conditions than to barriers. The review also points to limited examination of the alignment between knowledge sharing processes and organisational strategy, alongside a strong emphasis on financial outcomes.

Empirical research on AI-enabled knowledge sharing remains concentrated in specific organisational applications and outcome measures. Malik et al. (2021) situate AI-enabled knowledge sharing within global talent management in an IT-based MNE, whereas Olan et al. (2022) examine the integration of AI and knowledge sharing in relation to organisational performance. This emphasis leaves employees' routine use of AI-enabled tools less fully explained. Lee et al. (2023, pg. 2) similarly identify "*a lack of contextual understanding of why and how AI is being implemented by organizations"*. This concern is especially relevant to MNEs, where employees encounter AI through different organisational systems and local working arrangements.

In MNEs, knowledge sharing crosses organisational units and remains shaped by local working contexts (Gaur, Ma and Ge, 2019; Haas and Cummings, 2015). Existing research offers limited empirical explanation of how employees and project teams use AI-enabled tools under these conditions. As part of an ongoing research project for a PhD, the paper addresses the following research question:

How does AI influence knowledge sharing practices within an MNE?

5. Methodology

This study adopts a qualitative single case study design based on semi-structured interviews. The focal case is an anonymised MNE, referred to as *GlobalMFG*, which was selected as an information-rich case (Yin, 2018) because of its extensive multinational operations and active adoption of AI-enabled technologies. Established over 100 years ago, the organisation provides a mature organisational setting in which to examine the influence of AI on knowledge sharing practices over time. Employees routinely collaborate across functions and national locations, making knowledge sharing a central organisational activity. The case also provided access to participants from different organisational functions.

Primary data were collected through semi-structured interviews with managers and knowledge workers in GlobalMFG during Jan- June 2026. For this paper, the participants will be referred as P1–P6 as shown in Table 1. Names and operational details that could identify the enterprise were generalised. Participants were recruited from different roles and functions within GlobalMFG, and their familiarity with AI-enabled tools is varied. Semi-structured interviews provided a common focus across participants and allowed the interviewer to pursue relevant issues raised during each discussion (Brinkmann and Kvale, 2015).

Table 1: List of Interview Participants

	Role	Experience in the current role (Years)
P1	Motor Engineer	9
P2	Research and Development (R&D) Engineer	11
P3	Principal Testing Engineer	22
P4	Application Engineer	8
P5	Engineer Leader/Test Engineer	10
P6	Procurement Specialist	8

The interview guide included questions such as how participants shared and accessed knowledge in day-to-day work, and how AI-enabled tools affected these practices.

Secondary data were collected to establish the organisational context for the case including company press releases. Interview recordings were transcribed in Chinese and translated into English for analysis and the translations were independently reviewed by a professional translation service to provide a further quality check and enhance the reliability of the translated data. Thematic analysis was used for coding meaningful extracts; Codes were compared across participants and developed into final themes for interpretation NVivo 15 – a popular tool for qualitative data analysis was used to store the transcripts and code extracts and identify the core themes.

6. Case Study - GlobalMFG

GlobalMFG is an information-rich MNE, with international networks connecting multiple subsidiaries and operating units across many countries, making cross-border collaboration a routine feature of organisational work. Knowledge sharing therefore occurs repeatedly across locations and functions.

This organisation combines engineering-intensive manufacturing with advanced digital technologies. Documentary sources indicate that AI is embedded in operational technologies and enterprise-wide digital services across GlobalMFG. Its organisational reach extends across different functions and creates routine opportunities for employees to encounter AI-enabled tools in their work. These features create a strong setting for examining how AI influences knowledge sharing practices.

7. Analysis

The analysis of the interviews with the six participants produced five themes concerning how AI influences knowledge sharing practices in GlobalMFG:

- AI Supports Initial Access to Work-Related Knowledge
- AI Supports Cross-Border Communication
- Human Judgement Mediates AI-Supported Knowledge Sharing
- AI-Enabled Efficiency and Reconfiguration of Work
- Organisational Conditions Shape AI-Enabled Knowledge Sharing

Participants described AI use as localised within particular tools and work situations rather than through an enterprise wide AI-enabled knowledge sharing system. These practices occurred at the individual and team levels, and their use depended on employees' expertise, access to approved tools and the degree of integration between organisational systems.

7.1 AI Supports Initial Access to Work-Related Knowledge

Participants associated AI with faster initial access to work-related knowledge. This initial access represented individual knowledge acquisition rather than knowledge sharing. P1 used AI to develop a preliminary understanding of unfamiliar technical topics. When moving from motor-related work to sensors, he asked AI to explain the relevant product principles because this was "*faster than searching online for documents myself and saves time".* P4 identified a related possibility in application work: existing databases provided product information but offered limited support for questions tied to a specific application context. P4 therefore viewed an AI-supported knowledge base as a potentially useful future development rather than a tool currently used in knowledge sharing.

This use of AI changed the preparation that took place before interpersonal knowledge sharing. P1 still approached colleagues when he needed detailed explanations, but he first used AI to build enough background knowledge to ask a more focused question. As P1 explained, *"I do not need to ask them very basic questions. I can approach them with at least an introductory or preliminary understanding of the product".* AI therefore supported the preparatory stage of knowledge sharing rather than replacing colleagues as sources of contextual or specialist knowledge.

7.2 AI Supports Cross-border Communication

Engineers used AI-enabled functions when communicating with colleagues in other locations. The design engineer P1 used real-time subtitles when unfamiliar accents made spoken English difficult to follow. He explained, "*I can read the subtitles directly, which improves communication".* P3 who is a testing engineer, used Teams captions and translation in meetings with colleagues from other countries. P6 also used English captions when he could not clearly understand parts of a discussion.

Meeting-summary tools supported the work that followed these discussions. P4 used an AI-enabled function that organised the meeting content and recorded agreed actions and responsibilities. The resulting record helped employees return to the discussion after the meeting.

These uses were relevant to the MNE context because participants regularly communicated across national locations. Differences in accents and language proficiency sometimes made technical discussions difficult to follow. Captions and translation helped employees understand parts of these discussions as they occurred. Meeting summaries made some of the exchanged knowledge available afterwards. The findings therefore show that AI supported specific moments in cross-border knowledge sharing. Employees still needed contextual knowledge to interpret and use what had been communicated.

7.3 Human Judgement Mediates AI-supported Knowledge Sharing

Participants described human judgement as the mechanism through which AI-generated information became usable in knowledge sharing. Employees needed prior knowledge to formulate relevant questions, evaluate AI outputs and translate them into advice, discussion or work decisions that colleagues could use. P2 argued that useful AI use required an existing knowledge base: "*The precondition is that you already have half a bottle of knowledge, and AI helps fill it up*". Without basic understanding, employees might struggle to frame questions or respond to specialist terminology.

P6 connected output quality to the detail of the input, explaining that users needed to articulate their requirements clearly. P4 raised a related concern about specialised and local market contexts. AI could generate an initial view, but employees still needed to assess its relevance before making a decision. P5 placed the same boundary around interpersonal knowledge sharing, observing that tools could shorten communication time and that important issues still came down to direct discussion between colleagues.

The value of AI depended on the employee's ability to define the problem and interpret the response in relation to the work context. P5 made this boundary explicit: "*the most important factor in all information sharing and knowledge sharing is still the human factor*". Human expertise remained part of the process through which AI-generated material became usable organisational knowledge.

7.4 AI-Enabled Efficiency and Reconfiguration of Work

Efficiency was the most consistent benefit associated with AI. Participants described shorter search times and faster preparation of work materials. P5 stated that, in information sharing and knowledge acquisition, "*something that might previously have taken two hours may now be solved in twenty minutes*". He also questioned the completeness and reliability of AI answers, explaining that employees still needed to screen information and examine responses from different angles. P5's wider account connected the use of AI to the organisational setting. He described separate enterprise platforms whose integration was constrained by access controls and legal requirements. These conditions limited the extent to which faster retrieval could be extended across organisational units.

The time saved during retrieval or drafting changed how effort was distributed across the task. P6 stressed that "*the better and more detailed the input, the more accurate the AI output will be*". P4 described AI as capable of producing an initial version of a document, which the employee could then review and revise. AI reduced the time required for some activities and increased the significance of input preparation and output verification. Within the MNE context, these changes were relevant to work involving knowledge drawn from different functions and locations. AI could shorten the preparation required before employees exchanged information across organisational boundaries, although the resulting material still needed to be assessed against technical requirements and local working conditions. Efficiency therefore depended on employees' ability to connect AI-generated material with the distributed knowledge available across the organisation.

7.5 Organisational Conditions Shape AI-enabled Knowledge Sharing

Access permissions, awareness and fragmented organisational systems shaped whether AI-enabled functions could become part of employees' knowledge sharing practices. These conditions affected who could use AI-supported meeting, retrieval and documentation functions and whether such practices could extend across teams and locations. P1 described the formal use of AI in knowledge sharing as very limited. P3 observed that employees could already be using automated live captions or real-time translation during meetings without recognising these functions as AI-enabled. P2 was aware of AI-enabled meeting functions but lacked permission to use some of them: *"We do not have the permission. I know about it, but we do not have access".* AI-related functions could therefore be embedded in commonly used platforms without being recognised as AI or available under the same conditions to all employees.

Governance and system architecture further shaped use. P3 reported that the organisation *"has not yet issued an AI-related policy",* although existing IT controls placed strict limits on external access and data movement. P1 linked restricted use to confidentiality and intellectual-property concerns. P5 described barriers between AI functions embedded in different enterprise platforms and explained that broader integration would encounter security and legal boundaries. P3 also described a global platform that was being introduced gradually through separate functional modules. AI-enabled retrieval was discussed as a possible later development rather than a function currently used in the knowledge sharing practices reported by participants. This account provides evidence of the organisational conditions surrounding future AI integration rather than evidence of current AI-enabled knowledge sharing. Across the six interviews, AI use appeared to remain localised within particular tools and work situations. The interview evidence indicates that the organisational availability of AI-related functions had not yet translated into consistent knowledge sharing practices across the parts of GlobalMFG represented in the sample. P2 described his experience of fragmented systems by saying that "*all the functions you just mentioned are on separate websites"* and that *"there is no integration at all".* This account reflects one participant's experience of system fragmentation; it does not by itself show that the whole organisation lacked integration.

The findings show that AI influenced knowledge sharing in GlobalMFG through local changes in how employees accessed work-related knowledge, used meeting-support functions and recorded shared information. Employees continued to evaluate AI outputs and decide how they could be used in specific work contexts. Secondary data present a broader strategic picture of AI development. The interview accounts show that this corporate commitment had reached roles and units unevenly. AI use therefore remained distributed across separate platforms and work settings, with broader integration still developing at the level of employees' reported practice.

8. Discussion

Knowledge sharing in this study included routine exchanges between colleagues across teams and organisational locations. AI-supported search can help employees develop an initial understanding before they approach colleagues. Meeting functions can assist comprehension and preserve parts of a discussion for later use. AI can alter the timing and preparation of knowledge sharing even when an enterprise-wide AI knowledge system remains under development.

Faster access leaves interpretation as a central part of the task. Employees need prior knowledge to formulate useful questions and assess the relevance of a response. This finding supports Ackerman, Pipek and Wulf's (2003) account of the continuing need for expertise when information is removed from its original context. In GlobalMFG, AI expanded access to codified and semi-codified material. Its use remained dependent on situated judgement and knowledge of the work setting. This pattern is consistent with Orlikowski's (2002) view of knowing as something enacted through practice.

Participants described language-related difficulty during meetings involving colleagues from other countries. Live captions and real-time translation improved comprehension in these situations. Automated summaries supported the later retrieval of discussion content in the work settings as highlighted by participants P4 and P5. These functions addressed specific moments of cross-border interaction. Employees still relied on shared terminology and contextual interpretation when using the knowledge exchanged. AI therefore supported communication at identifiable points without resolving the wider organisational conditions surrounding cross-border knowledge sharing.

The case highlights a gap between organisation-level AI ambition and employees' everyday use. Organisation-level materials suggest that AI forms part of GlobalMFG's wider digital and innovation agenda. The interviews show a slower movement into local practice.

The findings also indicate performance-oriented accounts of AI-mediated knowledge sharing. AI reduced the time required for search, preparation and documentation. The surrounding work remained significant. Employees had to formulate requests carefully and carry out responsibility for deciding how each response could be applied to the task. Efficiency therefore involved a redistribution of effort across the activity. Some participants connected future AI development with job insecurity or reduced demand for expertise. These views add employee-level uncertainty to studies that emphasise employee experience and organisational performance (Malik et al., 2021; Olan et al., 2022).

Access to approved tools provides one part of the required infrastructure. Employees also need clear guidance on data use and support when interpreting AI outputs. This indicates the need for proper training and guidance for employees in the effective use of AI tools. Training can strengthen question formulation and critical evaluation. Governance needs to improve coordination between separate platforms and preserve confidentiality controls.

9. Conclusion

This paper examined how AI influences knowledge sharing practices within an MNE through the case of GlobalMFG. The findings provide a clearer account of how AI-enabled knowledge sharing develops in everyday organisational practice. AI was most prominently used before and after interpersonal interactions, with employees relying on it to prepare for discussions and to capture, organise, and retain information from meetings. However, experienced colleagues remained the primary source of knowledge when tasks required specialist expertise, prior experience, or an understanding of local contexts. While AI facilitated access to information and supported certain stages of the communication process, direct interaction with knowledgeable colleagues continued to play a central role in effective knowledge sharing.

Organisational documents demonstrated a strong corporate commitment to AI adoption, while interview accounts provided insight into how this commitment was experienced in employees' day-to-day work. Although AI technologies were being introduced across the organisation, access to AI-enabled tools varied between participants, and some applications remained disconnected from the systems used for routine work. Also, governance and data security requirements restricted the types of organisational information that could be entered into certain AI tools. These findings suggest a gap between corporate investment in AI and the organisational conditions required to support its consistent and effective use across the organisation.

For MNEs, investment in AI needs to be accompanied by practical arrangements at team level. Employees require clear guidance on approved tools, data use and responsibility for validating AI-generated outputs. Organisations should also improve integration between AI-enabled functions and existing knowledge management systems to support more consistent knowledge sharing.

Organisational support should also be aligned with employees' day-to-day work activities. Training should begin by developing employees' ability to formulate effective prompts and then progress to evaluating and validating AI-generated outputs using relevant workplace knowledge and professional judgement. Guidance on the appropriate use of organisational information should be embedded within training activities rather than presented as a separate compliance exercise. Using examples drawn from real workplace scenarios can help employees recognise when AI provides valuable support and when consultation with experienced colleagues remains essential. In addition, managers or designated AI experts can serve as local points of contact to assist employees when organisation-wide guidance does not adequately address specific issues. Finally, Organisations should also establish employee feedback mechanisms to refine AI access, governance and training over time.

The study is limited to one case organisation and six participants. Future research could examine whether the patterns identified are evident across different organisational contexts, providing a more comprehensive understanding of AI-enabled knowledge-sharing practices.

Acknowledgements

The authors would like to thank Dr Maher Alzyadat for his valuable feedback during the preparation of this paper.

Ethics Declaration: Ethical approval for this PhD research project was granted by the Research Ethics Committee of the School of Physics, Engineering and Technology, University of York. All participants provided informed consent before taking part in the interviews.

AI Declaration: Generative AI tools were used to assist with language editing, grammar checking and improving the clarity of the manuscript. The authors retained full responsibility for the interpretation of the data, the analysis, the conclusions and the final content of the paper.

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