Technology Deployment in the Media: Sensor-Based Journalism, Offerings Enhancements, Platform Use, and Divestments

Inauguraldissertation
zur
Erlangung des Doktorgrades
der
Wirtschafts- und Sozialwissenschaftlichen Fakultät
der
Universität zu Köln

2026

vorgelegt von

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Tag der Promotion:	09.04.2026

Acknowledgements

I would like to express my sincere gratitude to my first supervisor, Prof. Dr. Claudia Loebbecke, for her guidance, constructive feedback, and continuous support. I also thank Prof. Dr. Eldad Davidov for taking on the role of the second supervisor for the dissertation. My deepest thanks go to my colleague, Astrid Obeng-Antwi, for her professional collaboration and dedicated support over the past years.

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Summary

Media organizations (in television, print, or radio) increasingly deploy emerging technologies to enhance their media offerings. While Information Systems research has extensively examined the impact of deploying emerging technologies on organizational and production processes, it has barely focused on this phenomenon in the media context. The dissertation aims to fill this gap and investigates five research topics. It analyzes sensor-based journalism as a form of journalistic content that is based on data collected by sensors. Specifically, it explores its potential, its impact on decision making, and associated ethical concerns. It also examines credibility formation in this context. Furthermore, the dissertation studies the broader deployment of technology in the media, including algorithm-based personalization and Artificial Intelligence-based imagery analysis to enhance media offerings, platform use, and divestment strategies in response to digitization and technological advancements. To address these research topics, the cumulative dissertation integrates thirteen research papers that apply both qualitative and quantitative methods. The findings show that sensor-based journalism enables insights into previously inaccessible phenomena and supports decision making under uncertainty, but raises ethical concerns related to privacy, accountability, and surveillance. They highlight that argument strength emerges as the primary credibility driver in sensor-based journalism, alongside other individual and source-related factors. Moreover, they identify limited use of personalization across German legacy newspapers. The findings further point to Artificial Intelligence-based imagery analysis for thumbnail customization as a means to increase consumption of hedonic media goods on video and e-commerce platforms. The findings also illustrate the coexistence of empowerment and disempowerment that women with caregiving responsibilities face when using platforms. Finally, they derive causal configurations that theoretically ground divestment strategies as organizational responses to digitization and technological advancements. The dissertation provides a foundation for future Information Systems research on technology deployment in the media to safeguard a healthy, democracy-relevant journalism (Loebbecke et al., 2025).

Kurzfassung

Medienorganisationen (beispielsweise Fernsehen, Print oder Radio) setzen zunehmend neue Technologien ein, um ihr Medienangebot zu verbessern. Während die Wirtschaftsinformatik-Forschung die Auswirkungen des Technologieeinsatzes auf Organisations- und Produktionsprozesse umfassend untersucht hat, wurde dieses Phänomen im Medienkontext bisher wenig behandelt. Die Dissertation zielt darauf ab, diese Lücke zu schließen und betrachtet dabei fünf Forschungsthemen. Sie untersucht sensorbasierten Journalismus als eine Form journalistischer Inhalte, die auf durch Sensoren erhobenen Daten basieren. Insbesondere analysiert sie dessen Potenzial, die Auswirkungen auf Entscheidungsprozesse sowie damit verbundene ethische Bedenken. Ferner erforscht sie die Glaubwürdigkeitsbildung in diesem Kontext. Darüber hinaus prüft die Dissertation den breiteren Technologieeinsatz in den Medien: algorithmische Personalisierung und Bildanalyse mittels künstlicher Intelligenz zur Verbesserung des Medienangebots, Plattformnutzung und Veräußerungsstrategien als Reaktion auf die Digitalisierung und den technologischen Fortschritt. Um diese Forschungsthemen zu behandeln, umfasst die kumulative Dissertation dreizehn Beiträge, in denen sowohl qualitative als auch quantitative Methoden angewendet werden. Die Ergebnisse zeigen, dass sensorbasierter Journalismus Einblicke in bisher unzugängliche Phänomene ermöglicht und die Entscheidungsfindung unter Unsicherheit unterstützt, jedoch ethische Bedenken in Bezug auf Privatsphäre, Verantwortlichkeit und Überwachung aufwirft. Sie heben hervor, dass neben anderen individuellen und quellbezogenen Faktoren die Argumentationsstärke als primärer Glaubwürdigkeitsfaktor im sensorbasierten Journalismus hervortritt. Des Weiteren stellen sie fest, dass Personalisierung in deutschen etablierten Zeitungen kaum genutzt wird. Sie beleuchten zudem eine Bildanalyse mittels künstlicher Intelligenz zur Anpassung von Miniaturansichten als Mittel zur Steigerung des Konsums hedonistischer Mediengüter auf Video- und E-Commerce-Plattformen. Außerdem veranschaulichen die Ergebnisse die Koexistenz von Selbstermächtigung und Entmachtung, mit der Frauen mit Betreuungsaufgaben bei der Plattformnutzung konfrontiert sind. Schließlich erkennen sie kausale Konfigurationen, die Veräußerungsstrategien als organisatorische Reaktionen auf die Digitalisierung und den technologischen Fortschritt theoretisch untermauern. Die Dissertation bildet eine Grundlage für die zukünftige Wirtschaftsinformatik-Forschung zum Technologieeinsatz in den Medien, um einen gesunden, demokratie-relevanten Journalismus zu erhalten (Loebbecke et al., 2025).

1. Introduction

1.1 Problem Statement

Amid ongoing digitization across various sectors, media organizations (in television, print, or radio) increasingly deploy emerging technologies. Examples of such technologies are sensors, algorithm-based personalization, Artificial Intelligence (AI), and digital platforms. They support decision making processes, accelerate content generation, and thereby enrich content portfolios, distribution, and allow for content personalization (Diakopoulos, 2019).

However, media organizations face risks from relying on these technologies. Declining production costs increase competition and lead to an abundance of media content (Rifkin, 2012; Shirky, 2008). Alongside the growth of automated and user-generated content, the prevalence of misinformation and deepfakes expands (Diakopoulos, 2019). The "wealth of information creates a poverty of attention" (Simon, 1971, p. 40), as individuals have to process growing media content with their limited cognitive resources (Tversky & Kahneman, 1974). Ethical concerns appear regarding data privacy, transparency, accountability, and surveillance (Diakopoulos, 2019; Morini et al., 2023).

Information Systems (IS) research has extensively examined the impact of deploying emerging technologies on organizational and production processes (Chen et al., 2012; McAfee & Brynjolfsson, 2012). Furthermore, it has studied system design and the organizational, societal, and individual-level effects of deploying technologies (Galliers et al., 2017; Loebbecke & Picot, 2015; Zuboff, 2015). However, IS research has barely investigated technology deployment in the media, especially in the context of providing democracy-relevant journalism (Loebbecke et al., 2025). The dissertation aims to fill this gap.

1.2 Research Focus

1.2.1 Sensor-Based Journalism

In the first part [Papers #1 – #6], the dissertation analyzes sensor-based journalism, also named 'sensor journalism' (Diakopoulos, 2019; Howard, 2014). Sensor-based journalism refers to journalistic content based on data collected by sensors. It relies on sensor-based data collection on phenomena that are beyond direct reach and inaccessible without sensors (Chen et al., 2012; Howard, 2014; Osterlie & Monteiro, 2020). Sensors such as temperature, pressure, proximity, and humidity sensors capture signals of physical or chemical variations and convert them into data for analytics and AI-based systems (Chen et al., 2012; Osterlie & Monteiro, 2020). In journalism, early forms of sensor-based journalism emerged in the 1950s with the use of temperature data for weather reports (National Environmental Satellite, Data, and Information Service, 2025). More recent applications use sensor data to report on air pollution or recycling journeys (Flip, 2021; Hook et al., 2019). Prior journalism research highlights both opportunities and risks of sensor-based journalism. Sensors alongside drones enable science-like reporting and economic efficiencies (Howard, 2014), but also raise ethical concerns related to privacy, transparency, and accountability (Morini et al., 2023). Sensor-based journalism further blurs boundaries between journalism, science, and activism as it fosters collaborations among journalists, startups, media organizations, and citizens (Hamm, 2024; Hepp & Loosen, 2021). However, sensor-based journalism has received limited attention in research fields beyond journalism studies.

Hence, the first part of the dissertation examines two research topics in the context of sensor-based journalism. Drawing on prior research on human and organizational decision making (Galliers et al., 2017; Kahneman & Tversky, 1979; Loebbecke & Picot, 2015), it explores the potential of sensor-based journalism, its impact on decision making, and associated ethical concerns [Paper #1]. Referring to prior research on credibility formation as a key mechanism of persuasion (Hovland & Weiss, 1951; Metzger et al., 2003), it studies credibility in sensor-based journalism [Papers #2 – #6].

1.2.2 Technology-Enabled Offerings Enhancements, Platform Use, and Divestments

The second part of the dissertation [Papers #7 – #10] takes a broader perspective on technology deployment in the media, addressing three distinct research topics.

Although prior IS research has increasingly examined personalization and AI-based design for enhancing offerings (Gregor & Hevner, 2013; Tam & Ho, 2006), their application in media contexts has received less scientific attention. Accordingly, the second part of the dissertation investigates such technology-enabled offerings enhancements in the media. Building on prior research on algorithm-based content personalization to increase readership and revenues (Benlian, 2015), the dissertation analyzes such personalization in legacy newspapers [Paper #7]. It further leverages prior research on AI-based design (Gregor & Hevner, 2013; Yoon & Kim, 2019) to investigate AI-based imagery analysis for customizing thumbnail designs to increase consumption of hedonic media goods on media and e-commerce platforms [Paper #8].

Moreover, previous IS research has extensively studied how platform use transforms work processes (Deng & Galliers, 2024). As gender-specific effects remain underexplored in IS research, the second part of the dissertation builds on prior platform research (Ameen et al., 2024; Deng & Galliers, 2024) and examines how women with caregiving responsibilities use platforms for work [Paper #9].

Finally, the second part of the dissertation theorizes on divestment strategies, a concept increasingly studied in management research (Kaul, 2012) but still little understood in IS research. It particularly focuses on divestment strategies, such as downscoping, reconfiguring, asset sales, reallocations, spin-offs, and carve-outs, in response to digitization and technological advancements (Barney, 1991; Karim & Capron, 2016; Kaul, 2012; McKendrick et al., 2009). Drawing on two theoretical perspectives, the resource-based view (Wernerfelt, 1984) and the concept of ambidexterity (Montealegre et al., 2019), it explores divestment strategies [Paper #10].

1.3 Research Approach

The dissertation follows a methodological pluralism approach, applying various qualitative and quantitative research methodologies.

As the qualitative research methodologies, the dissertation utilizes a case-based discussion, a conceptual, and a configurational approach based on publicly available data from real-life cases and literature reviews. The dissertation conducts a case-based discussion based on insights from real-life cases to explore sensor-based journalism, including its potential, its impact on decision making, and the associated ethical concerns [Paper #1]. Case-based discussions facilitate the contextualization of emerging research phenomena, dynamics, and unintended consequences in understudied processes (Monteiro et al., 2022). Furthermore, the dissertation adopts a conceptual approach to synthesize the dynamics (Suddaby et al., 2023) observed in platform use for work processes into research propositions [Paper #9]. Finally, it applies a configurational approach to illustrate the theoretical multiplicity (El Sawy et al., 2010; Fink, 2010; Meyer et al., 1993) that explains divestment strategies [Paper #10].

Regarding quantitative methodologies, the dissertation runs statistical analyses, including regression analyses, analyses of variance, and structural equation modeling – all conducted in *R*. It further conducts a frequency analysis. These quantitative studies rely on data collected from online experiments on the crowdsourcing platform 'Prolific' and publicly available, observational data from a web-based simulation and digital media and e-commerce platforms. The dissertation evaluates experimental data with statistical analyses to explore credibility formation in sensor-based journalism [Papers #2 – #6]. Such statistical analyses on experimental data enable testing relationships between attributes in emerging phenomena and addressing issues for which real-world data are not yet available (Maruping et al., 2025;

Schwenk, 1982). Ultimately, the dissertation examines observational data from a web-based simulation and from video and e-commerce platforms to investigate technology-enabled offerings [Papers #7 – #8]. Such observational data provides insights into actual behavior in real-life settings (Cyr et al., 2009; Deng & Poole, 2010).

1.4 Research Structure

As outlined above, this cumulative dissertation includes a total of thirteen papers, divided into two parts. Part 1, titled 'Sensor-Based Journalism', entails nine papers, six of which are standalone [#1 – #6], alongside three papers [#2a, #2b, #2c] which are earlier versions of Paper #2. Part 2, titled 'Technology-Enabled Offerings Enhancements, Platform Use, and Divestments', contains four papers [#7 – #10].

Table 1 provides an overview of the thirteen papers included in the two parts of the dissertation.

Table 1: Overview of the Papers.

#	Author(s)	Title	Theoretical Background	Core Finding	Publication
1	Loebbecke, C., Boboschko, I.	Reflecting upon sensor-based data collection to improve decision making	Prospect theory (Kahneman & Tversky, '79)	Evidence-based insights, decision making support, and ethical concerns in sensor-based journalism	Journal of Decision Systems, '20a, 29(Sup1), 18-31, [VHB: B].
2	Boboschko, I., Loebbecke, C.	Reader information processing in sensor-based journalism: the impact of identity cues on credibility	Heuristic-based persuasion (Chaiken, '87)	Positive effect of contributor jobs on source credibility in sensor-based journalism	Information Technology & People [VHB: B] - under review. *prior versions: 2a-c.*
2a	Boboschko, I., Loebbecke, C.	Identity cues influencing article credibility in sensor-based journalism	Heuristic-based persuasion (Chaiken, '87)	Positive effect of contributor jobs on source credibility in sensor-based journalism	Europ. Conf. on Information Systems (ECIS '25), [VHB: A].
2b	Boboschko, I., Loebbecke, C.	Names below sensor-based articles impacting the credibility of the article	Heuristic-based persuasion (Chaiken, '87)	No impact of author and contributor names on credibility in sensor-based journalism	World Media Economics and Management Conf. (WMEMC '25).
2c	Boboschko, I.	The impact of seeing human involvement in sensor-based journalism on reader appreciation	Social translucence (Erickson & Kellogg, '00)	Two hypotheses and a research model for testing the impact of human involvement on credibility in sensor-based journalism	Int'l. Conf. on Information Resource Management (Conf-IRM '24), - Best Paper Award.
3	Boboschko, I., Loebbecke, C.	News outlet reputation and content credibility in sensor-based journalism	Heuristic-based persuasion (Chaiken & Maheswaran, '94)	Positive (negative) effect of (less) reputable news outlets on content credibility in sensor-based journalism	Europ. Conf. on Information Systems (ECIS '26), [VHB: A] - under review.
4	Boboschko, I., Loebbecke, C.	Information processing and content credibility in sensor-based journalism: a comparative elaboration-likelihood perspective	Elaboration Likelihood Model (Petty & Cacioppo, '86)	Stronger effect of argument strength than news outlet reputation on content credibility in sensor-based journalism	Information Systems Journal [VHB: A] - under review.
5	Boboschko, I., Loebbecke, C.	Argument strength and content credibility in sensor-based journalism: a comparative experiment	Argumentation-based persuasion (Hoeken & Hustinx, '09)	Positive effect of sensor-based articles on argument strength and content credibility	Europ. Journal of Information Systems [VHB: A] - under review.
6	Boboschko, I., Loebbecke, C.	Deploying online experiments to investigate content credibility in sensor-based journalism	Experimental research design (McCroskey, '69)	Appropriateness of online experiments to investigate credibility in sensor-based journalism	German Society for Online Research Conf. (GOR '26).
7	Loebbecke, C., Oberschulte, F., Boboschko, I.	Mass media deploying digital personalization: an empirical investigation	Concept of web personalization (Tam & Ho, '06)	Limited use of content personalization by German legacy newspapers in online contexts	Int'l. Journal on Media Management, '21, 23(3-4), 176-203, [VHB: C].
8	Loebbecke, C., Obeng-Antwi, A., Boboschko, I., Cremer, S.	Towards AI-based thumbnail design for fostering consumption on digital media platforms	Framing theory (Tversky & Kahneman, '81)	AI-based imagery analysis for customized thumbnail variations and increasing consumption of hedonic media goods	Int'l. Journal of Information Management, 2024, 78, 1-12, [VHB: B].
9	Hoedl, T., Boboschko, I.	The double-edged sword: empowerment and risks of platform-based work for women	Concept of women's empowerment (Kabeer, '99)	Four propositions illustrating gendered effects of platform use	Int'l. Conf. 'Wirtschaftsinformatik' (WI '25), [VHB: B].
10	Boboschko, I.	IT-driven divestments: towards theoretical multiplicity through a configurational approach	Resource-based view (Wernerfelt, '84), ambidexterity (Montealegre et al., '19)	Two causal configurations to theoretically ground technology-driven divestment strategies	Europ. Conf. on Information Systems (ECIS '22), [VHB: A].

Part 1: Sensor-Based Journalism

Paper #1 (Loebbecke & Boboschko, 2020a), titled "Reflecting upon sensor-based data collection to improve decision making", published in the Journal of Decision Systems, reflects on sensor-based journalism with regard to its potential, its impact on decision making, and associated ethical concerns along three cases. Based on views from behavioral economics explaining organizational and individual decision making, such as prospect theory (Kahneman & Tversky, 1979), it shows that sensor data can generate evidence-based insights into previously inaccessible phenomena and support decision making under uncertainty. It raises ethical concerns related to privacy, accountability, and surveillance.

Paper #2 (Boboschko & Loebbecke, 2025a), titled "Reader information processing in sensor-based journalism: the impact of identity cues on credibility", is under review at Information Technology & People [VHB: B]. Drawing on the literature on heuristic-based persuasion (Chaiken, 1987) and social presence heuristics (Gefen & Straub, 2004), it investigates how identity cues – contributor names and jobs – impact credibility in sensor-based journalism. Data from a between-subjects online experiment with 233 participants show that displaying contributor jobs increases source credibility, whereas displaying contributor names has no effect.

Paper #2 builds on three conference papers [Papers #2a, #2b, #2c]:

- Paper #2a (Boboschko & Loebbecke, 2025b), titled "Identity cues influencing article credibility in sensor-based journalism", appeared at the European Conference on Information Systems (ECIS '25), Amman, Jordan [VHB: A].
- Paper #2b (Boboschko & Loebbecke, 2025c), titled "Names below sensor-based articles impacting the credibility of the article", appeared at the World Media Economics and Management Conference (WMEMC '25), Warsaw, Poland.
- Paper #2c (Boboschko, 2024), titled "The impact of seeing human involvement in sensor-based journalism on reader appreciation", appeared at the International Conference on Information Resources Management (CONF-IRM '24), Cairo, Egypt.

Paper #3 (Boboschko & Loebbecke, 2025d), titled "News outlet reputation and content credibility in sensor-based journalism", is under review at the European Conference on Information Systems (ECIS '26), Milan, Italy [VHB: A]. Building on the literature on heuristic-based persuasion and particularly reputation and recognition heuristics (Chaiken & Maheswaran, 1994), it examines how news outlet reputation impacts credibility in sensor-based journalism. It evaluates data from a between-subjects online experiment with 809 participants. It shows that reputable news outlets slightly, but significantly, increase credibility.

Paper #4 (Boboschko & Loebbecke, 2025e), titled "Information processing and content credibility in sensor-based journalism: a comparative elaboration-likelihood perspective", is under review at the Information Systems Journal [VHB: A]. Guided by the Elaboration Likelihood Model (Petty & Cacioppo, 1986), it investigates how content-related, source-related, and individual factors shape credibility formation in sensor-based journalism compared to other forms of journalism. It analyzes data from a 2×2 online between-subjects experiment with 1,570 participants. It finds that argument strength remains the primary credibility driver, while news outlet reputation and individual factors play smaller, context-dependent roles.

Paper #5 (Boboschko & Loebbecke, 2025f), titled "Argument strength and content credibility in sensor-based journalism: a comparative experiment", is under review at the European Journal on Information Systems [VHB: A]. Grounded in views on argumentation-based persuasion (Hoeken & Hustinx, 2009), it studies whether arguments supported by evidence based on sensor data are perceived as stronger and thus more credible than those without such evidence. It analyzes data from a between-subjects online experiment with 853 participants. It shows that argument strength fully mediates the effect of evidence type on credibility. Mediation effects are slightly stronger when journalistic content includes evidence based on sensor data compared to journalistic content without such evidence.

Paper #6 (Boboschko & Loebbecke, 2026), titled "Deploying online experiments to investigate content credibility in sensor-based journalism (Extended Abstract)", appeared at the German Society for Online Research Conference (GOR '26), Cologne, Germany. By applying literature on experimental research design to study the effects of evidence in persuasive communication (McCroskey, 1969), it illustrates the suitability of online experiments for analyzing credibility formation in emerging journalistic practices. It exemplifies an experimental investigation into how argument strength impacts content credibility in sensor-based journalism.

Part 2: Technology-Enabled Offerings Enhancements, Platform Use, and Divestments

Paper #7 (Loebbecke et al., 2021), titled "Mass media deploying digital personalization: an empirical investigation", published in the International Journal on Media Management [VHB: C], draws on the concept of personalization in online contexts (Tam & Ho, 2006). It examines whether and to what extent mass media personalize their content delivery. Based on observational data from a one-week browsing simulation across five German legacy newspaper websites, it finds minimal personalization.

Paper #8 (Loebbecke et al., 2024), titled "Towards AI-based thumbnail design for fostering consumption on digital media platforms", published in the International Journal of Information Management [VHB: B], is grounded in framing theory (Tversky & Kahneman, 1981). It investigates how AI-based imagery analysis allows for automatic classification of visual cues to design customized thumbnail variations and, hence, to increase consumption of hedonic media goods on video and e-commerce platforms. Data from an AI-based imagery analysis on nearly 500,000 thumbnails from a video and an e-commerce platform show that faces with negative emotions and less text increase consumption.

Paper #9 (Hoedl & Boboschko, 2025), titled "The double-edged sword: empowerment and risks of platform-based work for women", appeared at the International Conference 'Wirtschaftsinformatik' (WI '25), Muenster, Germany [VHB: B]. Based on the concept of women's empowerment (Kabeer, 1999), it applies a conceptual approach and reflects on three cases of using platforms for work processes. It derives four propositions, conceptually illustrating how such platform use can both empower and disempower women with caregiving responsibilities.

Paper #10 (Boboschko, 2022), titled "IT-driven divestments: towards theoretical multiplicity through a configurational approach", appeared at the European Conference on Information Systems (ECIS '22), Timisoara, Romania [VHB: A]. It follows a configurational approach by drawing on two theoretical perspectives, the resource-based view (Wernerfelt, 1984) and the concept of ambidexterity (Montealegre et al., 2019). It derives two causal configurations theoretically grounding divestment strategies in response to digitization and technological advancements.

2. Sensor-Based Journalism

2.1. Reflecting upon sensor-based data collection to improve decision making

Loebbecke, C., & Boboschko, I. (2020a). Reflecting upon sensor-based data collection to improve decision making, Journal of Decision Systems, 29(Sup1), 18-31 [VHB: B], doi.org/10.1080/12460125.2020.1776926.

My contributions to this paper include the co-development of the literature review, draft of illustrative cases, and revision based on the comments from the co-author and reviewers.

2.2 Reader information processing in sensor-based journalism: the impact of identity cues on credibility

Reproduction from:

Boboschko, I., & Loebbecke, C. (2025a). Reader information processing in sensor-based journalism: the impact of identity cues on credibility, under review at Information Technology & People [VHB: B].

My contributions to this paper include the co-development of the research idea, literature review, experiment design, data collection, data analysis, manuscript draft, and revision based on the comments from the co-author.

Reader information processing in sensor-based journalism: the impact of identity cues on credibility

Anonymous for review

Abstract

Purpose: Sensor-based journalism leverages sensors to collect data to capture phenomena beyond human reach. However, the credibility of sensor-based articles is still little investigated. In this study, we aim to investigate how displaying different identity cues affects the credibility of sensor-based articles among readers.

Design/ methodology/ approach: Building on prior research on the heuristic-systematic model of information processing and social presence, we develop four hypotheses and test them using data from a between-group online experiment with 233 participants in Germany.

Findings: We find that displaying contributor jobs enhances social presence perceptions and hence the credibility of an article, while displaying contributor names does not make a difference. Neither media skepticism nor familiarity with sensor-based journalism moderate these effects.

Originality: This paper offers a novel contribution by examining how identity cues affect credibility assessments in the emerging field of sensor-based journalism. While prior research has shown that identity cues cause mixed or even negative effects on credibility – particularly due to concerns about human-driven bias – we demonstrate that cues signaling expertise, i.e., contributor jobs, enhance credibility assessments in this context. We extend the application of the heuristic-systematic model and research on social presence to sensor-based journalism, providing new theoretical insights into how readers process sensor-based content.

Keywords: Sensor-based journalism, Identity cues, Heuristic-systematic information processing, Social presence, Credibility perceptions.

Paper type: Research paper

1 Introduction

Sensor-based journalism has gained relevance as a journalistic practice in the past decade. It primarily centers on sensor-based data collection, i.e., it relies on sensors collecting real-time and continuous sensor data to explore and report on phenomena beyond human reach (Diakopoulos, 2019; Hamm, 2024). Sensor-based journalism may involve interdisciplinary contributors, including authors, data journalists, data scientists, domain specialists, and designers. They collectively contribute to the workflows and the choices of which phenomena to represent, how to operationalize variables, how and where to collect sensor data, how to curate and analyze it, and how to present it (Hamm, 2024; Parmiggiani *et al.*, 2022). Examples of sensor-based journalism include real-time traffic updates enabled by sensor data from sensors installed on highways, reports on air pollution made possible by sensor data from portable sensors carried by correspondents (Hook *et al.*, 2019), and articles revealing potential greenwashing facilitated by sensor data from sensors placed in shoes tracing the shoe material recycling journey (Flip, 2021). While the output of sensor-based journalism can take various online and offline formats (Hamm, 2024), this study focuses on sensor-based articles in print news media. These articles are rarely explicitly labeled as sensor-based journalism and thus are not necessarily recognizable by readers as such; rather, they are often classified under data-driven journalism in investigative contexts or appear in routine reporting, such as traffic or weather coverage.

Recent research on emerging forms of data-driven journalism (Graefe and Bohlken, 2020; Woelker and Powell, 2021) increasingly examines the role of identity cues in bylines to assess credibility. In traditional journalism, bylines positively impact reader perceptions of the corresponding articles (Graefe *et al*., 2018; Montal and Reich, 2017). Displayed within, below, or alongside an article, they usually consist of identity cues conveying contributor names or contributor jobs (Montal and Reich, 2017; Sundar, 2008). The identity cues may thus trigger perceptions of social presence, i.e., the perceived salience of another human behind the article (Short *et al.*, 1976). Those perceptions of social presence then may influence the credibility of an article, as explained by the heuristic-systematic model of information processing (Chaiken, 1980; Evans, 2008).

In emerging forms of automated journalism where human involvement becomes less visible, identity cues have shown mixed effects on perceived credibility (Graefe and Bohlken, 2020; Woelker and Powell, 2021). Hence, similar concerns about mixed effects of identity cues may arise in sensor-based journalism, where the data-driven nature of reporting can obscure human agency and editorial decision-making, particularly within the so-called 'black box' of data curation (Parmiggiani *et al.*, 2022). Yet, applying findings from automated journalism to sensor-based journalism may overlook key differences between the two.

The real-time and continuous collection of sensor data through sensor technologies that extend beyond human sensory and precision capabilities contributes to its perception as pursuing objectivity – even if true objectivity remains difficult to achieve (Carlson, 2019; Kitchin, 2014). Among readers, this pursuit may already foster a baseline level of credibility (Tandoc and Thomas, 2017). Unlike in automated journalism – where identity cues may raise questions about bias, we argue that in sensor-based journalism, identity cues may increase credibility perceptions by helping readers identify the contributors responsible for transforming raw sensor input into 'science'-like journalistic content.

Hence, we ask: How do identity cues influence the credibility of sensor-based articles? Particularly, we consider identity cues like contributor names or contributor jobs. We ground our work on the heuristic-systematic model of information processing (Chaiken, 1980; Evans, 2008) and take into account the level of media skepticism (Stroembaeck *et al*., 2020; Tsfati, 2003) and the familiarity with sensor-based journalism (Gefen, 2000; Jang *et al*., 2024; Komiak and Benbasat, 2006) as potential moderators. We derive four research hypotheses and conduct a between-group online experiment examining how different identity cues influence article credibility.

With our study, we contribute to the literature on social presence perceptions in data-driven settings such as sensor-based journalism (Ehsan *et al*., 2021; Gao *et al*., 2023; Graefe *et al.*, 2018). Further, we extend the application of the heuristic-systematic model of information processing to sensor-based journalism (Chaiken, 1980; Evans, 2008). Finally, we offer practical recommendations for media organizations on the design of bylines below sensor-based articles.

2 Research Context: Sensor-Based Journalism

For over 200 years, journalists have engaged in data-driven reporting, drawing on existing data. In 1821, *The Guardian* published one of the first known examples of a data-driven article, analyzing student enrollment figures and associated costs (Howard, 2014; The Guardian, 2011). Since the 1950s, journalists have accessed satellite and temperature data from established sensor networks to produce routine weather reports (National Environmental Satellite, Data, and Information Service, 2025). In the past decade, journalists have expanded the use of sensor data beyond routine coverage to pursue investigative reporting that requires newly generated data (Diakopoulos, 2019; Hamm, 2024; Howard, 2014). In this context, sensor-based journalism has gained relevance as a journalistic practice. It relies on sensors that collect real-time, continuous data streams, enabling a so-called "N=all" scenario, in which a phenomenon can be comprehensively datafied across all measurable dimensions within a defined scope (Bardhan *et al.*, 2020; Jones, 2019; Khakurel *et al.*, 2018). In the form of microphones or thermometers, sensors capture temporal variations in environments of various physical or chemical natures (Osterlie and Monteiro, 2020) and convert them into electronic signals, producing large amounts of continuous, real-time, structured, and unstructured data (Bardhan *et al.*, 2020; Monteiro and Parmiggiani, 2019; Newell and Marabelli, 2015). Therefore, sensors allow for digitizing physicalities, such as human seeing, hearing, tasting, smelling, and tactile sensation (Newell and Marabelli, 2015). Sensors placed on living creatures or objects act as mobile data generators (Newell and Marabelli, 2015). When embedded in networked systems, these sensors become part of the 'Internet of Things', allowing for multi-directional data flows and contextual responsiveness (Monteiro and Parmiggiani, 2019).

According to Hamm (2024), sensor-based journalistic outputs are developed through three phases: (1) formation, where journalists explore how sensor data can support a story and assemble interdisciplinary teams; (2) data practices, involving project design, sensor deployment, sensor data collection, and sensor data analysis; and (3) presentation, where insights are published across various transmedial, online and offline formats.

Recent journalism research has begun conceptualizing sensor-based journalism (Hamm, 2024) as part of the broader field of data-driven journalism (Diakopoulos, 2019; Graefe *et al.*, 2018). The following aspects distinguish sensor-based journalism from traditional, data-driven, and automated journalism.

- Unlike traditional journalism, which primarily relies on testimonial-based knowledge, both sensor-based and data-driven journalism depend on large streams of data, pursuing the objectivity and neutrality of the resulting journalistic publication (Carlson, 2019; Diakopoulos, 2019; Hamm, 2024; Kitchin, 2014). In this context, the pursued objectivity acts as a core journalistic ideal, aiming to present verifiable facts in a neutral, detached manner while minimizing the influence of journalists' personal opinions, values, or judgments (Carlson, 2019; Lesage and Hackett, 2014).
- While data-driven journalism usually utilizes static datasets, sensor-based journalism integrates real-time, continuous sensor data streams. This allows for dynamic and real-time reporting on long-term, systemic issues, such as climate change (Chen *et al.*, 2012; Hamm, 2024).
- While sensor-based journalism shares its data-driven nature with automated journalism, the latter typically involves autonomous article generation. In contrast, sensor-based journalism relies primarily on sensor data for reporting, rather than on automated article writing (Hamm, 2024).

While data-driven and automated journalism have been widely studied – both conceptually and in terms of reader perceptions – there is, to the best of our knowledge, no research to date examining how readers perceive sensor-based journalism.

3 Literature Review: Credibility Assessments in Journalism

The conceptual roots of the credibility construct trace back to Aristotle's notions of ethos (appeal based on a speaker's character), pathos (appeal based on emotion), and logos (appeal based on logic or reason) (Metzger and Flanagin, 2013). Due to the multifaceted nature of the credibility construct, scholars have discussed its definition for decades without arriving at a clear consensus. For example, while Hargittai *et al*. (2010) use the two terms interchangeably, Tseng and Fogg (1999) argue that trust and credibility are distinct: trust refers to the reliability or dependability of a person, object, or process, whereas credibility refers to the believability or trustworthiness of information. Pavlou (2002) views credibility as an antecedent of trust, whereas Hovland and Weiss (1951) consider trust as an antecedent of credibility.

Investigations on credibility assessments began in persuasion contexts, studying the impact of source credibility on interpersonal influence (Metzger *et al.*, 2003; Hovland *et al*., 1953). Later, investigations in journalism research explored the impact of content credibility, focusing on particular characteristics related to the content that could impact its credibility (Sundar, 1999). Furthermore, investigations in communication research looked at media credibility in mass communication contexts, determining the relative credibility of a particular medium (Kiousis, 2001). The emergence of the internet advanced credibility research by investigating credibility assessments in digital environments (Metzger *et al.*, 2003; Sundar, 2008) and contextualizing different types of emerging journalistic formats, such as automated or data-driven journalism (Graefe and Bohlken, 2020). In this context, journalism research increasingly started investigating the objectivity of data-driven journalism, that subsequently impacts the credibility of an article (Carlson, 2019; Tandoc and Thomas, 2017; Woelker and Powell, 2021). This traces back to early research claiming that people associate information displaying quantitative data with higher credibility because they perceive objectivity and a lack of bias (Porter, 1995). One research stream claims that data speaks for itself, signaling completeness, representativeness, objectivity, neutrality, and accuracy, with minimal personal impact – ultimately positively impacting credibility assessments (Carlson, 2019; Kitchin, 2014; Woelker and Powell, 2021). However, other research streams challenge these views, highlighting perceptions of human-driven bias that can arise during data collection, interpretation, and presentation – ultimately negatively influencing credibility assessments (Lesage and Hackett, 2014; Woelker and Powell, 2021). Recent research reflects this ambiguity, particularly where identity cues signaling human involvement and triggering perceptions of social presence have been found to reproduce such varying effects on credibility assessments (Tandoc and Thomas, 2017; Woelker and Powell, 2021).

While credibility assessments in data-driven journalism are gaining increased research interest, including the impact of displaying identity cues, it remains unclear whether these assessments differ in the context of sensor-based journalism – particularly given that journalistic outputs based on sensor data may be perceived as more objective than outputs based on other data collection methods.

4 Theoretical Background and Hypotheses Development

4.1 Information Processing and Identity Cues in Credibility Assessments in Journalism

We draw on the literature on dual-process models of information processing, which explains human cognition and judgment (Chaiken, 1980; Evans, 2008). It posits that human judgment is formed either through systematic processing or through heuristic processing. Systematic processing involves substantial cognitive effort and detailed analytical consideration of judgment-relevant information. Heuristic processing requires minimal cognitive effort by relying on pre-existing mental shortcuts or judgmental rules stored in memory (Chaiken, 1980).

The 'Modality, Agency, Interactivity, and Navigability' model transfers the ideas of the heuristic-systematic model to digital, journalistic contexts (Sundar, 2008). It theorizes that cues related to modality, agency, interactivity, and navigability trigger heuristics and subsequently impact reader perceptions and credibility assessments. Hence, the cues allow readers to quickly evaluate information and make loose associations between the cues and the information (Sundar, 2008).

Identity cues are one type of cues in the 'Modality, Agency, Interactivity, and Navigability' model. They trigger cognitive heuristics and shape how readers perceive journalistic information linked to those cues (Sundar, 2008). Identity cues convey a sense of social presence (Short *et al.*, 1976), which fosters social presence heuristics and hence evokes positive perceptions such as warmth and credibility (Gao *et al*., 2023; Sundar, 2008). They enhance user persuasion and accountability perceptions and thereby reduce user aversion toward opaque data-driven products and services (Ehsan *et al*., 2021; Gao *et al.*, 2023; Gefen and Straub, 2004). According to Gao *et al.* (2023), seeing the names of customer service agents improves user engagement and persuasion. Users accept the reasoning and apologies linked to human identities more than anonymous sources. Furthermore, following Ehsan *et al.* (2021), Gefen and Straub (2004), and Haque *et al.* (2023), identity cues help bridge knowledge gaps and enhance user understanding of complex data-driven products.

In the pre-digital era, readers assessed articles without any identity cues as dubious and suspicious (Montal and Reich, 2017). However, in emerging fields such as automated journalism, identity cues cause mixed effects and sometimes weaken credibility perceptions due to assumed human-driven biases embedded in algorithms (Graefe and Bohlken, 2020; Woelker and Powell, 2021; Sundar, 2008). Sensor-based journalism, while also data-driven, represents a distinct case. Rather than generating articles automatically, it primarily focuses on relying on real-time, continuous sensor data (Hamm, 2024). Because sensor data may be perceived as inherently objective, sensor-based articles may already benefit from a baseline of credibility driven by the systematic route of information processing (Tandoc and Thomas, 2017; Sundar, 2008). In this context, identity cues – such as contributor names or jobs – may not evoke bias concerns as they sometimes do in automated journalism (Woelker and Powell, 2021). Instead, making human agency visible in sensor-based journalism may bridge potential knowledge gaps between the raw sensor data and the various contributors and thereby enhance credibility perceptions by reinforcing transparency and accountability perceptions.

Beyond contributor names signaling personal responsibility and triggering social presence heuristics, contributor jobs may be effective, as they explicitly signal the presence of expert judgment behind the interpretation of otherwise technical or unfamiliar sensor data (Hamm, 2024; Sundar, 2008). According to Sundar (2008), contributor jobs below a journalistic article signal expertise. They activate authority heuristics, which link the expertise to credibility. This aligns with findings by Hovland and Weiss (1951) who find that the perceived credibility of an essay, comparable to an article in our study, differs depending on whether readers believe an expert or a novice authored the essay. They suggest that content credibility depends on whether a source signals expertise and reliability.

Acknowledging the different conceptualizations of the credibility construct in prior research, we investigate the impact of identity cues on article credibility, which we define as comprising both source credibility and content credibility. In particular, we refer to source credibility as encompassing the perceived trustworthiness and perceived expertise of the source (Hovland and Weiss, 1951; Pornpitakpan, 2004) and content credibility as referring to the perceptions of believability, accuracy, biasedness, objectiveness, and fairness related to the content (Sundar, 1999). Hence, we hypothesize:

H1a: Contributor names below a sensor-based article increase the article credibility.

H1b: Contributor jobs below a sensor-based article increase the article credibility.

4.2 Moderating Factors

4.2.1 Media Skepticism

Media skepticism is an attitude of alienation and mistrust toward offline and online media, here newspapers (Stroembaeck *et al.*, 2020; Tsfati, 2003). Skeptical readers often view media as biased and unfair (Tsfati, 2003), a subjective stance tied to the 'hostile media phenomenon'. According to Giner-Sorolla and Chaiken (1994), readers with strong partisan views see relatively neutral content as biased against their position. Due to resistance to change, such media biases often persist even when discredited (Howe and Krosnick, 2017).

Skeptical readers may also be more resistant to persuasive cues, such as identity cues like contributor names or contributor jobs. According to the heuristic-systematic model of information processing (Chaiken, 1980; Evans, 2008), identity cues function as heuristics that help readers evaluate credibility without deep processing. However, skeptical individuals may discount these cues or question their sincerity, particularly if they already mistrust the media in general. Consequently, the influence of identity cues on the credibility of a sensor-based article may depend on media skepticism. Media skepticism may moderate the effect of identity cues, with weaker skepticism enhancing credibility perceptions more than stronger skepticism. Therefore, we hypothesize:

H2: The effect of identity cues on the credibility of a sensor-based article is lower for readers with strong media skepticism than for those with weak media skepticism.

4.2.2 Familiarity with Sensor-Based Journalism

Familiarity refers to understanding a domain based on prior interactions, experience, and knowledge (Gefen, 2000; Jang *et al.*, 2024; Komiak and Benbasat, 2006). It influences cognitive processing and judgment. Familiarity with a domain enables individuals to interpret information more effectively due to a broader knowledge base, which enables them to evaluate content within the field critically (Robinson and Levy, 1986). In contrast, limited familiarity fosters reliance on social presence heuristics or authority heuristics when seeing identity cues (Jang *et al.*, 2024).

In the context of sensor-based journalism – a relatively new journalistic format – familiarity may determine the extent to which readers depend on identity cues. Readers unfamiliar with sensor-based journalism may use identity cues as cognitive shortcuts to compensate for their lack of domain knowledge, placing more weight on personal accountability or perceived expertise. In contrast, more familiar readers may already understand the processes and norms of sensor journalism and thus rely less on identity cues to assess credibility. Familiarity with sensor-based journalism could moderate the effect of identity cues below sensor-based articles on article credibility, with a reduced effect for highly familiar readers and a stronger effect for those less familiar with sensor-based journalism. Hence, we hypothesize:

H3: The effect of identity cues on the credibility of a sensor-based article is lower for readers who are familiar with sensor-based journalism than for those who are not familiar with sensor-based journalism.

Summing up, our research model is based on four hypotheses (Figure 1). The independent variable is the presence (or absence) of identity cues, i.e., contributor names or contributor jobs (binary variable, assigning 0 to its absence and 1 to its presence). The dependent variable is the perceived credibility of the sensor-based article, operationalized by two variables, i.e., content and source credibility (low to high). Media skepticism and familiarity with sensor-based journalism are the two moderating variables.

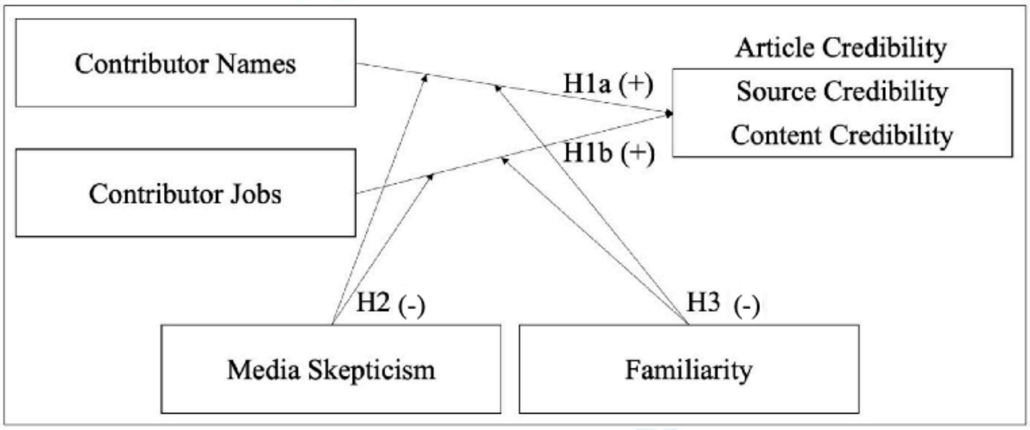

Figure 1. Research model.

5 Method

5.1 Experimental Procedure

We conduct an online experiment and recruit the participants via convenience sampling on a crowdsourcing platform, through which we send the experiment link to the participants.

Upon clicking the experiment link, participants see the introductory webpage that briefly explains the experiment and requests participants' informed consent. First, we ask the participants to fill out a short pre-test questionnaire on their demographics, their level of media skepticism, their self-reported familiarity with sensor-based journalism, and pose four quiz questions on sensor-based journalism to verify participants' familiarity with sensor-based journalism. Then, we assign participants randomly to three groups with Group 1 seeing no identity cues, Group 2 seeing contributor names, and Group 3 seeing contributor jobs. We selected contributor names and jobs as identity cues because they reflect commonly used byline formats and identity cues in both journalism as well as Information Systems settings (Ehsan *et* *al.*, 2021; Tandoc and Thomas, 2017). Names provide a basic signal of personal responsibility, while jobs additionally imply domain-specific expertise and professional accountability.

This design allows us to test the effects of identity cues on credibility perceptions of sensor-based articles. Specifically, H1a posits that displaying contributor names (Group 2) increases perceived credibility compared to the control group (Group 1), while H1b assumes a similar effect for contributor jobs (Group 3 vs. Group 1). In addition, we examine two moderating variables. H2 tests whether the effect of identity cues (Groups 2 and 3) is weaker among individuals with high media skepticism. H3 explores whether this effect increases for participants familiar with sensor-based journalism. This setup enables us to assess both the main effects of identity cues and how they interact with reader characteristics.

All participants read the same sensor-based article on a traffic concern from a German newspaper (see Figure 2). The approximately 450-word article features a 2-month test in Berlin, where 100 bikes were equipped with distance sensors to measure how closely vehicles overtook them, showing that about half of the overtaking drivers did not respect the legally required safety distance. At the bottom, all participants see a brief explanation of how the sensor-based data was collected. Depending on the group, participants see the identity cues (no identity cues, contributor names [1], contributor jobs). Upon reading the sensor-based article, participants complete a treatment check, answering a question on how many different contributor names and contributing professionals they had recognized, and subsequently evaluate the article credibility. Finally, the participants are debriefed and rewarded for their participation.

The required sample size of a minimum of 157 participants (53 per group) is estimated using a power analysis in G*Power (Faul *et al.*, 2009), based on an analysis of variance (ANOVA) with a significance level of 0.05, statistical power of at least 0.80, and a medium effect size f = 0.25 (Cohen, 1988).

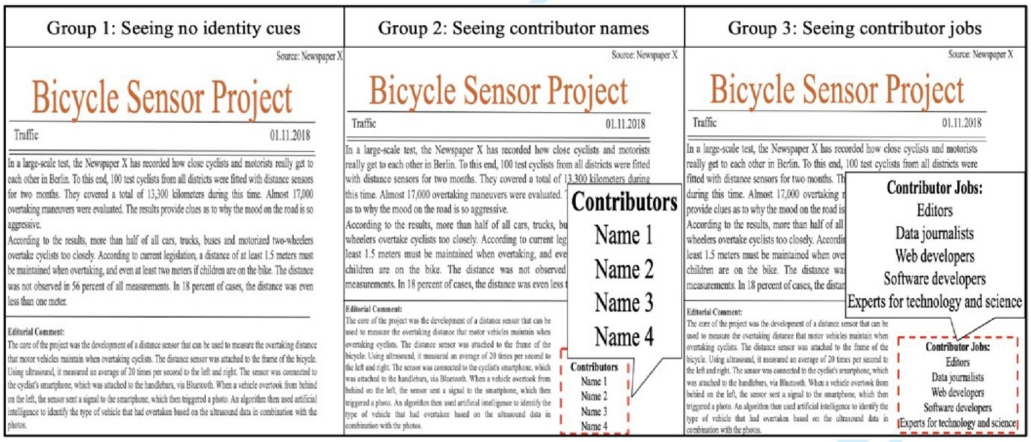

Figure 2. Sensor-based articles in the three groups (translated from German using DeepL).

5.2 Measurements

In the pre-test questionnaire, we ask about participants' *demographics* (gender, age range, educational level). Then we assess our two *moderating variables*. We measure participants' *level of media skepticism* regarding 'fair coverage', 'lack of bias', 'comprehensiveness', 'accuracy', and the 'separation of facts from opinions' in their country (Germany) – each on a 5-point Likert scale ranging from 1 = 'strongly disagree' to 5 = 'strongly agree' with high agreement indicating low media skepticism and vice versa (adapted from Stroembaeck *et al*., 2020; Tsfati 2003). The media skepticism items load strongly onto a single factor (> 0.46), supporting convergent validity. We evaluate *familiarity with sensor-based journalism* via (1) *self-reported familiarity* on a 5-point Likert scale ranging from 1='no familiarity' to 5='very high familiarity', asking "What level of familiarity do you have regarding the increasing use of sensors in journalism?" (Gran *et al*., 2021), and (2) *verified familiarity* measured with four True/False knowledge questions about sensor-based journalism (after Jang *et al*., 2024). The item measuring familiarity with sensor-based journalism shows a low factor loading (0.14), indicating discriminant validity. Since this construct is measured using a single item, internal consistency metrics such as Cronbach's alpha and convergent validity cannot be computed.

We run a *treatment check* to find out whether participants perceived the treatment as intended. They had to indicate how many different contributor names and contributing jobs they had recognized.

We measure the dependent variable *credibility of the article* via (1) *credibility of the source* and (2) *credibility of the content* using constructs validated in prior studies on media evaluations (Bhattacherjee, 2023; Pornpitakpan, 2004; Sundar, 1999). We quantify source credibility on a 5-point Likert scale (1='strongly disagree' to 5='strongly agree') asking participants about the trustworthiness and expertise of the article's source (Bhattacherjee, 2023; Pornpitakpan, 2004). We measure content credibility on the same 5-point Likert scale asking participants to assess the content as 'believable', 'accurate', 'biased', 'objective', and 'fair' (Sundar, 1999).

The average Cronbach's alpha for the credibility of the source and that for the credibility of the content is $\alpha = 0.85$, indicating very good reliability for both (see Table I for the measurement items).

Table I. Measurement items.

6 Results

We conducted the online experiment in October 2024. We recruited the participants via convenience sampling on the crowdsourcing platform 'Prolific'. Crowdsourcing platforms like Prolific or Amazon Mechanical Turk are widely recognized for their efficacy in behavioral research and experiments, yielding reliable and high-quality data (Bhattacherjee, 2023).

To ensure sufficient understanding of the sensor-based article, we restricted the sample to adults residing in Germany with German as their first language. From the initial sample of 318 participants, we excluded the data of 3 participants who claimed familiarity with sensor-based journalism but failed to answer related questions correctly. We also excluded the data of 58 participants who did not pass the treatment check. We also excluded another data of 24 participants who completed the study in under four minutes, which was below a reasonable threshold based on the article's length and expected reading and response time. Such short durations suggest insufficient engagement with the material. The procedure of excluding a total of 85 participants' data led to a final sample of 233 participants. To test the robustness of our findings, we also conducted all analyses with the full sample (see Results section). The final sample consists of 31.3% females, 67.4% males, 0.86% diverse, and 0.43% not disclosing. The median age range was 25 to 34 years and the median educational level a bachelor's degree (Table II).

Table II. Demographics.

The sample exceeded the minimum sample size of 157 (53 per group). Chi-squared tests confirmed the successful randomized assignment to the experimental groups without significant differences ($p > 0.05$) in participants' gender, age range, and level of education across the groups (see Table III).

Table III. Chi-squared tests.

For the data analysis, we use the open source software 'R' and 'RStudio' Version 2024.09.0+375.

Overall, we find a slightly higher article credibility (dependent variable) composed of source and content credibility when participants see contributor jobs compared to seeing contributor names or no identity cues. Participants who saw contributor jobs (Group 3) reported slightly higher article credibility than those who did not see any identity cues (see Table IV).

Table IV. Descriptive statistics.

Before comparing group differences, we evaluate whether the assumptions of parametric tests were met.

We conduct a Levene's test for homogeneity of variances to assess whether the assumption of equal variances is met across the three groups. For the source credibility, we find that Levene's test approaches significance, $F(2, 227) = 2.36$, $p = 0.096$, suggesting marginally unequal variances between the groups. For the content credibility, we find that Levene's test is not significant, $F(2, 227) = 0.32$, $p = 0.728$, suggesting equal variances across the groups.

Further, we conduct a Shapiro-Wilk test to assess the normality of the data. The results indicate a significant deviation from normality for both the source credibility ($W= 0.91$, $p < 0.001$) and for the content credibility ($W= 0.93$, $p < 0.001$). This suggests that the assumption of normal distribution is violated and requires non-parametric methods to analyze group differences.

To account for these violations, we conduct a non-parametric Kruskal-Wallis rank sum test to examine group differences. Such non-parametric methods avoid reliance on parametric assumptions and provide robust insights despite the observed distributional irregularities. Hence, we conduct a Kruskal-Wallis rank sum test to evaluate group differences across the three groups. Assessing the differences in the source credibility, we find a statistically significant difference in medians between the groups, $\chi^2 = 10.73$, $p = 0.005$ with a small effect size, $\eta^2 = 0.046$. This suggests that the groups differ significantly in assessing the source credibility. For the content credibility, we find no statistically significant differences between the three groups ($\chi^2 = 4.36$, $p = 0.113$). This suggests that the groups do not differ significantly in assessing the content credibility.

To assess the robustness of these findings, we repeat the analysis using the initial sample, including the participants' data that was excluded. The results remained consistent: group differences in source credibility remained statistically significant ($\chi^2 = 11.61$, $p = 0.003$), while differences in content credibility continued to be non-significant ($\chi^2 = 4.05$, $p = 0.132$). These findings support the robustness of our main results and suggest that the observed effects are not driven by the exclusion of participants.

Post-hoc pairwise comparisons of the source credibility, using Dunn's test with Bonferroni adjustment, reveal no significant difference between Group 2 and Group 1 (adjusted $p = 1.00$). However, we find significant differences in the source credibility between Group 3 and Group 1 (adjusted $p = 0.004$), as well as between Group 3 and Group 2 (adjusted $p = 0.014$). These results indicate that Group 3 shows higher source credibility than the other groups (see Table V).

Table V. Post-hoc Dunn's test with Bonferroni adjustment results.

We conduct two moderation analyses using ordinary least squares regression models. In each model, the main effect of the treatment group was entered using dummy-coded variables, followed by the moderator (media skepticism or familiarity with sensor-based journalism), and the interaction terms between the group and the moderator.

The first moderation analysis explores whether media skepticism moderates the effect of identity cues on article credibility, while the second investigates whether familiarity with sensor-based journalism moderates the effect.

Media skepticism consistently shows a significant positive direct effect on both source and content credibility (all p-values < 0.01). However, the interaction terms between the groups and media skepticism are not statistically significant (all p-values > 0.05). This indicates that media skepticism does not moderate the effect of identity cues on source and content credibility (see Table VI).

Table VI. Moderation analysis results for media skepticism.

Similarly, regarding the effect of familiarity with sensor-based journalism on credibility measures, none of the interaction terms between the treatments and the familiarity with sensor-based journalism is statistically significant (all p-values > 0.05). This suggests that familiarity with sensor-based journalism does not moderate the effect of identity cues on the source and the content credibility (see Table VII).

Table VII. Moderation analysis results for familiarity with sensor-based journalism.

Table VIII presents the regression results from the moderation analyses, examining whether media skepticism and familiarity with sensor-based journalism moderate the effects of identity cues on article credibility.

Table VIII. Regression results for moderation analyses.

Summing up, we identify significantly higher credibility of sensor-based articles when participants see contributor jobs below an article than when they see contributor names or no identity cues. However, the effect size is small, indicating limited practical impact. We indicate that media skepticism has a significant direct effect on article credibility. However, it does not moderate the effect of identity cues on the article credibility. Familiarity with sensor-based journalism shows neither direct nor moderating effects. See Table IX for a summary of the hypothesis testing results.

Table IX. Results of hypothesis testing.

7 Discussion

Our research indicates that signaling expertise and accountability through contributor jobs enhances the credibility of the source and thus the overall article credibility in sensor-based journalism.

Theoretical implications: Our findings contribute to the literature on information processing (Chaiken, 1980; Evans, 2008), particularly on social presence perceptions evoked by identity cues. We complement prior insights in data-driven journalistic contexts (Ehsan *et al*., 2021; Gao *et al*., 2023; Graefe *et al*., 2018; Sundar, 2008; Woelker and Powell, 2021) with our findings from the specific context of sensor-based journalism.

Practical implications: According to our findings, identity cues are crucial for signaling accountability in sensor-based journalism. Displaying contributor jobs signals accountability and expertise and thus enhances article credibility. Hence, media organizations should provide contributor jobs in bylines to improve article credibility and promote public acceptance of sensor-based journalism. This may help address the prevalent public skepticism toward the media industry (Stroembaeck *et al*., 2020).

Six issues suggest for discussion.

Source credibility outweighing content credibility in assessing article credibility: We find that displaying contributor jobs below a sensor-based article impacts the article credibility through source credibility. Hence, we suggest that authority heuristics (Sundar, 2008) play a significant role in the perceptions of sensor-based articles. Thereby, we match Sundar (2008), who suggests that contributor or author names do not necessarily convey expertise or accountability. We explain this finding by sensor-based journalism as our research context. Insights resulting from sensor-based data incorporate additional data-based layers, such as measurements, statistics, and real-time updates. When readers view insights resulting from sensor data as factual and less biased, they may rely on its assumed objectivity – not the named contributor – when assessing the content credibility (Kitchin, 2014; Sundar, 2008; Tandoc and Thomas, 2017). In line with Tandoc and Thomas (2017), our results highlight the dominance of perceived content objectivity over contributor identification in shaping article credibility perceptions.

Importance of communicating the social origin of data-driven products and services: Our findings support prior research (Ehsan *et al*., 2021; Parmiggiani *et al*., 2022) that emphasizes the importance of enhancing perceptions of social presence through identity cues for data-driven products. In the context of sensor-based journalism, readers prioritize clearly signaled expertise (e.g., contributor jobs) over merely seeing names. This aligns with insights (Montal and Reich, 2017; Sundar, 2008) that in data-driven journalism, readers expect more information about the source of the articles compared to traditional journalism.

Media skepticism and familiarity with sensor-based journalism barely relevant for article credibility: Contrary to our hypotheses regarding the moderating factors, our findings indicate that neither media skepticism nor familiarity with sensor-based journalism moderates article credibility when seeing identity cues. A possible explanation is that sensor-based journalism is a relatively new type of journalism, so readers are unable to apply any associations based on their media skepticism. Only 6.4% of participants indicated a high and a very high level of familiarity with sensor-based journalism. Hence, readers may default to evaluating article credibility based on the content alone rather than on identity cues. In that case, the assumed objectivity of sensor data would reduce the impact of any media skepticism on article credibility. Similarly, readers who are either familiar or unfamiliar with sensor-based journalism may find identity cues less relevant, especially if they view the sensor-based data collection process and the derived insights as inherently credible (Stroembaek *et al*., 2020).

Novelty of sensor-based journalism and inherent credibility of sensor data: The novelty of sensor-based journalism may shape how readers process and evaluate such content. As a relatively new form of reporting, sensor-based journalism may be perceived as more technical, data-driven, or 'scientific' in nature. In such cases, readers may find it difficult to apply familiar credibility heuristics drawn from traditional journalism (Sundar, 2008). Instead, readers may default to assuming the objectivity of the sensor data. This aligns with prior research suggesting that content containing numerical cues can appear inherently credible due to its perceived factual basis (Porter, 1995; Sundar, 2008). Consequently, additional credibility-evoking signals, such as identity cues, might add to the inherent credibility of the sensor data because of its assumed objectivity. This may also help explain why identity cues in our study did not significantly affect content credibility, which remained relatively high across conditions.

Contributor jobs outperforming contributor names: The finding that contributor jobs were more effective than names in increasing source credibility suggests that in data-intensive contexts like sensor-based journalism, readers may place greater value on perceived expertise than on mere human identification. This supports prior work on trust in automated or data-driven systems, where expert framing increases acceptance and reduces skepticism (Gefen and Straub, 2004; Ehsan *et al*., 2021). Thereby, job cues may help bridge knowledge gaps by validating the authority of those responsible for those systems and processes. However, it remains unclear why displaying contributor names is less impactful in credibility assessments within sensor-based journalism. One possible explanation is that readers may not consider the social origin of the sensor data to be relevant or simply do not require names to assess article credibility, leading them to disregard this information altogether.

Article credibility depending on the outlet or identity cues as source: We stress that the credibility of sensor-based articles depends on the displayed article source. Thereby, we confirm Tandoc and Thomas (2017), who claim that identity cues and a particular outlet reinforce or weaken the perceived article credibility. However, for the peculiar setting of sensor-based articles, we have not yet investigated to what extent this effect stems from the reputation of the outlet, the disclosed human contributors, or the interplay between the two (Stroembaeck *et al*., 2020).

8 Limitations and Suggestions for Future Research

We recognize that our study has several limitations, which each lead to a suggestion for future research.

Readers' implicit assumptions based on the news outlet: In our experiment, we used a known, widely read German newspaper. Participants may base their assessment of the source credibility and thereby of the article credibility more on the news outlet, the newspaper brand, than on the presence or absence of identity cues. Hence, it is uncertain whether similar findings would emerge with less reliable outlets. In line with prior studies comparing credibility assessments across multiple outlets with different inherent reputations (e.g., Bhattacherjee, 2023), future studies could address this issue by incorporating articles from various newspapers with different reputations and examine how credibility perceptions of sensor-based articles differ across the different outlets. Such distinctions would enhance our understanding of how readers assess different sources and the associated article, particularly whether the assumed objectivity of a sensor-based article can outweigh personal preconceptions linked to less reliable sources.

Limited topic variety: We exposed all participants to the same one, relatively neutral article. Future studies may want to show them multiple articles dealing with different topics to minimize topic-specific effects. In the context of computer-supported journalism, for example, Woelker and Powell (2021) find that particularly in sports articles, identity cues decreased article credibility. Future studies could also explore variations in article tone, distinguishing between emotional and neutral presentations, to examine how the credibility of sensor-based articles is influenced by emotionally charged topics. This investigation would provide insights into whether the tone of reporting interacts with the objectivity associated with sensor-based journalism and which heuristics may play a role in shaping reader perceptions. Depending on the experiment setup, this could be the same several articles in each group or participants randomly assigned to different articles.

Limitation to sensor-based newspaper articles: While our work focuses on sensor-based journalism, we exclude broader interpretations of data-driven journalism, where journalists work with pre-existing or indirectly sourced data leveraging manual and automated processes. Hence, our findings are currently limited in terms of generalizability to alternative forms of sensor-based journalism or non-sensor-based data. Future studies could expand the scope to include varied data-driven contexts to better understand the role of identity cues and credibility assessments across different journalistic frameworks. Also, future studies may want to expand the research to other settings, such as popular science journalism, regional versus national reporting, documentaries, or even academic research increasingly struggling with source authenticity and originality. Exploring other contexts could reveal how credibility assessments vary across different mediums and genres, taking into account perhaps varying objectivity expectations in fields beyond traditional journalism. It is also questionable whether the impact of displaying identity cues differs in contexts lacking the inherent objectivity of sensor-data-driven insights. In areas such as political journalism, for example, individual political polarization might play a significant – perhaps additional, moderating – role in shaping credibility assessments.

Absence of combined identity cues and other factors influencing article credibility: A key limitation of this study lies in the experimental design, which included conditions with either contributor names or contributor jobs, but not a combined condition featuring both identity cues (Woelker and Powell, 2021). While this approach allowed for testing the individual effects of contributor names and jobs on perceived article credibility, it did not permit the examination of potential interaction effects between the two. Including a fourth group that received both identity cues would offer more nuanced insights into how combinations of identity cues influence credibility perceptions. Furthermore, this design constraint limits our ability to fully interpret the hypothesized moderation effects. Hence, future research should explore not only the main effects but also potential interactions between different identity cues, as well as their interplay with individual reader characteristics, such as media skepticism and familiarity with sensor-based journalism. Also, future research may want to examine the impact of different positions of identity cues (Moravec *et al*., 2019) or additional background on persons or job activities (Tandoc and Thomas, 2017).

Absence of significant moderation effects: It is possible that limited variance in the moderator variables and an insufficient sample size for detecting interaction effects contributed to the absence of significant moderation. Future studies should aim for larger, more diverse samples and ensure greater variation in key audience traits to better understand how identity cues interact with individual reader characteristics in shaping perceptions of sensor-based journalism.

Sample size and non-normality: While our study met the required number of participants based on the power analysis, future research would benefit from a larger and more gender-balanced sample (Yin *et al*., 2018). This could increase the generalizability and reliability of the findings and potentially reveal effects and interactions that may have been underpowered in our study. Also, applying an alternative (random) sampling mechanism could help address the non-normal distribution and thus yield new insights.

9 Conclusion

In this study, we provide empirical insights into how identity cues such as contributor names or contributor jobs below a sensor-based article influence the credibility of the article among readers. We find that placing contributor jobs below a sensor-based article increases the article credibility. While the source credibility increases when participants see contributor jobs, the content credibility remains unaffected by the presence of any identity cues. We indicate that media skepticism has a significant direct effect on article credibility. However, we find that neither media skepticism nor familiarity with sensor-based journalism moderates credibility perceptions.

Strategies that convey transparency, expertise, accountability, and reliability in sensor-based journalism will be essential for fostering credibility in the evolving landscape of journalism – and hopefully promoting the acceptance of democracy-relevant journalism, in whatever form and shape it will be provided.

Footnote

[1] Contributors, whose names are shown to Group 2, are not commonly known in order to not influence participants' responses.

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Table I. Measurement items.

Part 1. Pre-Test Questionnaire:		
1	**Demographics**	
1.1	Age range: 18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, 65 or older	
1.2	Gender: female, male, divers, prefer not to disclose	
1.3	What is your highest level of education completed? No school leaving certificate; Secondary general school-leaving certificate; University entrance qualification; Apprenticeship; Bachelor University degree; Master University degree / Diploma; Doctor's degree; Other.	
2	**Media skepticism (Stroembaeck *et al.*, 2020; Tsfati, 2003)**	
	State your agreement on statements about the media in your country, that is newspapers, magazines, television, and radio (Reversed), (1='strongly disagree' to 5='strongly agree'; 5-point Likert scale)	The media are fair
		The media are unbiased
		The media tell the whole story
		The media are accurate
		The media separate facts from opinions
3	**Self-reported familiarity of sensor-based journalism (Gran *et al.*, 2021)**	
	What level of familiarity do you have regarding increasing use of sensors in journalism? (1 = 'no familiarity' to 5 = 'very high familiarity'; 5-point Likert scale)	
4	**Verification of self-reported familiarity of sensor-based journalism according to 5 True/False knowledge questions on sensor-based journalism (Jang *et al.*, 2022):**	
	Sensors used in journalism collect data from moving objects or living creatures that are beyond human access or barely perceptible to the human eye. (True)	
	Sensor-based journalism aims to address investigative questions that require new data. (True)	
	Sensor-based journalism requires the integration of expertise from multiple domains to effectively collect and analyze sensor data. (True)	
	The success of sensor-based journalism relies solely on the technological capabilities of the sensors, with minimal input from human experts. (False)	
Part 2. Article Perception (source credibility, content credibility)		
1	**Treatment Check:** How many different actors have participated in the creation of the sensor-data based content? (None, 4, 5)	
2	**Source Credibility (Bhattacherjee, 2023; Pornpitakpan, 2004)**	
	State your agreement on the following statements related to the content source (1 = 'strongly disagree' to 5 = 'strongly agree'; 5-point Likert scale)	I believe that the content source is trustworthy.
		I believe that the content source has the necessary expertise to do their job.
		I find following content source credible.
3	**Content Credibility (Sundar, 1999)**	
	State your agreement on adjectives related to the content (1 = 'strongly disagree' to 5 = 'strongly agree'; 5-point Likert scale)	Believable
		Accurate
		Unbiased
		Objective
		Fair

Table II. Demographics.

Variable	N	%
Gender	233	100
Male	157	67.4
Female	73	31.3
Diverse	2	0.86
NA	1	0.43
Age Range	233	100
18 to 24	51	21.9
25 to 34	100	42.9
35 to 44	54	23.2
45 to 54	18	7.73
55 to 64	8	3.43
65 and older	2	0.86
Educational Level	233	100
No school leaving certificate	3	1.29
Secondary general school-leaving certificate	10	4.29
University entrance qualification	61	26.2
Apprenticeship	38	16.3
Bachelor's degree	64	27.5
Master's degree / Diploma	53	22.8
PhD	3	1.29
Other	1	0.43

Table III. Chi-squared tests.

Variable	Chi-square (χ^2)	df	p-value
Gender	6.37	6	0.38
Age Range	5.68	10	0.84
Educational Level	12.67	14	0.55

Table IV. Descriptive statistics.

Dependent Variable (Article Credibility)	**Group 1: Seeing no cues**	**Group 2: Seeing contributor names**	**Group 3: Seeing contributor jobs**
Source Credibility	Mean=3.93 (SD=0.66)	Mean=3.92 (SD=0.80)	Mean=4.23 (SD=0.77)
Content Credibility	Mean=3.91 (SD=0.67)	Mean=3.85 (SD=0.77)	Mean=4.03 (SD=0.78)

Table V. Post-hoc Dunn's test with Bonferroni adjustment results.

Dependent Variable (Article Credibility)	Comparison	Z-Score	Adjusted p-value	Significance
Source Credibility	2 vs. 1	-0.39	1.000	Not Significant
Source Credibility	3 vs. 1	-2.98	0.004	** ($p < 0.01$)
Source Credibility	2 vs. 3	2.59	0.014	* ($p < 0.05$)

Table VI. Moderation analysis results for media skepticism.

Dependent Variable (Article Credibility)	Predictor	Estimate	Std. Error	t-value	p-value	Significance
Source Credibility	Media Skepticism	0.442	0.093	4.77	<0.001	***
Source Credibility	Group 2 × Media Skepticism	-0.070	0.132	-0.53	0.597	Not Significant
Source Credibility	Group 3 × Media Skepticism	-0.018	0.135	-0.13	0.894	Not Significant
Content Credibility	Media Skepticism	0.300	0.094	3.18	0.002	**
Content Credibility	Group 2 × Media Skepticism	0.136	0.134	1.01	0.312	Not Significant
Content Credibility	Group 3 × Media Skepticism	0.064	0.137	0.47	0.640	Not Significant

Table VII. Moderation analysis results for familiarity with sensor-based journalism.

Dependent Variable (Article Credibility)	Predictor	Estimate	Std. Error	t-value	p-value	Significance
Source Credibility	Familiarity with SBJ*	-0.150	0.098	-1.53	0.127	Not Significant
Source Credibility	Group 2 × Familiarity with SBJ	0.120	0.130	0.93	0.355	Not Significant
Source Credibility	Group 3 × Familiarity with SBJ	-0.083	0.137	-0.61	0.543	Not Significant
Content Credibility	Familiarity with SBJ	-0.055	0.099	-0.56	0.576	Not Significant
Content Credibility	Group 2 × Familiarity with SBJ	0.033	0.131	0.25	0.800	Not Significant
Content Credibility	Group 3 × Familiarity with SBJ	-0.086	0.138	-0.63	0.532	Not Significant

* Sensor-Based Journalism

Table VIII. Regression results for moderation analyses.

Variable	Source Credibility (Media Skepticism)	Content Credibility (Media Skepticism)	Source Credibility (Familiarity with SBJ)	Content Credibility (Familiarity with SBJ)
Adj. R^2	0.2171	0.156	0.053	0.0004
ΔR^2	0.001	0.004	0.011	0.004
Constant	2.721***	3.096***	4.185***	4.009***
Media Skepticism	0.442***	0.300**		
Group 2 × Media Skepticism	-0.070	0.136		
Group 3 × Media Skepticism	-0.018	0.064		
Familiarity with SBJ			-0.150	-0.055
Group 2 × Familiarity with SBJ			0.120	0.033
Group 3 × Familiarity with SBJ			-0.083	-0.086

*: P ≤ 0.05; **: P ≤ 0.01; ***: P ≤ 0.001

Table IX. Results of hypothesis testing.

No.	Hypothesis	Supported / Not Supported
H_{1a}	Contributor names below a sensor-based article increase the article credibility.	–
H_{2b}	Contributor jobs below a sensor-based article increase the article credibility.	✓
H_2	The positive effect of identity cues on the credibility of a sensor-based article is lower for readers with strong media skepticism than for those with weak media skepticism.	–
H_3	The positive effect of identity cues on the credibility of a sensor-based article is lower for readers who are familiar with sensor-based journalism than for those who are not familiar with sensor-based journalism.	–

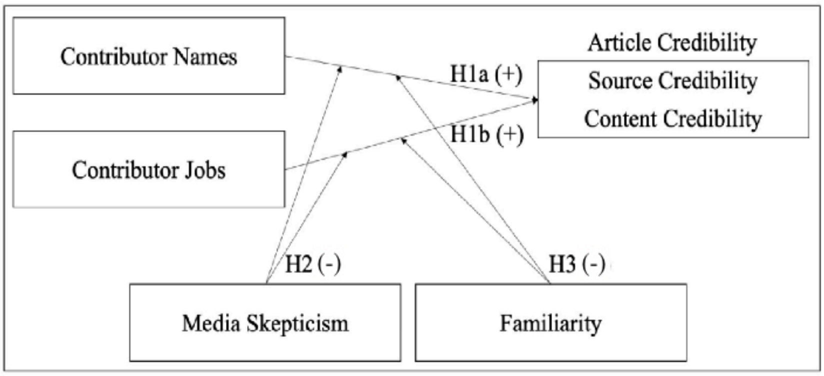

Figure 1. Research model.

303x126mm (144 x 144 DPI)

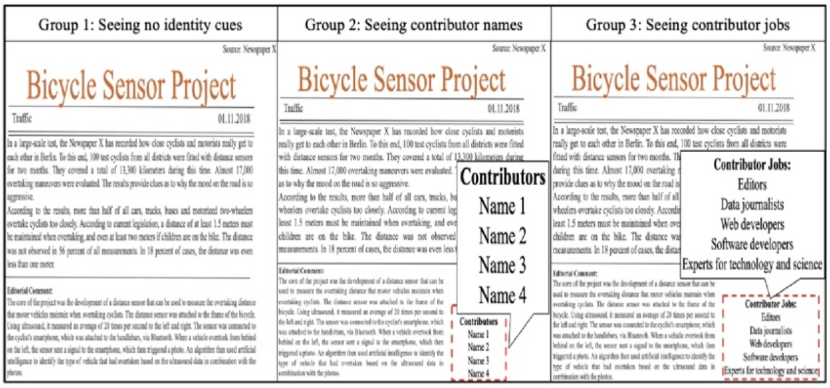

Figure 2. Sensor-based articles in the three groups (translated from German using DeepL).

326x139mm (144 x 144 DPI)

2.2a Identity cues influencing article credibility in sensor-based journalism

Boboschko, I., & Loebbecke, C. (2025b). Identity cues influencing article credibility in sensor-based journalism, European Conference on Information Systems (ECIS), Amman, Jordan [VHB: A], aisel.aisnet.org/ecis2025/digitsports/digitsports/2.

My contributions to this paper include the co-development of the research idea, literature review, experiment design, data collection, data analysis, manuscript draft, and revision based on the comments from the co-author and reviewers.

2.2b Names below sensor-based articles impacting the credibility of the article

Reproduction from:

Boboschko, I., & Loebbecke, C. (2025c). Names below sensor-based articles impacting the credibility of the articles, World Media Economics and Management Conference (WMEMC), Warsaw, Poland.

My contributions to this paper include the co-development of the research idea, literature review, experiment design, data collection, data analysis, manuscript draft, and revision based on the comments from the co-author and reviewers.

Names below Sensor-Based Articles Impacting the Credibility of the Article

Over the past decade, sensor-based journalism has gained importance as pertinent innovation for media management. It involves the use of sensors to collect data on phenomena that humans cannot observe directly and presumably fosters data-driven, seemingly neutral 'sensor-based' articles.

At the same time, bylines crediting authors have become important attributes in journalistic articles as they affect individuals' perceptions regarding the credibility of an article (Graefe et al., 2018). In journalism contexts, the heuristic-systematic model of information processing (Chaiken, 1980) puts forward that readers use systematic analysis and heuristics as cognitive shortcuts to evaluate an article. It suggests that identifying an author enhances social presence perceptions and triggers social presence heuristics, which influence the perceived credibility of an article (Sundar, 2008).

With our work, we combine both insights, as we investigate empirically whether and how author and contributor names displayed below a sensor-based article influence the perceived credibility of the article, i.e., content credibility of sensor-based articles. We also explore how readers' level of media skepticism and familiarity with sensor-based journalism play a role.

To this end, we conduct a between-group online experiment with 149 participants residing in Germany, who we recruited via Prolific in October 2024. First, we assess participants' demographics, level of media skepticism, and familiarity with sensor-based journalism. Then, we assign the participants randomly to one of two experimental groups, who we both ask to read a sensor-based article from a given news outlet. One group sees the article with author and contributor names displayed below the article; the other group does not see any names. Participants in both groups complete a questionnaire containing previously validated constructs (Graefe et al., 2018) on their level of media skepticism, familiarity with sensor-based journalism, and perceived credibility of the article's content. We analyze the data using ANOVA and moderation analysis.

Counterintuitively, we do not find any significant effect on the credibility of the article depending on whether participants see the author and contributor names or not. Hence, at this stage, we cannot confirm social presence theory when applied to sensor-based articles. Further, our data indicates that media skepticism directly impacts the credibility of the article. However, we do not indicate any moderation effects – neither from higher levels of media skepticism nor from familiarity with sensor-based journalism.

As we acknowledge the relatively low number of participants in our study, future research may want to enlarge the sample size to enhance the generalizability and reliability of the findings.

Our study contributes to the growing literature on social presence perceptions in journalistic environments (Graefe et al., 2018). It provides empirical insights showing that the presence of author and contributor names displayed below a sensor-based article does not influence readers' perceptions regarding the credibility of the article. Our work extends the application of the heuristic-systematic model of information processing to sensor-based journalism. Finally, it offers practical implications for media organizations on the design of bylines below sensor-based articles.

Key References

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Sundar, S. (2008). The MAIN Model: A Heuristic Approach to Understanding Technology Effects on Credibility, in Digital Media, Youth, and Credibility, Metzger, M., Flanagin, A. (eds.), MIT Press, Cambridge, MA, US, 73-100.

2.2c The impact of seeing human involvement in sensor-based journalism on reader appreciation

Boboschko, I. (2024). The impact of seeing human involvement in sensor-based journalism on reader appreciation, International Conference on Information Resource Management (Conf-IRM), Cairo, Egypt [Best Paper Award], aisel.aisnet.org/confirm2024/8/.

My contributions to this paper include the development of the research idea, literature review, experiment design, manuscript draft, and revision based on the comments from the reviewers.

2.3 News outlet reputation and content credibility in sensor-based journalism

Reproduction from:

Boboschko, I., & Loebbecke, C. (2025d). News outlet reputation and content credibility in sensor-based journalism, under review at European Conference on Information Systems [VHB: A].

My contributions to this paper include the co-development of the research idea, literature review, experiment design, data collection, data analysis, manuscript draft, and revision based on the comments from the co-author.

NEWS OUTLET REPUTATION AND CONTENT CREDIBILITY IN SENSOR-BASED JOURNALISM

Completed Research Paper

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Abstract

Sensor-based journalism has gained increasing attention as an Information Systems-relevant phenomenon. It relies on sensor-based data collection to capture phenomena beyond human reach. This study investigates whether and how different levels of news outlet reputation influence the credibility of content in sensor-based journalism. It draws on research on organizational credibility and heuristic-based persuasion based on reputation heuristics. It hypothesizes that in sensor-based journalism, reputable news outlets increase content credibility, whereas less reputable ones decrease it. Additionally, it hypothesizes that media skepticism moderates these effects. Data from a between-subjects online experiment (N = 809) show that reputable news outlets exert a positive effect on content credibility while less reputable ones show no effect. Media skepticism does not moderate these effects. This study contributes to prior research by highlighting that the context of sensor-based journalism may act as a contextual differentiator in shaping content credibility.

Keywords: Sensor-Based Journalism, News Outlet Reputation, Organizational Credibility, Reputation Heuristics, Content Credibility.

1 Introduction

Over the past decades, technological advances in data collection and processing, combined with the rise of Artificial Intelligence (AI), have transformed the journalism industry (Diakopoulos, 2019). These developments have driven the abundance of content, ranging from user-generated content to AI-generated content, or deepfakes. Consequently, they pose new challenges for media organizations in sustaining readers' credibility (Diakopoulos, 2019; Shirky, 2008).

Among these developments, sensor-based journalism has gained relevance as an Information Systems-related phenomenon that combines technology-enabled data collection with journalistic practices. It relies on sensor-based data collection to capture physical variations on a large scale, thereby reporting on phenomena that established journalistic practices could not previously capture (Diakopoulos, 2019; Hamm, 2024; anonymized for review). Examples of sensor-based journalism include reports on air pollution or articles revealing potential greenwashing facilitated by sensors placed in shoes tracing the shoe material recycling journey (Flip, 2021; Hook et al., 2019). The output of sensor-based journalism can take various online and offline formats (Hamm, 2024). This study focuses on newspaper articles that contain claims and arguments supported by evidence based on sensor data, which we define as sensor-based articles.

Emerging research investigating reader perceptions of sensor-based articles (anonymized for review) points to the limited applicability of well-established credibility frameworks and respective antecedents (Sundar, 2008). For example, it finds that identity cues have no effect on the content credibility of sensor-based articles, which refers to perceptions of believability, accuracy, bias, objectivity, and fairness related to the content (Sundar, 1999).

To this end, it remains unclear whether and how other, well-established content credibility antecedents shape content credibility of sensor-based articles. Among the various factors shaping content credibility, early research emphasizes source-related factors as strong antecedents of persuasion and credibility (Hovland, 1951; Hovland & Weiss, 1951; Hovland et al., 1953). Building on this perspective, Metzger et al. (2003) emphasize the role of perceptions of media organizations as the source of information, defined as organizational credibility, that shape content credibility. Research in different fields has increasingly examined that news outlet reputation as a key perceptual source-related factor of organizational credibility predicts content credibility (Appelman & Hettinga, 2020; Go et al., 2014; Kim & Dennis, 2019; Metzger & Flanagin, 2013; Sundar et al., 2007). Such news outlet reputation is shaped over time through accumulated readers' perceptions of experience, trustworthiness, expertise, and reliability related to the particular news outlet (Kim & Dennis, 2019). Thus, prior research emphasizes that readers' perceived reputation of a news outlet predicts how they evaluate the credibility of the content published by this news outlet. A reputable news outlet positively influences content credibility, while a less reputable news outlet negatively influences content credibility (Kim & Dennis, 2019; Metzger et al., 2003).

Prior work argues that contextual factors, such as content type, can amplify or attenuate the effect of source-related factors, like news outlet reputation, on credibility evaluations (Pornpitakpan, 2004). Hence, we ask whether and how different levels of news outlet reputation shape the perceived content credibility of a sensor-based article. Thereby, we examine whether sensor-based journalism functions as a contextual differentiator, challenging well-established research on the relationship between news outlet reputation and content credibility (Kim & Dennis, 2019; Pornpitakpan, 2004). While the question of the effect of news outlet reputation is not novel in principle, recent research shows growing interest in how readers evaluate journalistic content based on data-driven evidence (Chinn & Weeks, 2020; Henke et al., 2019; Kazmierczak et al., 2025). Such data-driven evidence derives from raw data, surveys, or public records and is expressed through numerical values, statistics, or frequencies (Freling et al., 2020; Godler et al., 2020). At the same time, scholars increasingly explore sensor-based journalism (Diakopoulos, 2019; Hamm, 2024; Kazmierczak et al., 2025; anonymized for review). However, the antecedents of content credibility in sensor-based journalism remain underexplored.

We ground our study in research on organizational credibility (Goldsmith et al., 2000; Metzger et al., 2003) and heuristic-based persuasion based on reputation heuristics (Chaiken, 1987; Gigerenzer et al., 1999; Metzger et al., 2010; Metzger & Flanagin, 2013; Sundar et al., 2007). In addition, we consider literature on media skepticism (Stroembaeck et al., 2020; Tsfati, 2003) and examine whether media skepticism moderates the relationship between news outlet reputation and the content credibility of sensor-based articles. We derive two hypotheses and test them in a between-subjects online experiment.

2 Conceptual Background

2.1 Sensor-based Data Collection in Journalism

Sensor-based data collection captures physicalities by complementing human sight, hearing, taste, smell, and tactile sensation (Newell & Marabelli, 2015). In the form of microphones or thermometers, for example, sensors capture temporal variations in environments of various physical or chemical natures (Osterlie & Monteiro, 2020) and convert them into large amounts of electronic signals, i.e., structured or unstructured data (Bardhan et al., 2020; Monteiro & Parmiggiani, 2019). Sensors placed on living creatures or objects may further act as mobile sensor data generators (Newell & Marabelli, 2015). When embedded in networked systems, these sensors become part of the 'Internet of Things' (or the 'Journalism of Things'), allowing for multi-directional data flows and contextual responsiveness (Monteiro & Parmiggiani, 2019). With the collected sensor data, sensors may 'feed' Big Data Analytics and AI-based systems for subsequent analysis.

Recent research positions sensor-based journalism within the broader field of journalism based on data-driven evidence. The journalistic practice of data-driven journalism emerged long before sensor-based journalism established as a distinct journalistic practice (Hamm, 2024; Howard, 2014). Since the 1950s, early forms of sensor-based journalism appeared when journalists began using temperature data from sensor networks to generate routinized weather reports (National Environmental Satellite, Data, and Information Service, 2025). In the past decade, the application of sensor technologies in journalism expanded to pursue further investigative reporting on phenomena that humans cannot easily access or observe efficiently (Diakopoulos, 2019; Hamm, 2024; Howard, 2014). In this context, sensor-based journalism has gained new relevance as a journalistic practice.

We distinguish sensor-based journalism from other types of journalism, i.e., testimony-based, data-driven, and automated journalism.

- Testimony-based journalism draws on testimonial evidence such as individual experiences, eyewitness statements, or opinions (Freling et al., 2020; Godler et al., 2020). In contrast, sensor-based journalism draws on evidence based on sensor data from sensors. Such sensors outperform human observation because they operate via standardized technological mechanisms. Consequently, sensors reduce potential observation errors, usually caused by limits of cognitive capabilities (Chen et al., 2012; anonymized for review). Hence, sensor-based journalism enables higher levels of precision, verifiability, and factuality than testimony-based journalism (Diakopoulos, 2019; Hamm, 2024; Kitchin, 2014; anonymized for review).
- According to broader notions in prior research, data-driven journalism typically relies on data drawn from various sources, e.g., public records or statistical bureaus (Diakopoulos, 2019; Kitchin, 2014). In contrast, sensor-based journalism relies solely on the remote collection of sensor data via sensors on phenomena difficult to capture by humans efficiently (Diakopoulos, 2019; Chen et al., 2012; Hamm, 2024; Kitchin, 2014).
- While sensor-based journalism shares its technology-enabled nature with automated journalism, the latter typically focuses on automated content creation (Diakopoulos, 2019). We conceptualize sensor-based journalism narrowly as focusing on the collection and usage of sensor data for journalistic reporting (anonymized for review) rather than automated content creation. Although automation can complement sensor-based journalism, it is not the focus of this study.

2.2 Credibility

Researchers vary in their distinction between the terms 'credibility' and 'trust'. For example, Self (1996) uses the two terms 'trust' and 'credibility' interchangeably. Tseng and Fogg (1999) argue that these terms are distinct, whereby trust refers to the reliability or dependability of a person, object, or process, and credibility refers to the believability or trustworthiness of information. Pavlou (2002) views credibility as an antecedent of trust, whereas Hovland and Weiss (1951) consider trust as an antecedent of credibility. In this study, we follow Hovland and Weiss's (1951) terminology and focus on the term 'credibility' determined by trust.

2.2.1 Source and Content Credibility

Early works in communication and persuasion research by Hovland (1951), Hovland and Weiss (1951), and Hovland et al. (1953) laid the groundwork for empirical credibility research and conceptualized credibility as source credibility. In this research context, an individual endorser acts as a source of information aimed at persuading an information recipient. Such source credibility is shaped by two dimensions: recipients' perceptions of trustworthiness and expertise of the source. Trustworthiness indicates the perceived honesty and reliability of the source, and expertise indicates the perceived skills and competence of the source in delivering genuine and accurate information. Source credibility shapes attitudes, with high-credibility sources causing greater shifts in attitudes than low-credibility sources (Hovland, 1951; Hovland & Weiss, 1951). Furthermore, Pornpitakpan (2004) adds that source credibility shapes persuasion in terms of both attitude and behavior, although the two different dimensions of source credibility may vary in importance in different contexts.

While the conceptualization of source credibility dominated credibility research in communication, persuasion, and psychology for many decades, later research placed greater emphasis on the construct of content credibility (Appelman & Sundar, 2015; Metzger et al., 2003; Metzger & Flanagin, 2013; Sundar, 1999). Sundar (1999) defines content credibility according to perceptions of believability, accuracy, bias, objectivity, and fairness related to the content. Scholars investigate content credibility as either an independent, a dependent, or a mediator variable (Appelman & Sundar, 2015; Metzger et al., 2003).

2.2.2 Organizational Credibility and Reputation

As a subtype of source credibility, organizational credibility gained research interest in organizational research, representing an organization as the source of information (Goldsmith et al., 2000). Organizational credibility is operationalized according to the perceived trustworthiness and expertise in delivering reliable products or services that meet individuals' needs (Fombrun, 1996; Goldsmith et al., 2000).

A broader concept of organizational credibility, not limited to the two dimensions of trustworthiness and expertise, is the concept of organizational reputation (Fombrun, 1996; Goldsmith et al., 2000). Organizational reputation is a perceptual representation of an organization's past actions and prospects, shaped by individuals' aggregated perceptions of the organization (Fombrun, 1996; Goldsmith et al., 2000). Individuals shape their perceptions of organizational reputation based on associations with accumulated experiences and information related to that organization gathered over time.

3 Hypothesis Development

3.1 Main Effect

Scholars in interdisciplinary fields argue that organizational reputation shapes individuals' attitudinal and behavioral responses (Fombrun, 1996; Goldsmith et al., 2000). Individuals favor recognized alternatives over less familiar ones, which is psychologically grounded in research on heuristic-based judgment through reputation and recognition heuristics (Chaiken & Maheswaran, 1994; Gigerenzer et al., 1999; McCracken, 1989; Metzger et al., 2010; Metzger & Flanagin, 2013). These heuristics may additionally relate to similar principles such as authority, endorsement, or consistency heuristics (Chaiken, 1987; Metzger et al., 2010; Metzger & Flanagin, 2013; Sundar, 2008).

For example, marketing research indicates that a reputable organization reduces uncertainties, positively impacts individuals' attitudes toward advertisements, and finally increases their purchase intentions (Goldberg & Hartwick, 1990; Lafferty & Goldsmith, 1999). Similarly, IS research (Deng et al., 2022; Dimoka et al., 2012) confirms that in e-commerce settings with transaction uncertainties, reputable organizations reduce perceptions of risk, which increases credibility and purchase intentions.

In journalism and communication research contexts, organizational credibility is commonly operationalized through the perceptual source-related factor of news outlet reputation (Bitektine, 2011; Kim & Dennis, 2019; Metzger et al., 2010; Metzger & Flanagin, 2013). Similarly to the effect of source and organizational credibility, news outlet reputation predicts how readers perceive and evaluate the credibility of journalistic content (Appelman & Hettinga, 2020; Kim & Dennis, 2019; Metzger & Flanagin, 2013). Kim and Dennis (2019) argue that readers perceive content as more credible when a news outlet with a reputation for experience, trustworthiness, expertise, and reliability publishes it. Conversely, readers are more likely to discount content from news outlets with a reputation for falsehood (Kim & Dennis, 2019; McCracken, 1989). Furthermore, readers favor content from recognized news outlets over less familiar alternatives (Gigerenzer et al., 1999; Kim & Dennis, 2019; Metzger et al., 2010).

Especially in times of increasing content abundance and information richness, the reputation of news outlets becomes a crucial factor in evaluating the credibility of journalistic content (Sundar et al., 2007). For example, during the rise of online news aggregators in the early 2000s, Sundar et al. (2007) find that news outlet reputation strongly predicts content credibility (Sundar et al., 2007). Kim and Dennis (2019) support this finding in the context of the growing prevalence of fake news.

Through its capacity to efficiently generate infinite reports based on continuous access to real-time sensor data streams, sensor-based journalism may further intensify content abundance in the media landscape (Diakopoulos, 2019; Shirky, 2008). Therefore, we argue that readers may rely on news outlet reputation to evaluate content credibility in the context of sensor-based journalism (Metzger et al., 2010; Sundar et al., 2007). Hence, we hypothesize that a reputable news outlet, i.e., a news outlet with a reputation for trustworthiness, expertise, experience, and reliability, has a positive effect on the content credibility of a sensor-based article. In contrast, a less reputable news outlet has a negative effect on content credibility.

H1: A reputable (less reputable) news outlet has a positive (negative) effect on the content credibility of sensor-based articles.

3.2 Moderating Effect

Media skepticism is an attitude of alienation and mistrust toward both offline and online media, such as newspapers, television, and radio (Stroembaeck et al., 2020; Tsfati, 2003). Skeptical individuals often view media as biased and unfair (Tsfati, 2003). Individuals with strong partisan views see relatively neutral content as biased against their position. Such perceptions of bias often persist even when challenged with contradictory arguments (Stroembaeck et al., 2020; Tsfati, 2003).

While reputation heuristics help readers to evaluate content credibility without extensive information processing, skeptical individuals may discount or question their inherent associations with certain news outlets (Stroembaeck et al., 2020). Especially when individuals' media skepticism extends to specific news outlets, the effect of even a reputable news outlet on content credibility may decrease when readers are highly skeptical (Stroembaeck et al., 2020; Tsfati, 2003). Accordingly, the content credibility of sensor-based articles may depend on the interplay between the news outlet reputation and media skepticism. We therefore hypothesize that media skepticism moderates the effect of news outlet reputation, such that higher media skepticism weakens its positive effect on perceived content credibility:

H2: The effect of news outlet reputation on the content credibility of a sensor-based article is lower for readers with strong media skepticism than for those with weak media skepticism.

Figure 1 displays our research model.

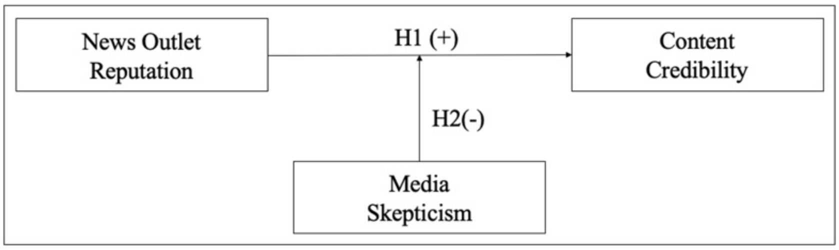


Figure 1. Research model.

4 Method

4.1 Experimental Procedure

To test the hypotheses, we developed an online experiment consisting of a pre-treatment questionnaire, a reading task, and a post-treatment questionnaire.

Upon receiving and clicking the experiment link, participants see an introductory webpage that briefly explains the experiment and requests their informed consent. After agreeing to the conditions and entering the first experiment page, participants complete a pre-treatment questionnaire on their demographics (gender category, age range, educational level), level of media skepticism (Stroembaeck et al., 2020; Tsfati, 2003), and whether they are familiar with specific news outlets and their perception of the reputation of the respective news outlet (Kim & Dennis, 2019).

To avoid deception, we inform the participants before the reading task that they will view one excerpt from a sensor-based article presented by either a real or a simulated news outlet. For the reading task, we assign the participants randomly to one of two treatment groups: one group seeing an excerpt of a sensor-based article presented by a reputable news outlet (high-reputation condition), and another group seeing the same excerpt presented by a less reputable news outlet (low-reputation condition).

After participants finish reading the excerpt and completing the treatment and attention check, we collect data on participants' perceived content credibility (Sundar, 1999) in the post-treatment questionnaire. Finally, we debrief the participants, present the complete article with the original news outlet name, including the link to the news website, and reward them for their participation.

We obtained ethical approval for this study.

4.2 Measurements

In the pre-test questionnaire, we ask about participants' *demographics* (gender categories, age range, educational level), their *level of media skepticism,* and their *perceived news outlet reputation* of selected news outlets:

- We measure participants' level of media skepticism using five items adapted from Stroembaeck et al. (2020) and Tsfati (2003). We ask participants to rate how strongly they associate the media (e.g., television, newspapers, and radio) with *fair coverage*, *lack of bias*, *comprehensiveness*, *accuracy*, and *separation of facts from opinions* in their country. Participants rate their responses on a 5-point Likert scale (1 = 'strongly disagree' to 5 = 'strongly agree'). High agreement indicates low media skepticism and vice versa. The media skepticism construct demonstrates adequate internal consistency (Cronbach's α = 0.90) and substantial average inter-item correlations ($\bar{r}$ = 0.65). Factor loadings range from 0.74 to 0.86.
- We add the *perceived news outlet reputation* as a measurement construct to verify and strengthen the validity of the group assignment. We measure *perceived news outlet reputation* using four items adapted from Kim & Dennis (2019). We ask participants to indicate whether they know two particular news outlets (one displayed in the high-reputation condition and the other displayed in the low-reputation condition). Also, we ask them to rate the two news outlets

according to whether they find those two news outlets 'reliable', 'trustworthy', 'credible', and whether they find that those news outlets have the 'necessary expertise to do the job'. Participants rate their responses on a 5-point Likert scale (1 = 'strongly disagree' to 5 = 'strongly agree'). The perceived news outlet reputation constructs for both news outlets show internal consistency (Cronbach's α = 0.96-0.98) and strong average inter-item correlations (high-reputation news outlet: $\bar{r}$ = 0.84; low-reputation news outlet: $\bar{r}$ = 0.94). Factor loadings range from 0.85 to 0.95 for the high-reputation news outlet and 0.95 to 0.98 for the low-reputation news outlet.

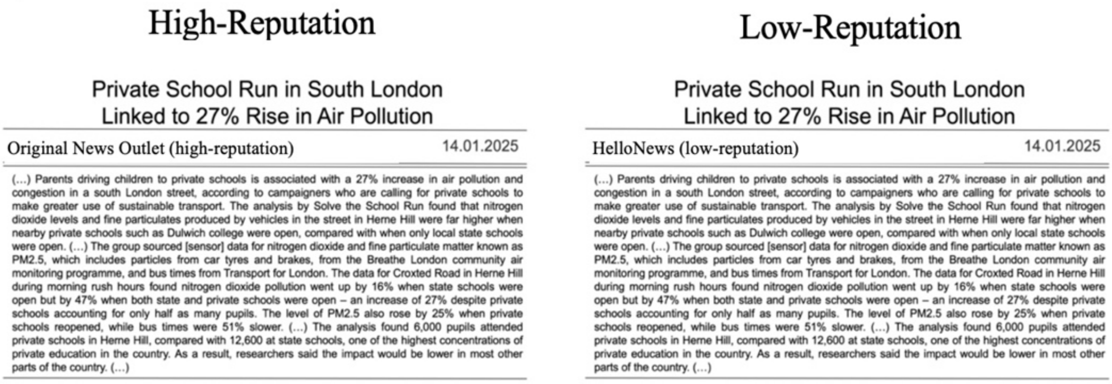
For the reading task and post-treatment questionnaire, we randomly assign the participants to one of two treatment groups. We code the group assignment as a dummy for the variable of *assigned news outlet reputation* (low-reputation condition = 0; high-reputation condition = 1).

In the post-treatment questionnaire, we conduct a *treatment and attention check* and ask about participants' perceived *content credibility*.

- In the *treatment* and *attention check*, we examine whether participants perceive the treatment as intended. We ask them to state which news outlet has published the presented excerpt and whether the excerpt includes evidence based on sensor data supporting the central claim.
- We measure *content credibility* on five items adapted from Sundar (1999). We ask the participants to evaluate the content according to whether they find it 'believable', 'accurate', 'biased', 'objective', and 'fair', each on a 5-point Likert scale (1 = 'strongly disagree' to 5 = 'strongly agree'). High agreement indicates high content credibility and vice versa. The content credibility scale demonstrates internal consistency in both groups (Cronbach's α = 0.91-0.92). Factor loadings range from 0.76 to 0.91 in both conditions.

4.3 Stimulus Material

In the reading task, we ask the participants to read an approximately 240-word excerpt from a sensor-based article featuring a traffic concern in London, United Kingdom. The excerpt reports on how traffic impacts air pollution during school journeys (see Figure 2). Across the two treatment groups, the publication date and content remain constant, while the displayed newspaper name varies according to the high-reputation and low-reputation condition. The central claim and argument within the excerpt (traffic causing higher pollution) are supported with data drawn from sensors measuring nitrogen dioxide levels and fine particles (e.g., "nitrogen dioxide pollution went up by 16%"). For the newspaper name in the high-reputation condition, we disclose the original newspaper name, which is a reputable and well-known newspaper in the United Kingdom (YouGov, 2023). For the newspaper name in the low-reputation condition, we fabricate a fictitious, i.e., less reputable and unknown, newspaper name '*HelloNews*'. Pre-tests confirm that participants can distinguish the reputation of the news outlet displayed in the high-reputation condition from the reputation of the news outlet displayed in the low-reputation condition.


High-Reputation

Private School Run in South London
Linked to 27% Rise in Air Pollution

Original News Outlet (high-reputation) 14.01.2025

(...) Parents driving children to private schools is associated with a 27% increase in air pollution and congestion in a south London street, according to campaigners who are calling for private schools to make greater use of sustainable transport. The analysis by Solve the School Run found that nitrogen dioxide levels and fine particulates produced by vehicles in the street in Herne Hill were far higher when nearby private schools such as Dulwich college were open, compared with when only local state schools were open. (...) The group sourced [sensor] data for nitrogen dioxide and fine particulate matter known as PM2.5, which includes particles from car tyres and brakes, from the Breathe London community air monitoring programme, and bus times from Transport for London. The data for Croxted Road in Herne Hill during morning rush hours found nitrogen dioxide pollution went up by 16% when state schools were open but by 47% when both state and private schools were open – an increase of 27% despite private schools accounting for only half as many pupils. The level of PM2.5 also rose by 25% when private schools reopened, while bus times were 51% slower. (...) The analysis found 6,000 pupils attended private schools in Herne Hill, compared with 12,600 at state schools, one of the highest concentrations of private education in the country. As a result, researchers said the impact would be lower in most other parts of the country. (...)

Low-Reputation

Private School Run in South London
Linked to 27% Rise in Air Pollution

HelloNews (low-reputation) 14.01.2025

(...) Parents driving children to private schools is associated with a 27% increase in air pollution and congestion in a south London street, according to campaigners who are calling for private schools to make greater use of sustainable transport. The analysis by Solve the School Run found that nitrogen dioxide levels and fine particulates produced by vehicles in the street in Herne Hill were far higher when nearby private schools such as Dulwich college were open, compared with when only local state schools were open. (...) The group sourced [sensor] data for nitrogen dioxide and fine particulate matter known as PM2.5, which includes particles from car tyres and brakes, from the Breathe London community air monitoring programme, and bus times from Transport for London. The data for Croxted Road in Herne Hill during morning rush hours found nitrogen dioxide pollution went up by 16% when state schools were open but by 47% when both state and private schools were open – an increase of 27% despite private schools accounting for only half as many pupils. The level of PM2.5 also rose by 25% when private schools reopened, while bus times were 51% slower. (...) The analysis found 6,000 pupils attended private schools in Herne Hill, compared with 12,600 at state schools, one of the highest concentrations of private education in the country. As a result, researchers said the impact would be lower in most other parts of the country. (...)

Figure 2. Excerpts across the two treatment conditions (high-reputation versus low-reputation).

5 Results

For the data analysis, we use the open-source software *R* and *RStudio* Version 2024.12.1+563.

5.1 Sample

We conducted a priori power analyses using G*Power (Faul et al., 2009) to determine the required sample sizes. We aimed to detect medium-sized group differences (Cohen's $d = 0.50$; Cohen, 1988) in independent-samples t-tests and small-to-medium effects ($f^2 = 0.10$) in multiple regression analyses. Results indicated a minimum of 128 participants for group comparisons and 212 participants for regression models with 17 predictors ($\alpha = 0.05$, power = 0.80).

We collected the data in July 2025. We recruited the participants via convenience sampling on the crowdsourcing platform *Prolific*, through which we sent the experiment link to the participants who voluntarily agreed to participate. Crowdsourcing platforms are widely recognized for yielding reliable and high-quality data in behavioral research and experiments (Bhattacherjee, 2023). We targeted our sampling to adults who are fluent in English and reside in the United Kingdom.

From the initial sample of 979 participants, we first filtered the data of 147 participants who failed the treatment and attention check, resulting in a sub-sample of 832 participants. To test whether the failure of the treatment and attention check introduced systematic demographic bias, we conducted Chi-squared and Fisher's exact tests on the relationship between gender categories, age range, educational level, and dropout status. We found no statistically significant relationships between dropout status and gender categories (Fisher's exact $p = 0.89$) or educational level (Fisher's exact $p = 0.76$). We found that the relationship between age range and dropout status approached, but did not reach statistical significance (Pearson's $\chi^2(5, N = 979) = 10.50$, $p = 0.06$).

Additionally, we applied a median-based filtering rule to filter data from participants with implausible completion times, i.e., faster than one-third the median or slower than three times the median (Curran, 2016). Such filtering based on time criteria resulted in additional filtering of data from 23 participants, reducing the sub-sample from 832 before to 809. To assess whether filtering based on implausible completion times introduced systematic demographic bias, we conducted Chi-squared and Fisher's exact tests on the relationship between gender categories, age range, educational level, and dropout status. We found no statistically significant associations between the three demographic variables and dropout status (gender categories: Fisher's exact $p = 0.36$; age range: Pearson's χ^2 with simulated p-value based on 10,000 replicates = 0.77; educational level: Pearson's χ^2 with simulated p-value based on 10,000 replicates = 0.70).

After filtering based on treatment and attention check failure and time criteria, the final, filtered sample comprised data from a total of 809 participants (443 participants in the high-reputation condition; 366 participants in the low-reputation condition). Although the group sizes were relatively unequal after filtering the data, random assignment supported internal validity of the group comparisons. The filtered sample exceeded both thresholds for the minimum sample size of 128 participants for group comparisons and 212 participants for regression models with 17 predictors. Therefore, the filtered sample is sufficiently powered for both types of analyses.

The filtered sample consisted of 55.7% female, 43.8% male, and 0.5% diverse participants. The median age range is 25 to 34 years, and the median educational level is a Bachelor's degree (see Table 1).

Variable	*N*	%
Gender	*809*	*100*
Male	354	43.8
Female	451	55.7
Diverse	4	0.5
NA	0	0.0
Age Range	*809*	*100*
18 to 24	65	8.0
25 to 34	212	26.2
35 to 44	196	24.2
45 to 54	167	20.6
55 to 64	121	15.0
65 and older	48	5.9
Educational Level	*809*	*100*
No School Leaving Certificate	3	0.4
Secondary General School-Leaving Certificate	182	22.5
University Entrance Qualification	55	6.8
Apprenticeship	28	3.5
Bachelor's Degree	361	44.6
Master's Degree / Diploma	148	18.3
PhD	18	2.2
Other	14	1.7

Table 1. Demographics.

To assess whether participants in the two groups differ systematically according to demographics, we conducted randomization checks via Chi-squared and Fisher's exact tests. We found no significant differences by gender categories (Fisher's exact $p = 0.56$), age range ($\chi^2(5, N = 809) = 2.46$, $p = 0.78$), and educational level (Pearson's χ^2 with simulated p-value based on 10,000 replicates = 0.56).

5.2 Group Differences

To confirm the effectiveness of the experimental treatment at the perceptual level, we tested whether participants' perceived news outlet reputation ratings differ substantially between the two news outlets shown in the pre-treatment questionnaire. A paired-samples t-test revealed that participants rated the original news outlet (displayed in the high-reputation condition) as significantly more reputable ($M = 3.36$, $SD = 0.85$) than the fictitious news outlet *HelloNews* (displayed in the low-reputation condition) ($M = 2.36$, $SD = 0.82$) ($t(808) = 23.73$, $p < 0.001$). The effect size is large (Cohen's $d = 0.83$), indicating that participants recognized the original news outlet as more reputable than the fictitious news outlet. Hence, we could confirm the effectiveness of the experimental treatment at the perceptual level.

Before comparing the group differences with regression analyses, we first evaluated whether the assumptions of parametric tests were met. We conducted a Shapiro-Wilk test, which showed that content credibility ratings deviate significantly from normality in both groups (high-reputation condition: $W = 0.97$, $p < 0.001$; low-reputation condition: $W = 0.98$, $p < 0.001$). However, according to the central limit theorem and given the large sample sizes ($n > 30$) in each group, we assumed that parametric tests are robust to these violations. Furthermore, we conducted a Levene's test for homogeneity of variances to assess whether the assumption of equal variances is met across the two groups. We found that the assumption of homogeneity of variances was met ($F(1, 807) = 0.46$, $p = 0.50$).

We run an independent-samples t-test to examine whether the content credibility of sensor-based articles differs across the two conditions. Participants in the high-reputation condition rated content as significantly more credible ($M = 3.32$, $SD = 0.86$) than participants in the low-reputation condition ($M = 3.17$, $SD = 0.82$) ($t(807) = -2.50$, $p < 0.05$). The effect size is negligible (Cohen's $d = 0.18$).

To assess whether and how news outlet reputation predicts content credibility of sensor-based articles, we conducted a simplified regression analysis. We included the binary variable based on the assigned news outlet reputation (high-reputation condition = 1, low-reputation condition = 0), media skepticism (reversed, centered), the interaction between the assigned news outlet reputation and media skepticism, and demographic covariates. The overall model is significant ($p < 0.001$). Participants rated the content as more credible when it was presented by a reputable news outlet ($B = 0.14$, $p < 0.05$) compared to a less reputable one. While the interaction between assigned news outlet reputation and media skepticism is non-significant ($B = -0.07$, $p = 0.32$), media skepticism has a negative direct effect on content credibility ($B = -0.27$, $p < 0.001$). Age range shows mixed direct effects on content credibility. Compared to participants aged 18-24, those aged 55-64 ($B = -0.36$, $p < 0.01$) and those 65 or older ($B = -0.34$, $p < 0.05$) report significantly lower content credibility ratings. Compared to participants with an apprenticeship, those without a school leaving certificate show significantly increased content credibility ratings ($B = 1.03$, $p < 0.05$). However, given the small size of this demographic category in the sample ($n = 3$), this result should be interpreted with caution.

With two follow-up models, estimated separately for each condition, we further tested the effect of perceived news outlet reputation and its interaction with media skepticism. This approach enabled more precise modeling of content credibility evaluations by focusing on individual perceptions rather than relying solely on the group assignment. To facilitate interpretation and reduce potential multicollinearity in the interaction terms, we z-standardized both media skepticism and perceived news outlet reputation ratings prior to inclusion in the regression models (Aiken & West, 1991). This z-standardization enabled the regression coefficients to reflect the effect of a one standard deviation change in the predictors. It further facilitated the interpretation of the interaction between centered media skepticism and perceived news outlet reputation. We also included the demographics as covariates (e.g., gender categories, age range, educational level) to increase statistical power and account for residual variance in the outcome.

The first model (high-reputation condition) is significant ($p < 0.001$). Perceived news outlet reputation shows a strong positive effect on content credibility ($B = 0.39$, $p < 0.001$). The interaction between perceived news outlet reputation and media skepticism is non-significant ($B = 0.04$, $p = 0.35$). Compared to participants aged 18-24, older participants report significantly lower content credibility ratings (aged 55-64: $B = -0.40$, $p < 0.05$; and 65 and older: $B = -0.55$, $p < 0.005$). Compared to participants with an apprenticeship, participants with no school leaving certificate report significantly higher content credibility ratings ($B = 1.03$, $p < 0.05$). However, given the small size of this demographic category in the sample ($n = 3$), this result should be interpreted with caution.

The second model (low-reputation condition) is also significant ($p < 0.001$), but with a smaller R^2 of 0.12 and adjusted R^2 of 0.08. Neither the effect of perceived news outlet reputation nor the interaction term is statistically significant. Media skepticism shows a significant negative direct effect on content credibility ($B = -0.26$, $p < 0.001$). Among demographics, only participants aged 55-64 report significantly lower credibility ratings ($B= -0.48$, $p < 0.01$).

Table 2 compares the results of the regression analyses using perceived news outlet reputation (simplified model) and perceived news outlet reputation (follow-up models).

	Simplified Model	Follow Up Models	
	High-/Low-Reputation	High-Reputation	Low-Reputation
Predictor	**B(SE)**	**B(SE)**	**B(SE)**
(Intercept)	2.80(0.43)***	3.26(0.75)***	2.64(0.54)***
Assigned / Perceived News Outlet Reputation	0.14(0.06)*	0.39(0.05)***	0.02(0.04)
Assigned / Perceived News Outlet Reputation x Media Skepticism	-0.07(0.07)	0.04(0.04)	0.04 (0.05)
Media Skepticism	-0.27(0.06)***	-0.07(0.06)	-0.26(0.06)***
Age: 25-34	0.04(0.12)	0.09(0.15)	-0.16(0.16)
Age: 35-44	-0.15(0.12)	-0.22(0.15)	-0.10(0.17)
Age: 45-54	-0.20(0.12)	-0.16(0.15)	-0.28(0.17)
Age: 55-64	-0.36(0.12)**	-0.40(0.16)*	-0.48(0.18)**
Age: 65+	-0.34(0.16)*	-0.55(0.20)**	-0.24(0.23)
Gender: Female	0.45(0.41)	0.17 (0.76)	0.59(0.47)
Gender: Male	0.59(0.41)	0.34(0.76)	0.74(0.47)
Education: No School Leaving Certificate	1.03(0.49)*	1.03(0.47)*	NA
Education: Secondary General School Leaving Certificate	-0.01(0.16)	0.03(0.21)	0.14(0.24)
Education: University Entrance Qualification	-0.01(0.19)	-0.03 (0.24)	0.20(0.28)
Education: Bachelor's Degree	0.03(0.16)	-0.04 (0.20)	0.15(0.23)
Education: Master's Degree / Diploma	-0.11(0.17)	-0.04(0.21)	-0.10 (0.25)
Education: PhD	0.25(0.24)	0.25 (0.34)	0.28(0.33)
Education: Other	0.16(0.26)	0.24(0.33)	0.35(0.40)
Model Fit	Residual standard error: 0.80 on 791 df; Multiple R^2: 0.13; Adjusted R^2: 0.11; $F(17, 791) = 7.095$, p-value: <0.001.	Residual standard error: 0.73 on 425 df; Multiple R^2: 0.31; Adjusted R^2: 0.28; $F(17, 425) = 11.2$, p-value < 0.001.	Residual standard error: 0.79 on 349 df; Multiple R^2: 0.12; Adjusted R^2: 0.08; $F(16, 349) = 2.927$; p-value < 0.001.

*: $P \leq 0.05$; **: $P \leq 0.01$; ***: $P \leq 0.001$

Simplified model: *Media Skepticism* is mean-centered; reference groups for the demographic characteristics: 'diverse' for gender categories, '18-24' for age range, and 'apprenticeship' for educational level.

Follow-up models: *Perceived News Outlet Reputation* and *Media Skepticism* are z-standardized; reference groups for the demographic characteristics: 'diverse' for gender categories, '18-24' for age range, and 'apprenticeship' for educational level.

Table 2. Regression results of perceived news outlet reputation by condition.

Multicollinearity diagnostics revealed acceptable levels of variance inflation in both models. All generalized variance inflation factors were below 1.30.

To assess the robustness of these findings from the three main models, we repeated the three regression analyses using the initial sample before filtering (N = 979). We found that the key findings remained robust: (1) assigned news outlet reputation (high-reputation) and perceived news outlet reputation (high-reputation) both increase content credibility of sensor-based articles, and (2) media skepticism does not moderate these effects (detailed results are available upon request).

Summing up, we found that readers rate the content of sensor-based articles as slightly but significantly more credible when it is presented by a reputable news outlet compared to a less reputable one. The effect size is small. Individual perceptions of news outlet reputation significantly increase content credibility in the high-reputation condition, while they do not play a role in the low-reputation condition. Hence, we partly support H1. Although media skepticism directly reduces content credibility when less reputable news outlets publish sensor-based articles, it does not moderate the effect of news outlet reputation on content credibility in either condition. Thus, we cannot support H2.

6 Discussion

We find four issues in our results that suggest for discussion.

Limited influence of assigned news outlet reputation: Although we could validate our experimental treatment by finding significantly different perceptions of news outlet reputation, the assignment itself was not a strong predictor of content credibility. This supports the view that news outlet reputation is less a binary attribute but rather a subjective construct that varies across readers (Kim & Dennis, 2019). This could also imply that news outlet reputation may be more nuanced in the context of sensor-based journalism, highlighting the importance of individual perceptions in shaping content credibility.

Higher content credibility among readers who perceive the news outlet as more reputable: Incorporating participants' perceived news outlet reputation ratings into the analyses reveals a more nuanced relationship than when considering assigned news outlet reputation alone. The perceived reputation of a reputable news outlet has a strong and significant effect on content credibility. In contrast, the perceived reputation of a less reputable news outlet does not play a role in such contexts. Moreover, these findings align with the idea that readers are more likely to rely on reputable news outlets when evaluating the content credibility of sensor-based articles (Kim & Dennis, 2019; Metzger et al., 2010; Metzger & Flanagin, 2013).

Marginal differences in content credibility evaluations: Although we observe a significant difference in content credibility ratings across the two treatment groups, the difference is marginal. A possible explanation is that the effect of news outlet reputation often depends on content-related factors (Pornpitakpan, 2004). In the context of sensor-based journalism, convincing, data-driven arguments may have reduced the weight of news outlet reputation, highlighting the need to examine how perceptions of content-related factors and news outlet reputation interplay to shape content credibility (McCroskey, 1969; Pornpitakpan, 2004).

No moderation effect of media skepticism: Our findings indicate that media skepticism does not moderate the relationship between news outlet reputation and content credibility of sensor-based articles. However, we find that media skepticism shows a direct effect on content credibility when readers see a sensor-based article presented by a less reputable news outlet. One explanation is that sensor-based articles presented by a reputable news outlet may reduce reliance on individual beliefs, such as media skepticism (Pornpitakpan, 2004). By contrast, a less reputable news outlet may act as a boundary condition, whereby readers' media skepticism becomes more relevant in shaping the content credibility in the context of sensor-based journalism.

Lower content credibility of sensor-based articles among older readers: Across both groups, our findings suggest that, independent of the news outlet reputation, older readers (55 and older) rate sensor-based articles as less credible. One possible explanation is that the design or presentation of evidence based on sensor data in quantified form may reduce understandability for older readers. As sensor-based articles often present information in numeric values, they can make it harder for readers, especially those used to consuming testimonial-based journalistic content, to interpret and positively evaluate the content (Liao & Fu, 2014). For older audiences, the unfamiliarity of this data-driven content and the lack of established skills for interpreting such content may lead to increased doubt. These findings highlight the importance of considering demographic factors like age, or other individual differences like skills, when investigating the perceptions of sensor-based articles (Faik et al., 2024; Liao & Fu, 2014).

7 Limitations and Suggestions for Future Research

We acknowledge that our study has several limitations, leading to suggestions for future research.

Unobserved effects: The limited explanatory power in our models (R^2) suggests that the content credibility of sensor-based articles further depends on other factors alongside news outlet reputation. We assume that the specific context of sensor-based journalism may play a role, with content-related factors or individual characteristics additionally exerting strong effects. Therefore, future research could extend the models and add content-related factors and individual differences that may shape content credibility of sensor-based articles. Furthermore, we exposed the participants to only one excerpt, which limits the generalizability of our findings. The topic and tone may have shaped participants' perceptions. Hence, future studies could present multiple articles spanning diverse topics and variations of tone to reduce potential topic- and tone-specific effects and help increase the generalizability and robustness of our findings.

Limited comparison to articles beyond sensor-based journalism: We did not directly compare content credibility evaluations between sensor-based and non-sensor-based articles. Consequently, we cannot determine whether news outlet reputation shows comparable effects in the absence of evidence based on sensor data. Therefore, future research may want to explicitly examine whether the effect of news outlet reputation varies depending on whether an article contains evidence based on sensor data or not.

Sampling: Although we randomly assigned participants to the two treatment groups, we have drawn the sample using convenience sampling. This limits the generalizability of our results to broader populations. To strengthen the robustness and external validity of our findings, future research could employ more representative sampling techniques.

8 Conclusion

In this study, we examined how news outlet reputation, as a direct predictor, and media skepticism, as a moderator, shape readers' content credibility of sensor-based articles. We find that readers' perceptions of a reputable news outlet show a positive effect on the content credibility of sensor-based articles. In contrast, readers' perceptions of less reputable news outlets show no significant effect. We also find that media skepticism shows no moderating but a direct effect on content credibility when sensor-based articles are presented by a news outlet perceived to be less reputable.

Theoretical implications: Overall, we extend prior credibility research in data-driven contexts to the context of sensor-based journalism (Chinn & Weeks, 2020; Henke et al., 2019; Kazmierczak et al., 2025). Our findings confirm prior research showing that perceptions of reputable news outlets increase content credibility (Appelman & Hettinga, 2020; Kim & Dennis, 2019; McCracken, 1989; Metzger et al., 2010; Metzger & Flanagin, 2013). However, they cannot confirm prior research claiming that less reputable news outlets decrease content credibility. In this context, we point to sensor-based journalism as a potential differentiator challenging well-established research on the relationship between news outlet reputation and content credibility (Gigerenzer et al., 1999; Kim & Dennis, 2019; Metzger et al., 2010). Moreover, we contribute to research on media skepticism (Stroembaeck et al., 2020; Tsfati, 2003) by demonstrating that a less reputable news outlet may serve as a boundary condition shaping the extent to which media skepticism predicts content credibility in the context of sensor-based journalism.

Recommendations for practice: We recommend media organizations to focus on maintaining a strong brand to maximize the impact of publishing sensor-based articles, especially as the journalism industry faces digital transformation and content abundance, leading to economic challenges (Diakopoulos, 2019; Pappas et al., 2023; Shirky, 2008). Established news outlets need to safeguard and reinforce their reputation, while emerging news outlets should invest in reputation-building strategies to offset their weaker brand status (Goldsmith et al., 2000). Furthermore, media organizations should account for perceptual differences across different demographic segments when creating and publishing sensor-based articles, with particular focus on age, as evaluations of content credibility vary substantially across different age groups (Faik et al., 2024; Liao & Fu, 2014).

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2.4 Information processing and content credibility in sensor-based journalism: a comparative elaboration-likelihood perspective

Reproduction from:

Boboschko, I., & Loebbecke, C. (2025e). Information processing and content credibility in sensor-based journalism: a comparative elaboration-likelihood perspective, under review at Information Systems Journal [VHB: A].

My contributions to this paper include the co-development of the research idea, literature review, experiment design, data collection, data analysis, manuscript draft, and revision based on the comments from the co-author.

information systems journal

Research Article

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Submission ID 38b509f3-4e67-43d8-970f-3225d5daecf9

Submission Version Initial Submission

PDF Generation 15 Nov 2025 12:12:19 EST by Atypon ReX

Files for peer review

All files submitted by the author for peer review are listed below. Files that could not be converted to PDF are indicated; reviewers are able to access them online.

Name	Type of File	Size	Page
ISJ-Sensor-Main-Manuscript.docx	Anonymized Main Document - MS Word	625.8 KB	Page 3

Information Processing and Content Credibility in Sensor-Based Journalism: A Comparative Elaboration-Likelihood Perspective

Abstract

Sensor-based journalism has gained increasing attention as an Information Systems-relevant phenomenon. It relies on sensor-based data collection to capture phenomena beyond human reach. Drawing on the Elaboration Likelihood Model, this study investigates whether evidence based on sensor data serves as a differentiator in information processing and content credibility formation in journalism. In a 2×2 online experiment (N = 1,570), varying the evidence type (sensor data versus no sensor data) and news outlet reputation (high versus low), this study examines the impact of content-related, source-related, and individual factors and their interplay on content credibility. The results indicate that argument strength emerges as the dominant predictor for content credibility in sensor-based journalism. The interplay with news outlet reputation and different levels of issue involvement and expertise exerts more nuanced effects. These results extend research on information processing, persuasion, and credibility formation.

Keywords: Sensor-Based Journalism, Elaboration Likelihood Model, Information Processing, Content Credibility.

Practitioner Points: Sensor-Based Journalism, Media Industry, Credibility.

1. Introduction

Sensor-based journalism has gained relevance as an Information Systems (IS)-related phenomenon that combines technology-enabled data collection with journalistic practices. It relies on sensor-based data collection to capture physical variations, thereby reporting on phenomena that established journalistic practices could not previously capture (Diakopoulos, 2019; Hamm, 2024). Examples of sensor-based journalism include reports on air pollution or articles revealing potential greenwashing facilitated by sensors placed in shoes tracing the shoe material recycling journey (Flip, 2021; Hook et al., 2019). The output of sensor-based journalism can take various online and offline formats (Hamm, 2024). This study focuses on newspaper articles that contain claims and arguments supported by evidence based on sensor data, which we define as sensor-based articles.

Research has long examined how different forms of evidence influence information processing and persuasion (Freling et al., 2020; Henke et al., 2019; McCroskey, 1969; Toulmin, 1958; Yi et al., 2013). Communication and media research distinguish between two major types of evidence: testimonial and data-driven (Chinn & Weeks, 2020; Godler et al., 2020; Hoeken & Hustinx, 2009). Testimonial evidence refers to personal accounts, individual experiences, eyewitness statements, or personal opinions (Freling et al., 2020; Godler et al., 2020). Data-driven evidence refers to quantified information derived from raw data, surveys, or public records, expressed as numerical values, statistics, or frequencies (Freling et al., 2020; Godler et al., 2020; Hoeken & Hustinx, 2009). As data-driven evidence becomes increasingly prevalent in journalistic reporting, recent research indicates a growing interest in how individuals process and evaluate journalistic content containing claims based on such evidence (Thaesler-Kordonouri et al., 2024). Data-driven evidence often enhances perceptions of factuality, precision, and rhetorical strength (Koetsenruijter, 2011; Porter, 1995; Van Dijk, 1988; Yalch & Elmore-Yalch, 1984). Yet, the excessive use of data-driven evidence can overload individuals and shift attention toward other peripheral, source-related factors when evaluating the journalistic content (Koetsenruijter, 2011; Thaesler-Kordonouri et al., 2024; Yalch & Elmore-Yalch, 1984).

Evidence based on sensor data shares the characteristics of data-driven evidence in terms of the quantifiable information, but differs in its origin. It relies on technology-enabled, sensor-based data collection on phenomena beyond human reach (Chen et al., 2012; Kazmierczak et al., 2025; Shim et al., 2020). In organizational and IS research, such sensor data serves as a key differentiator in providing operational understanding in persuasive contexts and consistently improving organizational decision making (Chen et al., 2012; McAfee & Brynjolfsson, 2012; Newell & Marabelli, 2015; O'Leary, 2013; Shim et al., 2020; anonymized for review). In journalism, however, the role of evidence based on sensor data in influencing information processing and credibility formation remains underexplored. Recent studies on the perceptions of sensor-based articles suggest that readers evaluate sensor-based articles differently compared to articles without such evidence. Seeing sensor-based articles increases content credibility through enhanced perceptions of argument strength more than seeing articles without such evidence (anonymized for review). However, peripheral factors such as identity cues or news outlet reputation exert limited effects on content credibility (anonymized for review). To the best of our knowledge, no study has investigated how content- and source-related factors, together with individual differences in issue involvement and expertise, shape the information processing and content credibility formation of sensor-based articles compared to articles without such evidence, i.e., non-sensor-based articles. This gap raises the question of *whether evidence based on sensor data serves as a differentiator in information processing and the content credibility formation in journalism*.

To address this gap, we build on dual-process theories of information processing (Chaiken, 1980; Evans, 2008; Petty & Cacioppo, 1986). We focus on the Elaboration Likelihood Model (ELM) (Petty & Cacioppo, 1986). The ELM explains how individuals process information either through scrutiny of content-related factors (central route of information processing) or through reliance on peripheral factors (peripheral route of information processing), depending on their level of issue involvement and expertise. Prior research has applied the ELM to identify differentiating factors in diverse communication contexts (Miller et al., 2024; Priester & Petty, 2003; Yalch & Elmore-Yalch, 1984). In this regard, we consider the ELM a suitable framework for comparing the information processing of sensor-based and non-sensor-based articles. We derive ten hypotheses that we test in a 2×2 between-subjects online experiment. With our study, we contribute to prior research on information processing (Chaiken, 1980; Evans, 2008; Petty & Cacioppo, 1986). We also extend the application of the ELM to sensor-based journalism, an underexplored context in IS and journalism research. Finally, we offer recommendations for media organizations on how to adapt persuasion mechanisms in sensor-based journalism.

2. Conceptual and Theoretical Background

2.1. Sensor-Based Data Collection in Journalism

Sensor-based data collection captures physicalities by complementing human sight, hearing, taste, smell, and tactile sensation (Newell & Marabelli, 2015). In the form of microphones or thermometers, sensors capture temporal variations in environments of various physical or chemical natures (Osterlie & Monteiro, 2020). Sensors convert these variations into large amounts of electronic signals, i.e., structured or unstructured data (Bardhan et al., 2020; Monteiro & Parmiggiani, 2019). Sensors placed on living creatures or objects may further act as mobile sensor data generators (Newell & Marabelli, 2015). When embedded in networked systems, these sensors become part of the 'Internet of Things' (or the 'Journalism of Things'), allowing for multi-directional data flows and contextual responsiveness (Monteiro & Parmiggiani, 2019).

Recent research positions sensor-based journalism within the broader field of journalism based on data-driven evidence. The journalistic practice of so-called 'data-driven journalism' emerged long before sensor-based journalism established as a distinct journalistic practice (Hamm, 2024; Howard, 2014). In 1821, *The Guardian* published one of its first articles based on data-driven evidence, disclosing student enrollment figures and associated costs (Howard, 2014; The Guardian, 2011). Since the 1950s, early forms of sensor-based journalism appeared when journalists began using temperature data from sensor networks to generate routinized weather reports (National Environmental Satellite, Data, and Information Service, 2025). Over the past decades, the application of sensor technologies in journalism expanded to pursue further investigative reporting on phenomena that humans cannot easily access or observe efficiently (Diakopoulos, 2019; Hamm, 2024; Howard, 2014). In this context, sensor-based journalism has gained new relevance as a journalistic practice.

We distinguish sensor-based journalism from other types of journalism, i.e., testimony-based, data-driven, and automated journalism.

- Testimony-based journalism draws on testimonial evidence such as individual experiences, eyewitness statements, or opinions (Freling et al., 2020; Godler et al., 2020). In contrast, sensor-based journalism draws on evidence based on sensor data from sensors. Such sensors outperform human observation because they operate via standardized technological mechanisms. Consequently, sensors reduce potential observation errors, usually caused by limits of cognitive capabilities (Chen et al., 2012; anonymized for review). Hence, sensor-based journalism enables higher levels of precision, verifiability, and factuality than testimony-based journalism (Diakopoulos, 2019; Hamm, 2024; Kitchin, 2014).
- According to broader notions in prior research, data-driven journalism typically relies on data drawn from various sources, e.g., public records or statistical bureaus (Diakopoulos, 2019; Kitchin, 2014). In contrast, sensor-based journalism relies solely on the remote collection of sensor data via sensors on phenomena difficult to capture by humans efficiently (Diakopoulos, 2019; Chen et al., 2012; Hamm, 2024; Kitchin, 2014).
- While sensor-based journalism shares its technology-enabled nature with automated journalism, the latter typically focuses on automated content creation (Diakopoulos, 2019). We conceptualize sensor-based journalism narrowly as focusing on the collection and usage of sensor data for journalistic reporting rather than automated content creation. Although automation can complement sensor-based journalism, it is not the focus of this study.

2.2. Elaboration Likelihood Model

For theoretical grounding, we build on dual-process theories of information processing (Chaiken, 1980; Evans, 2008; Petty & Cacioppo, 1986). In particular, we refer to the ELM developed by Petty and Cacioppo (1986), which explains human information processing and judgment when exposed to informational influence. Such informational influence aims at persuading and changing attitudes and behavior. Elaboration refers to the extent to which individuals critically scrutinize arguments in the information (Petty & Cacioppo, 1986). Because such elaboration requires cognitive effort, individuals do not elaborate on every component of the information in detail, and some elaborate less than others (Petty & Cacioppo, 1986; Sussman & Siegal, 2003). The ELM distinguishes between two routes of information processing (Petty & Cacioppo, 1986). Central information processing requires high levels of elaboration, characterized by significant cognitive engagement and careful evaluation of information and its arguments. Peripheral information processing is based on low levels of elaboration, whereby individuals rely on heuristics or pre-existing mental shortcuts, requiring minimal cognitive effort (Petty & Cacioppo, 1986).

The ELM has been widely applied to examine information processing and persuasion, including credibility formation (Bhattacherjee & Sanford, 2006; Cheung et al., 2012; Miller et al., 2024; Yalch & Elmore-Yalch, 1984). Throughout the past decades of research, it has been applied in both online and offline media communication contexts (Cyr et al., 2018; Yalch & Elmore-Yalch, 1984). For instance, Cheung et al. (2012) apply the ELM to investigate how individuals process online reviews, which then shapes credibility formation. Miller et al. (2024) apply the

ELM to investigate social media engagement depending on whether individuals see disinformation or factual information. Yalch and Elmore-Yalch (1984) apply the ELM to investigate how individuals process quantitative versus nonquantitative messages and how this shapes their attitudes and cognitive responses.

2.3. Credibility

Researchers vary in their distinction between the terms 'credibility' and 'trust'. For example, Self (1996) uses the two terms 'trust' and 'credibility' interchangeably. Tseng and Fogg (1999) argue that these terms are distinct, whereby trust refers to the reliability or dependability of a person, object, or process, and credibility refers to the believability or trustworthiness of information. Pavlou (2002) views credibility as an antecedent of trust, whereas Hovland and Weiss (1951) consider trust as an antecedent of credibility. In this study, we follow Hovland and Weiss's (1951) terminology and focus on the term 'credibility' determined by trust.

Early works in communication and persuasion research by Hovland (1951), Hovland and Weiss (1951), and Hovland et al. (1953) laid the groundwork for empirical credibility research and conceptualized credibility as *source credibility.* An individual endorser acts as a source of information aimed at persuading an information recipient. Such source credibility is shaped by two dimensions: trustworthiness and expertise of the source. Trustworthiness refers to the perceived honesty and reliability of the source. Expertise indicates the perceived skills and competence of the source in delivering genuine and accurate information. Source credibility shapes attitudes, with high-credibility sources causing greater shifts in attitudes than low-credibility sources (Hovland, 1951; Hovland & Weiss, 1951). Pornpitakpan (2004) adds that source credibility shapes persuasion in terms of both attitude and behavior. However, the two dimensions of source credibility may vary in importance across different contexts.

The conceptualization of source credibility dominated credibility research in communication, persuasion, and psychology for many decades. Later research placed greater emphasis on the construct of content credibility (Appelman & Sundar, 2015; Metzger et al., 2003; Metzger & Flanagin, 2013; Sundar, 1999). Sundar (1999) defines content credibility according to perceptions of believability, accuracy, bias, objectivity, and fairness related to the content. Scholars investigate content credibility as either an independent variable, a dependent variable, or a mediator (Appelman & Sundar, 2015; Metzger et al., 2003).

2.4. Factors Shaping Credibility Formation from the ELM Perspective

In the ELM (Cheung et al., 2012; Petty & Cacioppo, 1986; Sussman & Siegal, 2003), three sets of influential factors shape credibility formation: (1) content-related factors under the central information processing route; (2) source-related factors under the peripheral information processing route; and (3) recipient-related factors, such as individual levels of issue involvement and expertise. In this study, we adopt the term *argument strength* as a key content-related factor and *news outlet reputation* as a key source-related factor.

2.4.1. Argument Strength and the Central Information Processing Route

An argument consists of various components whose presence or absence distinguishes strong arguments from weak ones (Allen & Preiss, 1997; Boller et al., 1990; Hoeken & Hustinx, 2009; Yi et al., 2013). Stronger arguments yield more favorable cognitive responses than weaker ones (Petty & Cacioppo, 1986). As a measurable construct, Cheung et al. (2012) operationalize *argument strength* according to the extent to which individuals perceive the arguments in a message as convincing, strong, good, and persuasive. Such argument strength established as a content-related factor impacting knowledge adoption in organizations (Bhattacherjee & Sanford, 2006; Cyr et al., 2018; Sussman & Siegal, 2003). Furthermore, it established as a credibility antecedent across different communication contexts (Cheung et al., 2009; Cheung et al., 2012; Nicolaou & McKnight, 2006; Sussman & Siegal, 2003; Wathen & Burkell, 2002; Yi et al., 2013). When individuals engage in detailed elaboration of arguments, the perceived argument strength becomes the primary credibility antecedent through the central route of information processing (Areni & Lutz, 1988; Cheung et al., 2012; Petty & Cacioppo, 1986; Watts & Zhang, 2008).

2.4.2. News Outlet Reputation and the Peripheral Information Processing Route

In the journalism and newspaper context, news outlet reputation is a perceptual, source-related factor shaping content credibility perceptions (Appelman & Hettinga, 2020; Kim & Dennis, 2019; Metzger & Flanagin, 2013). News outlet reputation develops gradually over time and reflects the accumulated perceptions of trustworthiness, expertise, experience, and reliability (Kim & Dennis, 2019). Kim and Dennis (2019) argue that individuals perceive journalistic content as more credible when a news outlet with a reputation for experience, trustworthiness, expertise, and reliability publishes it. Conversely, individuals are more likely to discount content from outlets with a reputation for falsehood (McCracken, 1989). Furthermore, individuals favor articles from recognized news outlets over less familiar alternatives (Kim & Dennis, 2019; Metzger et al., 2010). As individuals cannot always thoroughly scrutinize arguments, they follow the peripheral route of information processing. Thereby, they evaluate information based on contextual, peripheral factors, such as the news outlet reputation. In this way, reputation and recognition heuristics guide evaluations of content credibility (Gigerenzer et al., 1999; Kim & Dennis, 2019; Metzger et al., 2010; Petty & Cacioppo, 1986).

2.4.3. Individuals' Issue Involvement and Expertise on Elaboration Likelihood

The degree of individuals' issue involvement and expertise shapes their elaboration likelihood (Cheung et al., 2012; Petty & Cacioppo, 1986; Sussman & Siegal, 2003). Different levels of elaboration likelihood guide whether individuals rely on central or peripheral information processing routes when evaluating information.

When issue involvement is high, individuals are more willing to exert cognitive effort and engage in thoughtful evaluation of information (Petty & Cacioppo, 1986). When issue involvement is low, individuals rely more on peripheral factors (Cheung et al., 2012; Petty & Cacioppo, 1986). High levels of prior expertise on a topic increase comprehension and the extent of issue-relevant thoughts. Low levels of prior expertise increase reliance on peripheral factors (Ratneshwar & Chaiken, 1991).

3. Hypotheses Development

We derive hypotheses by focusing on the three sets of influential factors central to the ELM (Cheung et al., 2012; Petty & Cacioppo, 1986; Sussman & Siegal, 2003). We argue that these three sets may explain how readers process and evaluate the credibility of the content of sensor-based articles compared to non-sensor-based articles. Thereby, we refer to the quantifiability of and technology-enabled origin of evidence based on sensor data as a major differentiating determinant of information processing and, hence, credibility formation.

3.1. Quantification as a Determinant of Information Processing Route

The type of evidence shapes how individuals perceive arguments (Hoeken & Hustinx, 2009; Koetsenruijter, 2011; Thaesler-Kordonouri et al., 2024; Toulmin, 1958; Yi et al., 2013). Communication research shows that data-driven evidence can impose high cognitive demands and reduce information comprehensibility (Cheung et al., 2012; Koetsenruijter, 2011; Petty & Cacioppo, 1986; Thaesler-Kordonouri et al., 2024; Yalch & Elmore-Yalch, 1984). Furthermore, data-driven evidence can reduce attention and interest (Koetsenruijter, 2011). Under such conditions, individuals rely more on peripheral, source-related factors, rather than scrutinizing the arguments to shape their evaluations (Metzger et al., 2010; Yalch & Elmore-Yalch, 1984). In contrast, testimonial evidence is easier to process, requires less numerical literacy, and strengthens persuasion via central information processing while reducing reliance on peripheral, source-related factors (De Wit et al., 2008; Thaesler-Kordonouri et al., 2024).

Sensor-based articles share the precision-oriented and quantifiable nature of articles containing data-driven evidence. Hence, sensor-based articles may present precise, quantified values of temperature, distances, or air quality (Diakopoulos, 2019; Hamm, 2024). We argue that information processing patterns established for articles with data-driven evidence may also apply to sensor-based articles, potentially increasing processing demands. Consistent with the ELM, seeing sensor-based articles may shift processing toward the peripheral route (Koetsenruijter, 2011; Pornpitakpan, 2004; Thaesler-Kordonouri et al., 2024).

H1a: For readers seeing sensor-based articles, peripheral information processing dominates: news outlet reputation has a stronger effect on content credibility than argument strength.

H1b: For readers seeing non-sensor-based articles, central information processing dominates: argument strength has a stronger effect on content credibility than news outlet reputation.

3.2. Interaction Effects

3.2.1. News Outlet Reputation and Argument Strength

Different perceptual levels of news outlet reputation may interact with perceptions of argument strength and jointly affect content credibility (Luo et al., 2013; Pornpitakpan, 2004; Sussman & Siegal, 2003). When individuals perceive arguments as strong, a reputable news outlet may enhance the positive effect of argument strength on content credibility more than a less credible one. In contrast, less reputable news outlets are less likely to increase the positive effect of argument strength on content credibility (Eagly & Chaiken, 1975; Luo et al., 2013). We argue that different levels of news outlet reputation may play a moderating role in information processing:

H2a: The positive effect of argument strength on content credibility will be stronger when a reputable news outlet presents the (sensor-based / non-sensor-based) article than when it is presented by a less reputable one.

H2b: When the news outlet is less reputable, the positive effect of argument strength on content credibility remains unchanged.

Because evidence based on sensor data may increase cognitive processing demands, readers may rely more on peripheral, source-related factors (Pornpitakpan, 2004; Yalch & Elmore-Yalch, 1984). We therefore argue that news outlet reputation may exert a stronger moderating role in processing sensor-based articles than in processing non-sensor-based articles.

H2c: The moderating effect of news outlet reputation on the relationship between argument strength and content credibility will be higher for readers seeing a sensor-based article than for readers seeing a non-sensor-based article.

3.2.2. Issue Involvement and Expertise

The extent to which individuals rely on central versus peripheral processing depends on their level of issue involvement and expertise. Together, these factors shape the degree of elaboration likelihood (Sussman & Siegal, 2003; Zaichkowsky, 1994).

Individuals with a high level of issue involvement are motivated to scrutinize information and its arguments. Similarly, individuals with high levels of expertise on the topic presented in the information are able to comprehend and evaluate the information and its arguments. Highly involved and expert individuals are more likely to scrutinize arguments based on argument strength. Such increased elaboration likelihood enables individuals to evaluate information based on content-related factors rather than peripheral factors (Sussman & Siegal, 2003).

Individuals with lower levels of issue involvement and expertise in the particular topic presented in the article are less motivated to process the information and its arguments in detail. Hence, they rely more on peripheral factors, such as news outlet reputation, when evaluating information (Petty & Cacioppo, 1986; Sussman & Siegal, 2003; Yalch & Elmore-Yalch, 1984).

H3a: When readers have higher levels of issue involvement and expertise, argument strength exerts a stronger effect on content credibility than news outlet reputation.

H3b: When readers have lower levels of issue involvement and expertise, news outlet reputation exerts a stronger effect on content credibility than argument strength.

With regard to sensor-based journalism, we propose that the moderating effect of issue involvement and expertise is stronger for readers seeing sensor-based articles than for readers seeing non-sensor-based articles. We argue that levels of issue involvement and expertise become more decisive in content credibility evaluations of sensor-based articles, because evidence based on sensor data may impose higher cognitive demands, making content credibility evaluations more dependent on readers' levels of issue involvement and expertise.

H3c: The moderating effect of issue involvement and expertise is stronger for readers seeing sensor-based articles than for readers seeing non-sensor-based articles.

However, under certain cognitive conditions, less reputable news outlets may paradoxically increase elaboration and the effects of content-related factors (Heesacker et al., 1983; Pornpitakpan, 2004). Priester and Petty (2003) find that when individuals have higher levels of expertise but lower levels of issue involvement, less reputable news outlets can prompt them to examine arguments more carefully. Under these conditions, a less reputable news outlet can increase elaboration, thereby increasing the effect of argument strength on content credibility.

H4a: When readers have low issue involvement but high expertise, and the news outlet is less reputable, argument strength exerts a stronger effect on content credibility than news outlet reputation.

We argue that this paradox may emerge more strongly when seeing sensor-based articles compared to non-sensor-based articles. Compared to information processing with average elaboration likelihood (H1a & H1b), readers with low personal interest but high ability to comprehend quantifiable evidence based on sensor data may be more likely to engage in deeper processing of sensor-based articles. When sensor-based articles originate from a less reputable news outlet, such expert readers may not be overwhelmed and rely more strongly on factual and verifiable evidence based on sensor data than on arguments based on other evidence, such as personal observations or testimonies (Koetsenruijter, 2011; Porter, 1995; Van Dijk, 1988; Yalch & Elmore-Yalch, 1984).

H4b: Such an override effect is stronger for readers seeing sensor-based articles compared to readers seeing non-sensor-based articles.

4. Method

4.1. Experimental Procedure

To test the hypotheses, we developed an online 2 x 2 experiment, consisting of a pre-treatment questionnaire, a reading task, and a post-treatment questionnaire.

Upon receiving and clicking the experiment link, participants see an introductory webpage that briefly explains the experiment and requests their informed consent. After agreeing to the conditions and entering the first experiment page, the participants complete a pre-treatment questionnaire on their demographics, their level of media skepticism, and whether they know particular news outlets and how they perceive their reputation.

To avoid deception, we inform the participants before the reading task about the treatment variations. We inform them that they will view one excerpt from an article containing evidence based on sensor data or an excerpt without such evidence. Also, we inform them that these excerpts will be presented by either a real or a fictitious news outlet. For the reading task, we assign the participants randomly to one of four treatment groups;

- First group seeing an excerpt of an article with evidence based on sensor data presented by a reputable and well-known news outlet ("sensor-based – high-reputation" condition),
- Second group seeing an excerpt of an article with evidence based on sensor data presented by a less reputable and unknown news outlet ("sensor-based – low-reputation" condition),
- Third group seeing an excerpt of an article without evidence based on sensor data presented by a reputable and well-known news outlet ("non-sensor-based – high-reputation" condition),
- Fourth group seeing an excerpt of an article without evidence based on sensor data presented by a less reputable and unknown news outlet ("non-sensor-based – low-reputation" condition).

After participants finish reading the excerpt and answering the treatment and attention check, we ask the participants to complete a post-treatment questionnaire. We collect data on participants' perceived argument strength (Cheung et al., 2012), content credibility (Sundar, 1999), their degree of issue involvement (Zaichkowsky, 1994), and expertise on the topic (Sussman & Siegal, 2003).

Finally, we debrief the participants, present the complete article with the original news outlet name, including the link to the news website, and reward them for their participation.

We obtained ethical approval for this study.

4.2. Measurements

In the pre-treatment questionnaire, we ask about participants' *demographics* (gender category, age range, educational level), their *perceived news outlet reputation* of selected news outlets, and their *level of media skepticism*:

- We measure the *perceived news outlet reputation* to verify the treatment and strengthen the validity of our findings. We measure *perceived news outlet reputation* according to whether participants find two selected news outlets (as presented in the treatments) 'reliable', 'trustworthy', 'credible', and whether they find that those news outlets have the 'necessary expertise to do their job' (adapted from Kim & Dennis, 2019). Participants rate their responses on a 5-point Likert scale (1 = 'strongly disagree' to 5 = 'strongly agree').
- Because prior research on the perceptions of sensor-based articles identifies participants' *level of media skepticism* under certain conditions as a direct predictor of content credibility (anonymized for review), we include this variable as a control variable to improve explanatory power. Media skepticism is an attitude of alienation and mistrust toward the media, both online and offline, such as television, newspapers, and radio (Stroembaeck et al., 2020; Tsfati, 2003). Skeptical individuals often perceive the media as biased and unfair (Tsfati, 2003). Individuals with strong partisan views see relatively neutral content as biased against their position (Giner-Sorolla & Chaiken, 1994). Such perceptions are resistant to change and may persist even when challenged with contradictory arguments (Howe & Krosnick, 2017). We measure participants' level of media skepticism by asking them to rate whether they associate the media (e.g., television, newspapers, and radio) with 'fair coverage', 'lack of bias', 'comprehensiveness', 'accuracy', and the 'separation of facts from opinions' in their country (United Kingdom). Participants rate their responses on a 5-point Likert scale (1 = 'strongly disagree' to 5 = 'strongly agree'), with high agreement indicating low media skepticism and vice versa (adapted from Stroembaeck et al., 2020, and Tsfati, 2003).

For the reading task and post-treatment questionnaire, we assign the participants randomly to one of four treatment groups. We code the group assignment regarding the variation of the evidence used in the excerpt as a dummy (evidence based on sensor data = 1; without evidence based on sensor data = 0). Additionally, we include *assigned news outlet reputation* as a dummy (low-reputation = 0; high-reputation = 1).

In the post-treatment questionnaire, we conduct a *treatment and attention check* to examine whether participants perceive the treatment as intended. We ask them to state which news outlet has published the presented excerpt and whether the excerpt includes evidence based on sensor data supporting the central claim within the excerpt. Furthermore, we measure *argument strength* on four items according to whether participants find the presented arguments 'convincing', 'good', 'strong', and 'persuasive' (adapted from Cheung et al., 2012). Then, we measure *content credibility* on five items asking participants to evaluate the content according to whether it is 'believable', 'accurate', 'biased', 'objective', and 'fair' (adapted from Sundar, 1999). Moreover, we measure participants' level of *issue involvement* on six items asking participants to evaluate whether the topic of the excerpt is 'important', 'interesting', 'relevant', 'exciting', 'appealing', and whether they feel greatly 'involved' in the topic (adapted from Zaichkowsky, 1994). Finally, we measure participants' *expertise* on three items asking participants to indicate whether they are 'informed', 'an expert', and have 'knowledge' about the topic of the excerpt (adapted from Sussman & Siegal, 2003). For the constructs argument strength, content credibility, issue involvement and expertise, participants rate their responses on a 5-point Likert scale (1 = 'strongly disagree' to 5 = 'strongly agree').

We find that all multi-item scales in our sample demonstrate sufficient internal consistency and reliability. We find high consistency levels for the *perceived news outlet reputation* (high-reputation: Cronbach's α = 0.95; low-reputation: Cronbach's α = 0.98); *media skepticism* (Cronbach's α = 0.89); *argument strength* (Cronbach's $\alpha \approx 0.95$); *content credibility* ($\alpha \approx 0.90$-0.92); *issue involvement* (Cronbach's $\alpha \approx 0.89$-0.91) and *expertise* (Cronbach's $\alpha \approx 0.80$-0.83). Mean inter-item correlations (MICs) range from 0.58 to 0.94. All one-factor solutions indicate strong loadings (> 0.68), supporting the unidimensionality and construct validity of the measures. See Appendix A for complete reliability and validity indices for the measured constructs, per treatment group.

4.3. Stimulus Material

In the reading task, we ask participants to read one of two approximately 200 or 240-word excerpts from an article featuring a traffic concern in London, United Kingdom. The excerpt reports on how traffic impacts air pollution during school journeys (Figure 1). Across the four treatment groups, the publication date remains constant. The content varies depending on whether it includes evidence on air pollution derived from sensor data (sensor-based condition) or other evidence, such as testimonies (non-sensor-based condition). In the excerpt containing evidence based on sensor data, the central claim and argument within the excerpt –traffic causing higher pollution – are supported with data collected from sensors measuring nitrogen dioxide levels and fine particles (e.g., "nitrogen dioxide pollution went up by 16%"). In the excerpt without such evidence, the claim and argument are supported with testimonies about stress due to congestion and figures on pupil attendance during school periods (e.g., "It feels like you can breathe again (…) there isn't the stress of noise and pollution. It's just a much calmer and more enjoyable journey to school."). Additionally, both excerpts contain a statistical figure as a form of additional, data-driven evidence well-established in journalistic reporting (e.g., "The analysis found 6,000 pupils attended private schools in Herne Hill, compared with 12,600 at state schools, one of the highest concentrations of private education in the country."). We included this element to ensure comparability, allowing us to examine whether evidence based on sensor data provides effects beyond 'conventional' data-driven evidence. Furthermore, the news outlet name varies according to its reputation (high-reputation versus low-reputation). For the high-reputation news outlet, we disclose the original newspaper name, which is a well-known and, according to a ranking (YouGov, 2023), reputable newspaper in the United Kingdom. For the low-reputation news outlet, we fabricate a fictitious newspaper name, *HelloNews*. Pre-tests confirm that participants can recognize sensor-based articles as such and distinguish reputable news outlets from less reputable ones.

Figure 1. Excerpts Across Four Conditions
(Sensor-Based vs. Non-Sensor-Based × High- vs. Low-Reputation).

Sensor-Based – High-Reputation

Private School Run in South London
Linked to 27% Rise in Air Pollution

Original News Outlet (high-reputation) 14.01.2025

(…) Parents driving children to private schools is associated with a 27% increase in air pollution and congestion in a south London street, according to campaigners who are calling for private schools to make greater use of sustainable transport. The analysis by Solve the School Run found that nitrogen dioxide levels and fine particulates produced by vehicles in the street in Herne Hill were far higher when nearby private schools such as Dulwich college were open, compared with when only local state schools were open. (…) The group sourced [sensor] data for nitrogen dioxide and fine particulate matter known as PM2.5, which includes particles from car tyres and brakes, from the Breathe London community air monitoring programme, and bus times from Transport for London. The data for Croxted Road in Herne Hill during morning rush hours found nitrogen dioxide pollution went up by 16% when state schools were open but by 47% when both state and private schools were open – an increase of 27% despite private schools accounting for only half as many pupils. The level of PM2.5 also rose by 25% when private schools reopened, while bus times were 51% slower. (…) The analysis found 6,000 pupils attended private schools in Herne Hill, compared with 12,600 at state schools, one of the highest concentrations of private education in the country. As a result, researchers said the impact would be lower in most other parts of the country. (…)

Sensor-Based – Low-Reputation

Private School Run in South London
Linked to 27% Rise in Air Pollution

HelloNews (low-reputation) 14.01.2025

(…) Parents driving children to private schools is associated with a 27% increase in air pollution and congestion in a south London street, according to campaigners who are calling for private schools to make greater use of sustainable transport. The analysis by Solve the School Run found that nitrogen dioxide levels and fine particulates produced by vehicles in the street in Herne Hill were far higher when nearby private schools such as Dulwich college were open, compared with when only local state schools were open. (…) The group sourced [sensor] data for nitrogen dioxide and fine particulate matter known as PM2.5, which includes particles from car tyres and brakes, from the Breathe London community air monitoring programme, and bus times from Transport for London. The data for Croxted Road in Herne Hill during morning rush hours found nitrogen dioxide pollution went up by 16% when state schools were open but by 47% when both state and private schools were open – an increase of 27% despite private schools accounting for only half as many pupils. The level of PM2.5 also rose by 25% when private schools reopened, while bus times were 51% slower. (…) The analysis found 6,000 pupils attended private schools in Herne Hill, compared with 12,600 at state schools, one of the highest concentrations of private education in the country. As a result, researchers said the impact would be lower in most other parts of the country. (…)

Non-Sensor-Based – High-Reputation

Private School Run in South London
Linked to Rise in Air Pollution

Original News Outlet (high-reputation) 14.01.2025

(…) Parents driving children to private schools is associated with a[n] increase in air pollution and congestion in a south London street, according to campaigners who are calling for private schools to make greater use of sustainable transport. (…) Ben Barratt, a professor in environmental exposures and public health at Imperial College London, said the "sheer number of private schools" in the area made it an unusual case. (…) Nicola Pastore, a local parent who co-founded Solve the School Run (…), said: "It's well established in the area that in the weeks when only state schools are open, the traffic is much lighter, partly because those schools have much lower driving rates. (…) It feels like you can breathe again because you don't have to worry so much about your children getting hit, and there isn't the stress of noise and pollution. It's just a much calmer and more enjoyable journey to school." (…) The analysis found 6,000 pupils attended private schools in Herne Hill, compared with 12,600 at state schools, one of the highest concentrations of private education in the country. As a result, researchers said the impact would be lower in most other parts of the country. (…)

Non-Sensor-Based – Low-Reputation

Private School Run in South London
Linked to Rise in Air Pollution

HelloNews (low-reputation) 14.01.2025

(…) Parents driving children to private schools is associated with a[n] increase in air pollution and congestion in a south London street, according to campaigners who are calling for private schools to make greater use of sustainable transport. (…) Ben Barratt, a professor in environmental exposures and public health at Imperial College London, said the "sheer number of private schools" in the area made it an unusual case. (…) Nicola Pastore, a local parent who co-founded Solve the School Run (…), said: "It's well established in the area that in the weeks when only state schools are open, the traffic is much lighter, partly because those schools have much lower driving rates. (…) It feels like you can breathe again because you don't have to worry so much about your children getting hit, and there isn't the stress of noise and pollution. It's just a much calmer and more enjoyable journey to school." (…) The analysis found 6,000 pupils attended private schools in Herne Hill, compared with 12,600 at state schools, one of the highest concentrations of private education in the country. As a result, researchers said the impact would be lower in most other parts of the country. (…)

5. Results

For the data analysis, we use the open-source software *R* and *RStudio* Version 2024.12.1+563.

5.1. Sample

We conduct a priori power analyses using G*Power (Faul et al., 2009) to determine the required sample sizes. We aim to detect (1) small-to-medium effects ($f = 0.20$) in a 2 × 2 between-subjects analysis of variance (ANOVA) (Cohen, 1988), and (2) small effects in multiple regression models ($f^2 = 0.02$). Results indicate a minimum of 200 participants for the ANOVA and 439 participants for regression models with a maximum of 46 predictors ($\alpha = 0.05$, power = 0.80).

We collected the data in July 2025. We recruited participants via convenience sampling on the crowdsourcing platform *Prolific*, through which we sent the experiment link to participants who voluntarily agreed to participate. Crowdsourcing platforms are widely recognized for yielding reliable and high-quality data in behavioral research and experiments (Bhattacherjee, 2023). We targeted our sampling to adults who are fluent in English and reside in the United Kingdom.

From the initial sample of 2,027 participants, we first filter the data of 419 participants who failed the treatment and attention check, resulting in a sub-sample of 1,608 participants. To examine whether such data filtering introduced systematic demographic bias, we conduct a series of Chi-squared and Fisher's exact tests. We find that the proportion of retained versus filtered participants does not differ significantly across gender categories (Fisher's exact $p = 0.59$) or educational levels (Pearson's $\chi^2(5) = 4.49$, $p = 0.67$). The proportion differs slightly according to age range (Pearson's $\chi^2(5) = 11.69$, $p < 0.05$), with younger participants more likely to dropout due to failure of treatment and attention check.

Additionally, we apply a median-based filtering rule to filter data of participants with implausible completion times, i.e., faster than one-third the median or slower than three times the median (Curran, 2016). This results in filtering additional data of 38 participants, reducing the sub-sample from 1,608 to a final, filtered sample of 1,570. To examine whether such data filtering introduced systematic demographic bias, we conduct another series of Chi-squared and Fisher's exact tests. We indicate no significant differences between retained and filtered participants by gender categories (Fisher's exact $p = 0.59$), age range (Pearson's $\chi^2(5) = 1.79$, $p = 0.88$), or educational level (Fisher's exact with 10,000 simulations, $p = 0.91$).

The filtered sample of $N = 1{,}570$ exceeds the thresholds for the minimum sample size of 200 participants for ANOVA group comparisons and 439 participants for regression models with 46 predictors. Hence, our filtered sample is sufficiently powered for both types of analyses.

The filtered sample consists of 53.9% female, 45.4% male, and 0.7% diverse participants. The median age range is 35 to 44 years, and the median educational level is a Bachelor's degree (Table 1).

Table 1. Demographics.

Variable	*N*	%
Gender	1,570	100
Male	712	45.4
Female	847	53.9
Diverse	11	0.7
NA	0	0.0
Age Range	1,570	100
18 to 24	119	7.6
25 to 34	393	25.0
35 to 44	394	25.1
45 to 54	329	21.0
55 to 64	241	15.4
65 and older	94	6.0
Educational Level	1,570	100
No School Leaving Certificate	9	0.6
Secondary General School-Leaving Certificate	347	22.1
University Entrance Qualification	116	7.4
Apprenticeship	65	4.1
Bachelor's Degree	670	42.7
Master's Degree / Diploma	286	18.2
PhD	45	2.9
Other	32	2.0

To assess whether participants in the four groups differ systematically in the demographics, we conduct Chi-squared and Fisher's exact tests. The results for the four treatment groups reveal no significant differences by gender categories (Fisher's exact with 10,000 simulations, $p = 0.56$), age range (Pearson's $\chi^2(15) = 16.40$, $p = 0.36$), and educational level (Fisher's exact with 10,000 simulations, $p = 0.45$).

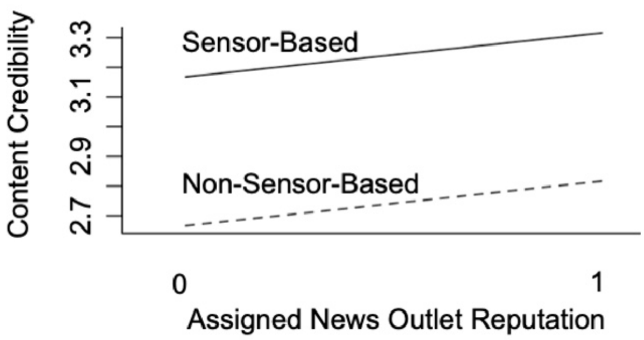
See Table 2 for final group sizes, means, and standard deviations for the measured independent and dependent variables across the four groups.

Table 2: Means and Standard Deviations for the Measured Independent and Dependent Variables Across the Four Conditions.

Condition	n	Media Skepticism	Argument Strength	Content Credibility	Issue Involvement	Expertise
Sensor-Based, High-Reputation	443	3.75 (0.78)	3.47 (0.96)	3.32 (0.86)	3.07 (0.90)	2.24 (0.93)
Non-Sensor-Based, High-Reputation	411	3.74 (0.74)	2.78 (1.01)	2.82 (0.83)	2.87 (0.91)	2.07 (0.84)
Sensor-Based, Low-Reputation	366	3.78 (0.77)	3.43 (0.97)	3.17 (0.82)	3.11 (0.85)	2.14 (0.81)
Non-Sensor-Based, Low-Reputation	350	3.74 (0.73)	2.73 (1.00)	2.67 (0.80)	2.89 (0.90)	2.08 (0.82)

Participants rate the content of excerpts with evidence based on sensor data presented by high-reputation news outlets as more credible. Still, the content credibility advantage of high-reputation news outlets is not substantially different in mean ratings between excerpts with evidence based on sensor data and excerpts without such evidence (see Figure 2).

Figure 2: Content Credibility as a Function of Assigned News Outlet Reputation.



Assigned News Outlet Reputation: high-reputation = 1; low-reputation = 0;
Evidence Type: sensor-based versus non-sensor-based

5.2. Empirical Analysis

5.2.1. Preliminary Tests

To confirm the effectiveness of the variation of the news outlet in the experimental treatment, we test whether participants' perceived news outlet reputation differs substantially between the two news outlets. We conduct an independent-samples t-test and find that participants rate the high-reputation news outlet as significantly more reputable ($M = 3.33$, $SD = 0.84$) than the low-reputation news outlet ($M = 2.36$, $SD = 0.82$) ($t(1566.3) = 21.16$, $p < 0.001$). The effect size is large, Cohen's $d = 1.06$, indicating that participants, on average, recognized the original news outlet as more reputable. Hence, we can confirm the effectiveness of the experimental treatment at the perceptual level.

Before conducting ANOVA and regression analyses, we test key assumptions of normality, homogeneity of variance, and multicollinearity.

Shapiro-Wilk tests indicate deviations from normality in all treatment groups (all $p < 0.001$). However, given the relatively large sample sizes and the robustness of ANOVA to moderate departures from normality, we continue the analyses (Schmider et al., 2010). Levene's test indicates that the assumption of homogeneity of variance is met ($F(3, 1566) = 0.24$, $p = 0.87$). All predictors show variance inflation factors (VIFs) ranging from 1.06 to 3.27, indicating no multicollinearity concerns (O'Brien, 2007).

We conduct a 2 × 2 between-subjects ANOVA. Factors include evidence type (sensor-based versus non-sensor-based) and assigned news outlet reputation (high-reputation versus low-reputation), predicting content credibility. We find a main effect of evidence type ($F(1, 1566) = 143.34$, $p < 0.001$), with content with evidence based on sensor data rated as more credible than content without such evidence. We also find a main effect of assigned news outlet reputation ($F(1, 1566) = 12.69$, $p < 0.001$), such that participants rate content from the high-reputation news outlet as more credible than the content from the low-reputation news outlet. The interaction effect is non-significant ($F(1, 1566) = 0.00$, $p = 0.98$).

5.2.2. Testing H1a and H1b

To test H1a and H1b, we estimate two stratified Ordinary Least Squares (OLS) models (including controls for demographics, media skepticism, issue involvement, and expertise). For the demographic characteristics, we set the following reference groups: 'diverse' for gender categories, '18-24' for age range, and 'apprenticeship' for educational level. For participants seeing excerpts with evidence based on sensor data (H1a), the model explains 57% of the variance in content credibility ratings ($F(19, 789) = 55.62$, $p < 0.001$). Argument strength is the dominant predictor ($B = 0.61$, $p < 0.001$). Assigned news outlet reputation shows a smaller but significant effect ($B = 0.11$, $p < 0.01$) (H1 not supported). For participants seeing excerpts without evidence based on sensor data (H1b), the model explains 55% of the variance in content credibility ratings ($F(19, 741) = 48.59$, $p < 0.001$). Argument strength is the dominant predictor ($B = 0.58$, $p < 0.001$). Assigned news outlet reputation exerts a smaller but significant effect ($B = 0.13$, $p < 0.01$) (H1b supported). Table 3 displays the regression results.

Table 3: Results of Regression Analysis (Testing H1a, H1b).

	Condition							
	Sensor-Based				Non- Sensor-Based			
Predictor	**B**	**SE**	**t**	**p**	**B**	**SE**	**t**	**p**
Intercept	2.43	0.30	8.00	<0.001 ***	3.18	0.24	13.13	<0.001 ***
Assigned News Outlet Reputation	0.11	0.04	2.70	0.007 **	0.13	0.04	3.09	0.002 **
Argument Strength	0.61	0.03	22.33	<0.001 ***	0.58	0.03	22.48	<0.001 ***
Issue Involvement	-0.03	0.03	-1.02	0.310	-0.06	0.03	-2.01	0.045 *
Expertise	0.05	0.03	2.03	0.043 *	0.08	0.03	2.93	0.003 **
Media Skepticism	-0.16	0.03	-6.07	<0.001 ***	-0.14	0.03	-4.89	<0.001 ***
Age: 25-34	0.13	0.08	1.59	0.113	-0.04	0.09	-0.51	0.610
Age: 35-44	0.05	0.08	0.59	0.553	-0.09	0.09	-1.01	0.311
Age: 45-54	0.00	0.08	0.06	0.953	-0.14	0.09	-1.64	0.102
Age: 55-64	-0.05	0.09	-0.53	0.595	-0.18	0.09	-1.90	0.058
Age: 65+	-0.15	0.11	-1.40	0.161	-0.33	0.11	-2.91	0.004 **
Gender: Female	0.45	0.28	1.59	0.113	-0.07	0.22	-0.32	0.750
Gender: Male	0.54	0.29	1.89	0.059	-0.06	0.22	-0.26	0.797
Edu: No School Leaving Certificate	0.57	0.34	1.66	0.097	0.02	0.25	0.10	0.920
Edu: Secondary General School Leaving Certificate	0.09	0.11	0.77	0.444	-0.01	0.10	-0.07	0.948
Edu: University Entrance Qualification	0.04	0.13	0.28	0.781	-0.16	0.12	-1.36	0.175
Edu: Bachelor's Degree	0.10	0.11	0.89	0.377	-0.06	0.10	-0.62	0.533
Edu: Master's Degree / Diploma	0.09	0.12	0.74	0.461	-0.11	0.10	-1.03	0.303
Edu: PhD	0.21	0.17	1.22	0.223	0.03	0.14	0.24	0.814
Edu: Other	0.01	0.18	0.06	0.956	-0.21	0.16	-1.31	0.190
Model Fit	Residual standard error: 0.56 on 789 DF; Multiple R^2: 0.57; Adjusted R^2: 0.56; F(19, 789) = 55.62; p < 0.001.				Residual standard error: 0.55 on 741 DF; Multiple R^2: 0.55; Adjusted R^2: 0.54; F(19, 741) = 48.59; p < 0.001.			

*: P ≤ 0.05; **: P ≤ 0.01; ***: P ≤ 0.001.
Assigned news outlet reputation: high-reputation = 1; low-reputation = 0.

5.2.3. Testing H2a and H2b

To test H2a-c, we conduct further OLS regression analyses. To facilitate interpretation of the regression coefficients and reduce multicollinearity in models with interaction terms, we effect-code categorical predictors (assigned news outlet reputation, evidence type). We mean-center continuous predictors (media skepticism, argument strength, issue involvement, and expertise).

We find that argument strength is a strong positive predictor of content credibility (B = 0.59, p < 0.001). Simple slopes analysis shows that argument strength strongly predicts content credibility both when the assigned news outlet reputation is low (B = 0.59, p < 0.001) and when it is high (B = 0.60, p < 0.001). Assigned news outlet reputation also exerts a positive effect (B = 0.12, p < 0.001). However, the interaction between argument strength and assigned news outlet reputation is non-significant (B = 0.02, p = 0.58) (H2a and H2b not supported). The three-way interaction with the evidence type is non-significant (B = 0.01, p = 0.90) (H2c not supported). Table 4 displays the regression results.

Table 4: Results of Regression Analysis (Testing H2a, H2b, H2c).

Predictor	B	SE	t	p
Intercept	2.89	0.19	15.29	< 0.001***
Assigned News Outlet Reputation	0.12	0.03	3.03	0.002**
Evidence Type	0.09	0.03	3.02	0.003**
Argument Strength	0.59	0.02	32.05	< 0.001***
Issue Involvement	-0.05	0.02	-2.16	0.031*
Expertise	0.07	0.02	3.56	< 0.001***
Media Skepticism	-0.15	0.02	-7.87	< 0.001***
Argument Strength × Assigned News Outlet Reputation	0.02	0.03	0.56	0.575
Argument Strength × Evidence Type	0.04	0.03	1.26	0.208
Assigned News Outlet Reputation × Evidence Type	-0.02	0.06	-0.39	0.694
Argument Strength × Ass. News Outlet Reputation × Evidence Type	0.01	0.06	0.13	0.895
Age 25-34	0.05	0.06	0.83	0.410
Age 35-44	-0.02	0.06	-0.25	0.801
Age 45-54	-0.07	0.06	-1.08	0.282
Age 55-64	-0.11	0.06	-1.68	0.094
Age 65+	-0.25	0.08	-3.13	0.002**
Gender: Female	0.12	0.17	0.70	0.486
Gender: Male	0.17	0.17	1.01	0.313
Edu: No School Leaving Certificate	0.24	0.20	1.20	0.229
Edu: Secondary General School Leaving Certificate	0.04	0.08	0.46	0.649
Edu: University Entrance Qualification	-0.06	0.09	-0.63	0.532
Edu: Bachelor's Degree	0.01	0.07	0.20	0.844
Edu: Master's Degree / Diploma	-0.01	0.08	-0.17	0.866
Edu: PhD	0.13	0.11	1.18	0.239
Edu: Other	-0.11	0.12	-0.91	0.364

*: P ≤ 0.05; **: P ≤ 0.01; ***: P ≤ 0.001

Categorical variables are effect-coded; continuous variables are mean-centered.

Residual standard error: 0.56 on 1545; Multiple R^2: 0.60; Adj. R^2: 0.59; F(24, 1545) = 95.6, p < 0.001.

5.2.4. Testing H3a, H3b, and H3c

To test H3a, H3b, and H3c, we conduct further OLS regression analyses with three-way interactions (Argument Strength × Issue Involvement × Expertise and Assigned News Outlet Reputation × Issue Involvement × Expertise). Also, we add their extensions regarding the evidence type and control for demographics and media skepticism. We effect-code the categorical variables and mean-center the continuous variables.

We find that argument strength is a strong positive predictor of content credibility (B = 0.58, p < 0.001). We also find significant three-way interactions for Argument Strength × Issue Involvement × Expertise (B = 0.03, p < 0.05), Evidence Type × Assigned News Outlet Reputation × Expertise (B = 0.18, p < 0.05), and Evidence Type × Assigned News Outlet Reputation × Expertise × Issue Involvement (B = -0.14, p = 0.05). The interaction Evidence Type × Argument Strength × Issue Involvement × Expertise is non-significant (p = 0.67).

We conduct simple slope contrasts to indicate 'dominance' contrasts. We compare the relative slopes of argument strength and assigned news outlet reputation at ±1 SD of issue involvement and expertise. At high issue involvement and expertise levels (+1 SD), the results show the opposite of the hypothesized effect (B = -0.17, p < 0.01). No dominance emerges when seeing excerpts without evidence based on sensor data (B = -0.06, p = 0.40) (H3a not supported).

At low issue involvement and expertise levels (−1 SD), assigned news outlet reputation has a stronger effect than argument strength on content credibility when participants see excerpts without evidence based on sensor data (B = 0.21, p < 0.01). We cannot find the same effect when participants see excerpts with evidence based on sensor data (B = -0.04, p = 0.63; Δ = -0.25, p < 0.05) (H3b partially supported).

We find that at high issue involvement and expertise levels (+1 SD), the difference between seeing excerpts with and without evidence based on sensor data is non-significant ($\Delta = -0.11$, $p = 0.26$). At low issue involvement and expertise levels (−1 SD), the difference between seeing excerpts with and without evidence based on sensor data is significant ($\Delta = -0.25$, $p < 0.05$). The dominance effect of the assigned news outlet reputation appears when participants see excerpts without evidence based on sensor data. Such a dominance effect is reduced as participants see excerpts with evidence based on sensor data (H3c not supported).

Table 5 displays the regression results. Table 6 displays the simple slope contrasts.

Table 5: Results of Regression Analysis (Testing H3a, H3b).

Predictor	B	SE	t	p
Intercept	2.84	0.19	15.02	<0.001***
Assigned News Outlet Reputation	0.13	0.03	4.08	<0.001***
Evidence Type	0.08	0.04	2.26	0.024*
Argument Strength	0.58	0.02	30.24	<0.001***
Issue Involvement	-0.05	0.02	-2.24	0.025*
Expertise	0.04	0.02	1.78	0.075
Media Skepticism	-0.15	0.02	-7.65	<0.001***
Age: 25-34	0.06	0.06	0.95	0.345
Age: 35-44	-0.00	0.06	-0.06	0.953
Age: 45-54	-0.05	0.06	-0.89	0.373
Age: 55–64	-0.10	0.06	-1.53	0.126
Age: 65+	-0.25	0.08	-3.17	0.002**
Gender: Female	0.16	0.17	0.92	0.359
Gender: Male	0.21	0.17	1.23	0.220
Edu: No Certificate	0.27	0.20	1.35	0.176
Edu: Secondary General School Leaving Certificate	0.03	0.08	0.42	0.672
Edu: University Entrance Qualification	-0.06	0.09	-0.70	0.487
Edu: Bachelor's Degree	0.01	0.07	0.16	0.875
Edu: Master's Degree / Diploma	-0.01	0.08	-0.18	0.859
Edu: PhD	0.13	0.11	1.18	0.240
Edu: Other	-0.10	0.12	-0.81	0.416
Argument Strength × Expertise	0.03	0.02	1.09	0.278
Argument Strength × Issue Involvement	-0.03	0.02	-1.71	0.088
Expertise × Issue Involvement	0.00	0.02	0.17	0.863
Expertise × Assigned News Outlet Reputation	0.02	0.04	0.49	0.623
Issue Involvement × Assigned News Outlet Reputation	-0.01	0.04	-0.14	0.887
Argument Strength × Evidence Type	0.03	0.04	0.70	0.486
Expertise × Evidence Type	-0.06	0.04	-1.28	0.202
Issue Involvement × Evidence Type	0.05	0.05	1.18	0.237
Assigned News Outlet Reputation × Evidence Type	0.03	0.06	0.54	0.591
Argument Strength × Expertise × Issue Involvement	0.03	0.02	2.11	0.035*
Expertise × Issue Involvement × Assigned News Outlet Reputation	-0.03	0.04	-0.88	0.381
Argument Strength × Expertise × Evidence Type	-0.00	0.05	-0.03	0.978
Argument Strength × Issue Involvement × Evidence Type	-0.03	0.03	-0.51	0.611
Expertise × Issue Involvement × Evidence Type	0.07	0.05	1.56	0.119
Expertise × Assigned News Outlet Reputation × Evidence Type	0.18	0.08	2.36	0.018*
Issue Involvement × Ass. News Outlet Reputation × Evidence Type	0.03	0.07	0.38	0.704
Argument Strength × Expertise × Issue Inv × Evidence Type	-0.01	0.03	-0.42	0.674
Expertise × Issue Inv. × Ass. News Outlet Rep. × Evidence Type	-0.14	0.07	-1.96	0.050

*: $P \leq 0.05$; **: $P \leq 0.01$; ***: $P \leq 0.001$.
Categorical variables are effect-coded; continuous variables are mean-centered.
Residual standard error: 0.55 on 1531; Multiple $R^2 = 0.60$, Adj. $R^2 = 0.59$, $F(38, 1531) = 61.4$, $p < 0.001$.

Table 6: Simple Slope Contrasts (Testing H3c).

Moderator Level	Evidence Type	Contrast Tested	B	SE	t	p
High Expertise & High Issue Involvement (+1 SD, +1 SD)	Sensor-Based	Argument Strength – Assigned News Outlet Reputation	-0.17	0.06	-2.79	0.005
	Non-Sensor-Based		-0.06	0.07	-0.84	0.401
	Δ (Sensor-Based – Non-Sensor-Based)		-0.11	0.09	-1.14	0.256
Low Expertise & Low Issue Involvement (−1 SD, −1 SD)	Sensor-Based	Assigned News Outlet Reputation– Argument Strength	-0.04	0.07	-0.48	0.633
	Non-Sensor-Based		0.21	0.07	3.29	0.001**
	Δ (Sensor-Based – Non-Sensor-Based)		-0.25	0.10	-2.55	0.011*

*: P ≤ 0.05; **: P ≤ 0.01; ***: P ≤ 0.001.
Categorical variables are effect-coded; continuous variables are mean-centered.
DF = 1531.
Slopes represent the relative effect of argument strength compared to issue involvement and expertise on content credibility.

5.2.5. Testing H4a and H4b

To test H4a and H4b, we examine whether the effect of argument strength outweighs the effect of assigned news outlet reputation in shaping content credibility under the conditions of low issue involvement, high expertise, and an assigned low-reputation news outlet. At low issue involvement (–1 SD), high expertise (+1 SD), and an assigned low-reputation news outlet (–0.5), argument strength has a stronger effect on content credibility than assigned news outlet reputation. This override effect is significant for participants who see excerpts with evidence based on sensor data ($B = 0.38$, $p < 0.05$) and for participants who see excerpts without evidence based on sensor data ($B = 0.57$, $p < 0.01$) (H4a supported). The difference between the participants who see excerpts with evidence based on sensor data and participants who see excerpts without evidence based on sensor data is non-significant ($p = 0.42$) (H4b not supported). Table 7 displays the simple slope contrasts.

Table 7: Simple Slope Contrasts (Testing H4a, H4b).

Moderator Level	Evidence Type	Contrast Tested	B	SE	t	p
High Expertise (+1 SD) & Low Issue Inv. (–1 SD) & Low-Reputation News Outlet (–0.5)	Sensor-Based	Argument Strength – Assigned News Outlet Reputation	0.38	0.15	2.49	0.013*
	Non-Sensor-Based		0.57	0.18	3.12	0.002**
	Δ (Sensor-Based − Non-Sensor-Based)		-0.19	0.24	-0.82	0.415

*: P ≤ 0.05; **: P ≤ 0.01; ***: P ≤ 0.001.
Categorical variables are effect-coded; continuous variables are mean-centered.
DF = 1523.
Slopes represent the relative effect of argument strength compared to assigned news outlet reputation on content credibility at low issue involvement (–1 SD), high expertise (+1 SD), and low assigned news outlet reputation (–0.5).

5.2.6. Hierarchical Models

We conduct a series of hierarchical OLS regression analyses to predict content credibility (see Appendix B for results of hierarchical regression models predicting content credibility).

Model 1 includes the main effects of evidence type, assigned news outlet reputation, and argument strength, as well as all control variables (testing H1a and H1b). Model 2 (testing H2a, H2b, and H2c) adds the interactions, which do not improve model fit ($\Delta R^2 = 0.001$, F-change = 0.50, non-significant). Model 3 (testing H3a, H3b, and H3c) adds three three-way interactions, which significantly improve the model fit ($\Delta R^2 = 0.006$, F-change = 1.71, p <

0.05). Model 4 (testing H4a and H4b) adds further four- and five-way interactions, which do not improve model fit ($\Delta R^2 = 0.001$, F-change = 0.67, non-significant). To assess the relative importance of predictors, we compute standardized regression coefficients (β) for the hierarchical model. Argument strength emerges as the strongest predictor of content credibility ($\beta = 0.70$), followed by media skepticism ($\beta = -0.13$). Assigned news outlet reputation ($\beta = 0.08$) and evidence type ($\beta = 0.05$) contribute modestly. Issue involvement exerts a small effect ($\beta = -0.05$). The effect of expertise is non-significant. We conduct multicollinearity diagnostics and find no problematic correlations among the predictors. All generalized variance inflation factors (GVIFs) are below 3 (O'Brien, 2007).

5.2.7. Robustness Checks

We re-run all hierarchical regression models using the initial sample ($N = 2{,}027$) and with the variable of participants' *perceived news outlet reputation* instead of the *assigned news outlet reputation*. We find that the results remain substantively unchanged compared to those from the filtered sample. See Appendix C for detailed results from robustness checks.

5.3. Summary of Results

We find full support for two and partial support for one out of ten hypotheses (see Table 8). Argument strength remains the major predictor for content credibility evaluations in both sensor-based and non-sensor-based conditions. When readers see non-sensor-based articles, argument strength has a stronger effect on content credibility than news outlet reputation. When readers have low levels of issue involvement but high expertise and perceive the news outlet as low in reputation, perceived argument strength exerts a stronger effect on content credibility than the news outlet reputation.

Table 8. Results of Hypothesis Testing.

No.	Hypothesis	Supported / Not Supported
1a	For readers seeing sensor-based articles, peripheral information processing dominates: news outlet reputation has a stronger effect on content credibility than argument strength.	X
1b	For readers seeing non-sensor-based articles, central information processing dominates: argument strength has a stronger effect on content credibility than news outlet reputation.	✓
2a	The positive effect of argument strength on content credibility will be stronger when a reputable news outlet presents the (sensor-based / non-sensor-based) article than when it is presented by a less reputable one.	X
2b	When the news outlet is less reputable, the positive effect of argument strength on content credibility remains unchanged.	X
2c	The moderating effect of news outlet reputation on the relationship between argument strength and content credibility will be higher for readers seeing a sensor-based article than for readers seeing a non-sensor-based article.	X
3a	When readers have higher levels of issue involvement and expertise, argument strength exerts a stronger effect on content credibility than news outlet reputation.	X
3b	When readers have lower levels of issue involvement and expertise, news outlet reputation exerts a stronger effect on content credibility than argument strength.	(X)
3c	The moderating effect of issue involvement and expertise is stronger for readers seeing sensor-based articles than for readers seeing non-sensor-based articles.	X
4a	When readers have low issue involvement but high expertise, and the news outlet is less reputable, argument strength exerts a stronger effect on content credibility than news outlet reputation.	✓
4b	Such an override effect is stronger for readers seeing sensor-based articles compared to readers seeing non-sensor-based articles.	X

6. Discussion

We find three issues in our results that suggest for discussion.

Superiority of argument strength in sensor-based journalism: We find that news outlet reputation does not outweigh argument strength in shaping content credibility when readers see sensor-based articles. Our findings suggest that the substance of arguments remains the cornerstone of content credibility evaluations in the context of sensor-based journalism. We explain this finding by arguing that the evidence based on sensor data from technology-enabled origin may signal high factuality, precision, and verifiability. Such signals may increase perceptions of argument strength and, consequently, motivate readers to allocate cognitive resources to the central route information processing (Koetsenruijter, 2011).

Role of individual factors in processing sensor-based articles: In sensor-based journalism, issue involvement and expertise do not consistently strengthen central route information processing. Instead, they heighten reliance on source-related factors. Such an effect complicates traditional predictions derived from the ELM (Priester & Petty, 2003). One potential explanation may be that readers with higher issue involvement and expertise are more aware of the potential limitations of evidence based on sensor data. Consequently, readers may become more attentive to the news outlet reputation when evaluating the content in sensor-based journalism.

Negative effect of media skepticism on content credibility: The consistent negative effect of media skepticism on content credibility, regardless of the type of evidence, highlights a broader societal challenge. High levels of media skepticism continue to undermine perceptions of content credibility. We argue that this finding aligns with prior research that links media skepticism to difficulties in sustaining readership and engagement (Stroembaeck et al., 2020).

7. Limitations and Suggestions for Future Research

Our study has several limitations, leading to suggestions for future research.

Sampling approach leading to generalizability concerns: We employed convenience sampling, which may limit the generalizability of our results. While the sample size was large and adequately powered, it does not represent all demographics equally. Additionally, we employed a one-shot, between-subjects experimental design, which cannot observe long-term effects. Future studies may want to employ random sampling and longitudinal designs to enhance generalizability and capture long-term effects of content credibility evaluations. Moreover, our study is culturally and contextually situated in the media environment of the United Kingdom, further limiting the generalizability of our findings. Media skepticism and its effect on reader perceptions may differ across countries, especially when comparing polarized media systems, societies with low versus high institutional trust, or contexts where technology-driven attributes are perceived differently (Davidov et al., 2014). Future studies could employ cross-cultural comparisons to reveal whether the processing of sensor-based versus non-sensor-based articles is country-dependent.

Filtering criteria: We filtered a notable proportion of participants' data (approximately 20%). Although robustness checks indicate that results remain substantively unchanged when including the data of filtered participants, filtering the data may still introduce subtle selection biases. In our study, younger participants were more likely to fail the treatment and attention check. Future research could explore whether the treatment design needs adjustment in terms of clarity or whether certain participant groups require additional assistance.

Operationalization of news outlet reputation and evidence type: While the experimental treatments were effective in this study, they represent rather simplified operationalizations. We varied news outlet reputation by assigning two outlets as either reputable and well-known or less reputable and unknown. However, news outlet reputation in the real world is more complex and multifaceted, involving additional dimensions, such as partisan leanings or long-term audience loyalty. Similarly, our variation of the two evidence types may not fully reflect the diverse ways in which sensor-based journalism can be implemented into journalistic practice. Future research could employ more nuanced variations. For example, it could vary the partisan leanings of news outlets, incorporate long-term reputational trajectories, or present mixed formats of evidence based on sensor data (numerical values versus visualizations).

Limited topic variety: We exposed the participants to only one excerpt, which limits the generalizability of our findings. The topic and tone may have shaped participants' perceptions. Hence, future studies could present multiple articles spanning diverse topics and variations of tone to reduce potential topic- and tone-specific effects and help increase the generalizability and robustness of our findings.

8. Conclusion

In this study, we applied the ELM perspective to investigate whether evidence based on sensor data acts as a differentiator in information processing and in shaping content credibility. We find that argument strength remains the dominant predictor of content credibility when seeing sensor-based articles. Furthermore, we find that a nuanced interplay of content-related, source-related, and individual factors predicts evaluations of content credibility of sensor-based articles. Readers with high elaboration levels, i.e., high issue involvement and high expertise, rely more on peripheral factors, such as news outlet reputation, when evaluating the content credibility of sensor-based articles. In contrast, no dominant effects emerge for readers with low elaboration levels. The effect of argument strength becomes dominant when readers have high expertise but low issue involvement and see sensor-based articles presented by a less reputable news outlet. Furthermore, our findings highlight that in certain contexts, sensor-based journalism may serve as a boundary condition for information processing and credibility formation.

Theoretical implications: Our findings contrast with earlier applications of the ELM investigating information processing of data-driven evidence (Koetsenruijter, 2011; Yalch & Elmore-Yalch, 1984). The effects of seeing evidence based on sensor data on information processing and credibility formation differ from those of seeing evidence based on data-driven evidence. Furthermore, our findings on the role of news outlet reputation and readers' individual factors confirm prior research claiming that decreased elaboration likelihood may reinforce elaboration of arguments (Priester & Petty, 2003). Our findings contribute to prior credibility research from an ELM perspective (Cheung et al., 2012; Cheung et al., 2009; Petty & Cacioppo, 1986; Pornpitakpan, 2004). They suggest that various journalism contexts shape how individuals process information and, consequently, evaluate content credibility. This implies that content credibility formation should be conceptualized not as a uniform process but as one that is contingent on the informational environment. Based on our findings, sensor-based journalism represents another boundary condition for established ELM assumptions.

Recommendations for practice: First, media organizations and IS professionals should account for different persuasion patterns. They should design and use systems that not only capture sensor data and report the insights straightforwardly but also support journalists in contextualizing and communicating such data in persuasive ways. Second, the dominance of argument strength in shaping content credibility suggests that media organizations should prioritize investments in creating strong argumentation. Such investments seem critical for sustaining content credibility and hence readers' willingness to consume and potentially purchase journalistic content (Zhang et al., 2014). Third, media organizations should invest in maintaining a strong brand to maximize the impact of publishing sensor-based articles (Kim & Dennis, 2019). Established news outlets should safeguard and reinforce their reputation, while emerging news outlets may strategically invest in reputation-building strategies to offset weaker brand status. Fourth, media organizations and institutions need to pursue credible infrastructures, technologies, and journalism. Reducing media skepticism is not only a normative goal but also a business concern, whereby content credibility deficits can directly affect sales (Stroembaeck et al., 2020).

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Appendices

Appendix A: Reliability and Validity Indices for Measured Constructs.

Scale	k	α	ω	MIC	Min Load.	Max Load.
Perceived News Outlet Reputation – high-reputation	4	0.953	0.954	0.835	0.837	0.945
Perceived News Outlet Reputation – low-reputation	4	0.983	0.983	0.935	0.942	0.981
Media Skepticism	5	0.891	0.892	0.621	0.727	0.848
Argument Strength – sensor-based, high-reputation	4	0.950	0.951	0.828	0.887	0.927
Argument Strength – non-sensor based, high-reputation	4	0.949	0.949	0.823	0.894	0.929
Argument Strength – sensor-based, low-reputation	4	0.949	0.950	0.825	0.861	0.929
Argument Strength – non-sensor-based, low-reputation	4	0.947	0.948	0.819	0.856	0.926
Content Credibility – sensor-based, high-reputation	5	0.921	0.922	0.701	0.764	0.913
Content Credibility – non-sensor-based, high-reputation	5	0.909	0.912	0.670	0.729	0.915
Content Credibility – sensor-based, low-reputation	5	0.909	0.911	0.669	0.766	0.910
Content Credibility – non-sensor-based, low-reputation	5	0.899	0.902	0.644	0.734	0.893
Issue Involvement – sensor-based, high-reputation	6	0.905	0.906	0.614	0.734	0.850
Issue Involvement – non-sensor-based, high-reputation	6	0.913	0.914	0.636	0.740	0.859
Issue Involvement – sensor-based, low-reputation	6	0.893	0.895	0.584	0.707	0.881
Issue Involvement – non-sensor-based, low-reputation	6	0.908	0.910	0.624	0.718	0.865
Expertise – sensor-based, high-reputation	3	0.831	0.841	0.629	0.696	0.914
Expertise – non-sensor-based, high-reputation	3	0.825	0.839	0.630	0.730	0.878
Expertise – sensor-based, low-reputation	3	0.795	0.811	0.577	0.679	0.902
Expertise – non-sensor-based, low-reputation	3	0.812	0.826	0.609	0.741	0.852

Appendix B: Results of Hierarchical Regression Models Predicting Content Credibility.

Predictor	M1 Main + Ctrls	M2 + H2	M3 + H3	M4 + H4
Evidence Type	0.091** (0.030) β = 0.052	0.092** (0.030) β = 0.053	0.079* (0.035) β = 0.046	0.086* (0.035) β = 0.050
Assigned News Outlet Reputation	0.117*** (0.028) β = 0.067	0.117*** (0.030) β = 0.067	0.125*** (0.031) β = 0.071	0.147*** (0.035) β = 0.084
Argument Strength	0.594*** (0.019) β = 0.715	0.594*** (0.019) β = 0.715	0.582*** (0.019) β = 0.700	0.580*** (0.019) β = 0.697
Issue Involvement	-0.045* (0.021) β = -0.046	-0.046* (0.021) β = -0.048	-0.051* (0.023) β = -0.053	-0.049* (0.023) β = 0.051
Expertise	0.065*** (0.018) β = 0.065	0.066*** (0.018) β = 0.065	0.040 (0.022) β = 0.039	0.042 (0.023) β = 0.041
Media Skepticism	-0.154*** (0.019) β = -0.134	-0.153*** (0.019) β = -0.133	-0.149*** (0.019) β = -0.129	-0.147*** (0.020) β = -0.128
Age: 25-34	0.049 (0.059) β = 0.024	0.049 (0.059) β = 0.024	0.056 (0.059) β = 0.028	0.055 (0.06) β = 0.028
Age: 35-44	-0.017 (0.059) β = 0.009	-0.015 (0.059) β = -0.007	-0.004 (0.059) β = -0.002	-0.008 (0.06) β = -0.004
Age: 45-54	-0.066 (0.06) β = -0.031	-0.065 (0.06) β = -0.030	-0.054 (0.061) β = -0.025	-0.059 (0.061) β = -0.027
Age: 55-64	-0.108 (0.064) β = -0.045	-0.107 (0.064) β =-0.044	-0.098 (0.064) β = -0.041	-0.100 (0.064) β = -0.042
Age: 65+	-0.247 (0.079) β = -0.067	-0.247** (0.079) β =-0.067	-0.250** (0.079) β = -0.068	-0.263*** (0.079) β = -0.072
Gender: Female	0.122 (0.171) β = 0.070	0.119 (0.171) β = 0.068	0.158 (0.172) β =0.091	0.167 (0.173) β = 0.096
Gender: Male	0.178 (0.171) β = 0.102	0.173 (0.171) β = 0.099	0.211 (0.172) β = 0.121	0.221 (0.173) β = 0.127
Edu: No School Leaving Certificate	0.248 (0.199) β = 0.022	0.241 (0.20) β = 0.021	0.271 (0.20) β = 0.024	0.288 (0.201) β = 0.025
Edu: Secondary General School Leaving Certificate	0.026 (0.076) β = 0.013	0.035 (0.076) β = 0.017	0.032 (0.076) β = 0.015	0.033 (0.076) β =0.016
Edu: University Entrance Qualification	-0.060 (0.087) β = -0.018	-0.055 (0.087) β = -0.016	-0.061 (0.088) β = -0.018	-0.057 (0.088) β = -0.017
Edu: Bachelor's Degree	0.009 (0.073) β = 0.005	0.014 (0.073) β = 0.008	0.011 (0.073) β = 0.007	0.012 (0.073) β = 0.007
Edu: Master's Degree / Diploma	-0.018 (0.077) β = -0.008	-0.013 (0.077) β = -0.006	-0.014 (0.077) β = -0.006	-0.013 (0.077) β = -0.006
Edu: PhD	0.125 (0.108) β = 0.024	0.128 (0.108) β = 0.025	0.128 (0.109) β = 0.025	0.135 (0.109) β = 0.026

Edu: Other	-0.110 (0.121) β = -0.018	-0.110 (0.121) β = -0.018	-0.098 (0.121) β = -0.016	-0.091 (0.121) β = -0.015
Argument Strength × Assigned News Outlet Reputation	—	0.016 (0.029) β = 0.010	—	0.008 (0.038) β = 0.005
Argument Strength × Assigned News Outlet Reputation × Evidence Type	—	0.008 (0.058) β = 0.002	—	-0.096 (0.077) β = -0.029
Argument Strength × Expertise × Issue Involvement	—	—	0.032* (0.015) β = 0.047	0.032* (0.016) β = 0.048
Assigned News Outlet Reputation × Expertise × Issue Involvement	—	—	—	0.009 (0.048) β = 0.005
Argument Strength × Assigned News Outlet Reputation × Expertise × Issue Involvement	—	—	—	0.042 (0.031) β = 0.031
Argument Strength × Assigned News Outlet Reputation × Expertise × Issue Involvement × Evidence Type	—	—	—	-0.019 (0.063) β = -0.007
Multiple R^2	0.597	0.598	0.604	0.605
Adjusted R^2	0.592	0.591	0.594	0.593
ΔR^2 (vs. previous)	—	0.001	0.006*	0.001
F-change	—	0.50 (non-significant)	1.71*	0.67 (non-significant)

*p < 0.05, **p < 0.01, ***p < 0.001.
Continuous variables are mean-centered; categorical variables are effect-coded.
Unstandardized coefficients (B) with standard errors in parentheses; standardized betas (β) on the next line.

8.1. Appendix C: Results from Robustness Checks.

Predictor	Filtered Sample (Assigned News Outlet Reputation)	Initial Sample (Assigned News Outlet Reputation)	Filtered Sample (Perceived News Outlet Reputation)
Evidence Type	0.086* (0.035)	0.050 (0.031)	0.089* (0.035)
Assigned News Outlet Reputation / Perceived News Outlet Reputation	0.147*** (0.035)	0.111*** (0.031)	0.085*** (0.018)
Argument Strength	0.580*** (0.019)	0.585*** (0.017)	0.579*** (0.019)
Media Skepticism	-0.147*** (0.020)	-0.122*** (0.017)	-0.107*** (0.021)
Expertise	0.042 (0.023)	0.025 (0.020)	0.052* (0.022)
Issue Involvement	-0.049* (0.023)	-0.042* (0.020)	-0.062** (0.023)
Age 25-34	0.055 (0.060)	0.023 (0.053)	0.049 (0.059)
Age 35-44	-0.009 (0.060)	-0.019 (0.053)	0.013 (0.059)
Age 45-54	-0.059 (0.061)	–0.074 (0.054)	-0.069 (0.060)
Age 55-64	-0.100 (0.064)	–0.109 (0.057)	-0.109 (0.064)
Age 65+	-0.263*** (0.079)	-0.242*** (0.068)	-0.274*** (0.079)
Gender: Female	0.167 (0.173)	0.045 (0.166)	0.153 (0.170)
Gender: Male	0.221 (0.173)	0.099 (0.166)	0.212 (0.171)
Edu: No School Leaving Certificate	0.288 (0.201)	0.043 (0.174)	0.237 (0.199)
Edu: Secondary General School Leaving Certificate	0.033 (0.076)	0.021 (0.065)	0.038 (0.076)
Edu: University Entrance Qualification	-0.057 (0.088)	-0.057 (0.077)	-0.042 (0.087)
Edu: Bachelor's Degree	0.012 (0.073)	0.024 (0.063)	0.005 (0.073)
Edu: Master's Degree / Diploma	-0.013 (0.077)	-0.007 (0.066)	-0.017 (0.077)
Edu: PhD	0.135 (0.109)	0.156 (0.095	0.122 (0.108)
Edu: Other	-0.091 (0.121)	-0.025 (0.105)	-0.108 (0.120)
Argument Strength × Assigned News Outlet Reputation // Argument Strength × Perceived News Outlet Reputation	0.008 (0.038)	–0.001 (0.034)	0.017 (0.018)
Argument Strength × Assigned News Outlet Reputation × Evidence Type // Argument Strength × Perceived News Outlet Reputation × Evidence Type	-0.096 (0.077)	-0.040 (0.068)	0.006 (0.035)
Argument Strength × Expertise × Issue Involvement	0.032* (0.016)	0.035** (0.012)	0.016 (0.017)
Assigned News Outlet Reputation × Expertise × Issue Involvement // Perceived News Outlet Reputation × Expertise × Issue Involvement	0.009 (0.048)	−0.026 (0.041)	0.021 (0.021)
Argument Strength × Assigned News Outlet Reputation × Expertise × Issue Involvement // Argument Strength × Perceived News Outlet Reputation × Expertise × Issue Involvement	0.042 (0.031)	0.037 (0.025)	0.019 (0.013)
Argument Strength × Assigned News Outlet Reputation × Expertise × Issue Involvement × Evidence Type // Argument Strength × Perceived News Outlet Reputation × Expertise × Issue Involvement × Evidence Type	-0.019 (0.063)	-0.043 (0.050)	-0.003 (0.025)
N	1,570	2,027	1,570
Multiple R^2	0.605	0.597	0.613
Adjusted R^2	0.593	0.588	0.601
F	50.752	63.808	52.373

*p < 0.05, **p < 0.01, ***p < 0.001.
Continuous variables are mean-centered and categorical variables are effect-coded.
Unstandardized coefficients (B) with standard errors in parentheses.

2.5 Argument strength and content credibility in sensor-based journalism: a comparative experiment

Reproduction from:

Boboschko, I., & Loebbecke, C. (2025f). Argument strength and content credibility in sensor-based journalism: a comparative experiment, under review at European Journal of Information Systems [VHB: A].

My contributions to this paper include the co-development of the research idea, literature review, experiment design, data collection, data analysis, and manuscript draft, and revision based on the comments from the co-author.

European Journal of Information Systems

Argument strength and content credibility in sensor-based journalism: a comparative experiment

Submission ID	259660757
Article Type	Research Article
Keywords	Sensor-Based Journalism, Argument Strength, Credibility, Structural Equation Modeling

Argument strength and content credibility in sensor-based journalism: a comparative experiment

Abstract

Sensor-based journalism has gained increasing attention as it relies on sensor-based data collection to capture phenomena beyond human reach. Drawing on research on argument strength as a content-related factor shaping content credibility, this study examines whether journalistic articles containing evidence based on sensor data increase argument strength. It further investigates whether this increased argument strength leads to higher content credibility compared to articles without such evidence. Data from a between-subjects online experiment ($N = 853$), analyzed via multi-group covariance-based structural equation modeling, show that journalistic articles with evidence based on sensor data increase argument strength. This increased argument strength, in turn, leads to higher content credibility compared with articles that do not include such evidence. These results demonstrate that sensor-based data collection serves as a differentiator in shaping content credibility in journalism. They contribute to research inconsistencies regarding the persuasive effects of different evidence types.

Keywords: Sensor-Based Journalism, Argument Strength, Credibility, Structural Equation Modeling.

1. Introduction

Sensor-based journalism has gained relevance as a journalistic practice. It relies on sensor-based data collection to capture physical variations on a large scale and in real-time, thereby reporting on phenomena that established journalistic practices could not previously capture (Diakopoulos, 2019; Hamm, 2024; anonymized for review). Examples of sensor-based journalism include real-time traffic updates from highway sensors, reports on air pollution made possible by sensor data from portable sensors carried by correspondents, or articles revealing potential greenwashing facilitated by sensor data from sensors placed in shoes tracing the shoe material recycling journey (Flip, 2021; Hook et al., 2019). While the output of sensor-based journalism can take various online and offline formats (Hamm, 2024), this study focuses on newspaper articles that contain claims and arguments supported by evidence based on sensor data, which we define as sensor-based articles.

Emerging research on perceptions of sensor-based articles challenges established concepts of credibility (anonymized for review). Whereas earlier work identifies identity cues as a key antecedent of content credibility[1] (Sundar, 2008), more recent research (anonymized for review) show that such cues exert no effect in the context of sensor-based journalism. Similarly, subsequent research insights suggest that news outlet reputation, a source-related factor once considered a strong antecedent of content credibility (Kim & Dennis, 2019; Metzger et al., 2010), has only marginal effects on content credibility in sensor-based journalism (anonymized for review).

Prior research claims that beyond source-related factors, content-related factors, such as argument strength, shape credibility perceptions (Boller et al., 1990; Cheung et al., 2009; Miller & Levine, 1996; Nicolaou & McKnight, 2006; Sussman & Siegal, 2003; Wathen & Burkell, 2002; Yi et al., 2013). Among various definitions of argument strength, we refer particularly to

[1] Content credibility refers to the perceptions of believability, accuracy, bias, objectivity, and fairness related to the content (Sundar, 1999).

the degree to which individuals find arguments as convincing, strong, good, and persuasive (Cheung et al., 2009; Sussman & Siegal, 2003). The presence or absence of specific components within an argument, such as the evidence type supporting the argument, distinguishes strong arguments from weak ones (Allen & Preiss, 1997; Boller et al., 1990; Hoeken & Hustinx, 2009; Yi et al., 2013). In this regard, research has long examined how different forms of evidence shape argument strength and, subsequently, persuasion and credibility (Freling et al., 2020; Henke et al., 2019; McCroskey, 1969; Toulmin, 1958; Yi et al., 2013). However, the effectiveness of each evidence type is inconsistent and context-dependent (Freling et al., 2020).

Communication and media research distinguish between two types of evidence: testimonial and data-driven (Chinn & Weeks, 2020; Godler et al., 2020; Hoeken & Hustinx, 2009). Testimonial evidence refers to personal accounts, individual experiences, eyewitness statements, or personal opinions (Freling et al., 2020; Godler et al., 2020). Data-driven evidence refers to quantified information derived from raw data, surveys, or public records, expressed as numerical values, statistics, or frequencies (Freling et al., 2020; Godler et al., 2020; Hoeken & Hustinx, 2009). Due to the increased prevalence of data-driven evidence used in journalistic reporting, recent research shows growing interest in how readers evaluate journalistic content that contains claims based on such evidence (Chinn & Weeks, 2020; Godler et al., 2020; Henke et al., 2019; Kazmierczak et al., 2025; Thaesler-Kordonouri et al., 2024).

Evidence based on sensor data shares the characteristics of data-driven evidence in terms of the quantifiable information but differs in its origin: it relies on technology-enabled, sensor-based data collection rather than manual methods typically used for generating other types of evidence (Chen et al., 2012; Shim et al., 2020). In organizational and Information Systems (IS) research, such technology-enabled data collection serves as a key differentiator in providing operational understanding in persuasive contexts and consistently improving organizational decision making (Chen et al., 2012; Kitchin, 2014; Loebbecke & Picot, 2015; McAfee & Brynjolfsson, 2012; Newell & Marabelli, 2015; O'Leary, 2013; Shim et al., 2020). In journalism, however, the role of the technology-enabled origin of evidence as a differentiating factor in shaping argument strength and, consequently content credibility remains underexplored, specifically in terms of the extent to which these relationships differ compared to evidence that is not based on sensor data.

In the context of sensor-based journalism, it remains unclear whether articles containing evidence based on sensor data – sensor-based articles – increase argument strength and, subsequently, content credibility more than articles without such evidence – non-sensor-based articles. To address this gap, we build on research on argument strength as a content-related factor predicting content credibility (Boller et al., 1990; Cheung et al., 2009; Miller & Levine, 1996; Nicolaou & McKnight, 2006; Sussman & Siegal, 2003; Wathen & Burkell, 2002; Yi et al., 2013). We derive three hypotheses and test them in a between-subjects online experiment, evaluating them with multi-group, covariance-based Structural Equation Modeling (SEM).

With our study, we contribute to the literature on argument strength as a content-related factor shaping content credibility. Furthermore, we extend communication and journalism research to the context of the underexplored domain of sensor-based journalism. Finally, we offer practical implications by showing how media organizations may leverage sensor-based journalism to enhance argumentation and, ultimately, content credibility.

2. Conceptual Background

2.1 Sensor-Based Data Collection in Journalism

Sensor-based data collection captures physicalities by complementing human sight, hearing, taste, smell, and tactile sensation (Newell & Marabelli, 2015). In the form of microphones or thermometers, sensors capture temporal variations in environments of various physical or chemical natures (Osterlie & Monteiro, 2020). Sensors convert these variations into large amounts of electronic signals, i.e., structured or unstructured data (Bardhan et al., 2020; Monteiro & Parmiggiani, 2019). Sensors placed on living creatures or objects may further act as mobile sensor data generators (Newell & Marabelli, 2015). When embedded in networked systems, these sensors become part of the 'Internet of Things' (or the 'Journalism of Things'), allowing for multi-directional data flows and contextual responsiveness (Hamm, 2024; Monteiro & Parmiggiani, 2019; Oberlaender et al., 2018). The collected sensor data may then serve as input data for Big Data Analytics and AI-based systems for subsequent analysis (Chen et al., 2012).

Recent research positions sensor-based journalism within the broader field of journalism based on data-driven evidence. The journalistic practice of so-called 'data-driven journalism' emerged long before sensor-based journalism established as a distinct journalistic practice (Hamm, 2024; Howard, 2014). In 1821, *The Guardian* published one of its first articles based on data-driven evidence, disclosing student enrollment figures and associated costs (Howard, 2014; The Guardian, 2011). Since the 1950s, early forms of sensor-based journalism appeared when journalists began using temperature data from sensor networks to generate routinized weather reports (National Environmental Satellite, Data, and Information Service, 2025). Over the past decades, the application of sensor technologies in journalism expanded to pursue further investigative reporting on phenomena that humans cannot easily access or observe efficiently (Diakopoulos, 2019; Hamm, 2024; Howard, 2014). In this context, sensor-based journalism has gained new relevance as a journalistic practice.

We distinguish sensor-based journalism from other forms of journalism, including testimony-based, data-driven, and automated journalism. Testimony-based journalism relies on testimonial evidence, such as individual experiences, eyewitness statements, or opinions (Freling et al., 2020; Godler et al., 2020). By contrast, sensor-based journalism draws on evidence generated through sensor data. Such sensors often outperform human observation because they operate via standardized technological mechanisms and are less prone to observation errors (Chen et al., 2012; anonymized for review). Sensor-based journalism enables higher levels of precision, verifiability, and factuality than testimony-based journalism (Diakopoulos, 2019; Hamm, 2024; Kitchin, 2014). Data-driven journalism typically relies on datasets from various sources, such as public records or statistical authorities (Diakopoulos, 2019; Kitchin, 2014). In contrast, sensor-based journalism relies on the remote collection of sensor data in contexts where direct human observation is difficult or inefficient (Diakopoulos, 2019; Chen et al., 2012; Hamm, 2024; Kitchin, 2014). Although sensor-based journalism shares its technology-enabled character with automated journalism, automated journalism generally centers on the automated production of journalistic content (Diakopoulos, 2019). In this study, we conceptualize sensor-based journalism more narrowly as the collection and use of sensor data for journalistic reporting rather than automated content creation. While automation may complement sensor-based journalism, it is not the focus here.

2.2 Argument Strength and Evidence Type

Scholars vary slightly in their terminology, conceptualization, and operationalization of argument strength. Early research refers to this construct as *argument quality*, emphasizing individuals' subjective perceptions of whether arguments are persuasive, strong, or plausible (Boller et al., 1990; Cheung et al., 2009). Later studies increasingly adopt the term *argument strength*, defined similarly as the degree to which information is of sufficient quality and perceived by recipients as convincing or valid, thereby motivating belief adoption or behavioral change (Cheung et al., 2009; Sussman & Siegal, 2003). In this study, we adopt the term *argument strength* and, following Cheung et al.'s (2009) operationalization, define it as the extent to which individuals perceive the arguments in a message as convincing, strong, good, and persuasive.

An argument consists of various components whose presence or absence distinguishes strong arguments from weak ones (Allen & Preiss, 1997; Beisecker et al., 2024; Boller et al., 1990; Hoeken & Hustinx, 2009; Yi et al., 2013). According to Toulmin's model of argumentation (Toulmin, 1958), evidence is a key component of an argument presented as proof to support the argument.

2.3 Credibility

Researchers vary in their distinction between the terms 'credibility' and 'trust'. For example, Self (1996) uses the two terms 'trust' and 'credibility' interchangeably. Tseng and Fogg (1999) argue that these terms are distinct, whereby trust refers to the reliability or dependability of a person, object, or process, and credibility refers to the believability or trustworthiness of information. Pavlou (2002) views credibility as an antecedent of trust, whereas Hovland and Weiss (1951) consider trust as an antecedent of credibility. In this study, we follow Hovland and Weiss's (1951) terminology and focus on the term 'credibility' determined by trust.

Early works in communication and persuasion research by Hovland (1951), Hovland and Weiss (1951), and Hovland et al. (1953) laid the groundwork for empirical credibility research and conceptualized credibility as *source credibility*. An individual endorser acts as a source of information aimed at persuading an information recipient. Such source credibility is shaped by two dimensions: trustworthiness and expertise of the source. Trustworthiness refers to the perceived honesty and reliability of the source, and expertise indicates the perceived skills and competence of the source in delivering genuine and accurate information. Source credibility shapes attitudes, with high-credibility sources causing greater shifts in attitudes than low-credibility sources (Hovland, 1951; Hovland & Weiss, 1951). Pornpitakpan (2004) adds that source credibility shapes persuasion in terms of both attitude and behavior. However, the two dimensions of source credibility may vary in importance across different contexts.

The conceptualization of source credibility dominated credibility research in communication, persuasion, and psychology for many decades. Later research placed greater emphasis on the construct of content credibility (Appelman & Sundar, 2015; Metzger et al., 2003; Metzger & Flanagin, 2013; Sundar, 1999). Sundar (1999) defines content credibility according to perceptions of believability, accuracy, bias, objectivity, and fairness related to the content. Scholars investigate content credibility as either an independent variable, a dependent variable, or a mediator (Appelman & Sundar, 2015; Metzger et al., 2003).

3. Hypothesis Development

Research has long examined how different evidence types supporting an argument shape argument strength, although findings remain inconclusive (Chinn & Weeks, 2020; Freling et al., 2020; Hoeken & Hustnix, 2009; McCroskey, 1969; Metzger et al., 2003; Toulmin, 1958; Yi et al., 2013). In the journalism context, some studies show that data-driven evidence strengthens arguments, as readers perceive it as more factual (Koetsenruijter, 2011; Porter, 1995; Van Dijk, 1988). Other studies, however, show that excessive use of quantitative figures in journalistic reporting overloads readers, leading to less favorable effects (Thaesler-Kordonouri et al., 2024). However, the effect of evidence based on technology-enabled data collection techniques such as sensor-based data collection remains underexplored (Kazmierczak et al., 2025). To derive the first hypothesis, we refer to prior research from neighboring fields that investigates the effect of evidence based on technology-enabled data collection techniques on providing stronger arguments.

Recent IS and organizational research suggests that decision making is more effective when it is supported by evidence generated through technology-enabled data collection, as it facilitates the observation of longitudinal and systematic developments in real-time and at low cost, enhances operational transparency, and enables not only informed decision making but in timely strategic and operational responses to environmental dynamics (Chen et al., 2012; O'Leary, 2013; Newell & Marabelli, 2015; Shim et al., 2020). Such evidence from technology-enabled data collection provides more convincing arguments and leads to better organizational outcomes. McAfee and Brynjolfsson (2012) argue that such evidence may outperform intuition-driven information and reduce reliance on the so-called "HiPPO" – the highest-paid person's opinion. Such HiPPOs used to be highly influential in organizations but often relate to bias and bounded rationality due to limitations of human cognitive capabilities (Chen et al., 2012; Loebbecke & Picot, 2015; McAfee & Brynjolfsson, 2012; Newell & Marabelli, 2015; O'Leary, 2013; Shim et al., 2020; anonymized for review).

Sensor-based data collection enables monitoring of, e.g., temperature, air quality, or noise levels. It offers access to more precise, factual, accurate, and verifiable insights than through personal observations or testimonies (Hamm, 2024; Kazmierczak et al., 2025; anonymized for review). Therefore, we argue that sensor-based articles present stronger arguments than comparable articles on the same topic that lack evidence based on sensor data. Thus, we hypothesize:

H1: Sensor-based articles increase argument strength more than non-sensor-based articles.

Argument strength grounds in research on persuasive messages, which are defined as a set of arguments shaping attitudes, beliefs, or behaviors (Areni & Lutz, 1988; Boller et al., 1990; Fishbein & Ajzen, 1975; O'Keefe, 2002). Hence, argument strength plays a crucial role in persuasion processes and credibility formation, with stronger arguments yielding more favorable cognitive responses than weaker ones (Boller et al., 1990; Cheung et al., 2009; Sussman & Siegal, 2003; Yi et al., 2013). As a content-related factor, it shapes persuasion in terms of knowledge adoption in organizations (Sussman & Siegal, 2003) and credibility across different communication contexts (Cheung et al., 2009; Nicolaou & McKnight, 2006; Sussman & Siegal, 2003; Wathen & Burkell, 2002; Yi et al., 2013).

As we propose that evidence based on sensor data conveys higher precision, verifiability, and factuality than other types of evidence, argument strength may therefore play an even greater persuasive role in shaping the content credibility of sensor-based articles compared to non-sensor-based articles. Thus, we hypothesize:

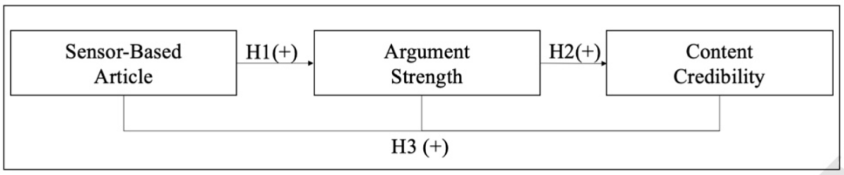
H2: The positive effect of argument strength on content credibility is stronger when seeing sensor-based articles in comparison to when seeing non-sensor-based articles.

Building on prior research that evidence provides the supporting proof for persuasion (Allen & Preiss, 1997; Toulmin, 1958; Yi et al., 2013), we argue that seeing sensor-based articles increases content credibility more than seeing non-sensor-based articles because readers perceive the arguments of sensor-based articles as stronger than those in comparable articles without evidence based on sensor data. Thus, we hypothesize a mediating relationship in which argument strength serves as a mechanism linking sensor-based articles to content credibility:

H3: Sensor-based articles increase content credibility through stronger arguments more than non-sensor-based articles.

Figure 1 presents our research model.

Figure 1. Research Model.



4. Method

4.1 Experimental Procedure

To test the hypotheses, we developed an online experiment, consisting of a pre-treatment questionnaire, a reading task, and a post-treatment questionnaire.

Upon receiving and clicking the experiment link, participants see an introductory webpage that briefly explains the experiment and requests their informed consent. After agreeing to the conditions and entering the first experiment page, the participants complete a pre-treatment questionnaire on their demographics, their level of media skepticism (Stroembaeck et al., 2020; Tsfati, 2003), and whether they know particular news outlets and how they perceive their reputation (Kim & Dennis, 2019).

To avoid deception, we inform the participants before the reading task that they will view one excerpt from an article containing either evidence based on sensor data or an excerpt without such evidence supporting the arguments in the excerpt. For the reading task, we assign the participants randomly to one of two treatment groups (one group seeing an excerpt of an article containing evidence based on sensor data, i.e., sensor-based condition, and the second group seeing an excerpt of the same article without evidence based on sensor data, i.e., non-sensor-based condition).

After participants finish reading the excerpt and answering the treatment and attention check, we collect data on participants' perceived argument strength (Cheung et al., 2009) and the perceived content credibility (Sundar, 1999) in the post-treatment questionnaire. Finally, we debrief the participants, present the complete article, including the link to the news website, and reward them for their participation.

We obtained ethical approval for this study.

4.2 Measurements

In the pre-treatment questionnaire, we ask about participants' *demographics* (gender category, age range, and educational level). Also, we measure additional control variables, i.e., participants' *level of media skepticism* and *perceived news outlet reputation* of selected news outlets (see Appendix A for a complete list of measurement items):

- Because prior research on the perceptions of sensor-based articles identifies participants' *level of media skepticism* under certain conditions can negatively influence content credibility (anonymized for review), we include this variable as a control variable to improve explanatory power. Media skepticism is an attitude of alienation and mistrust toward the media, both online and offline, such as television, newspapers, and radio (Stroembaeck et al., 2020; Tsfati, 2003). Skeptical individuals often perceive the media as biased and unfair (Tsfati, 2003). Individuals with strong partisan views see relatively neutral content as biased against their position (Giner-Sorolla & Chaiken, 1994). Such perceptions are resistant to change and may persist even when challenged with contradictory arguments (Howe & Krosnick, 2017). We measure participants' level of media skepticism by asking them to rate whether they associate the media (e.g., television, newspapers, and radio) with 'fair coverage', 'lack of bias', 'comprehensiveness', 'accuracy', and the 'separation of facts from opinions' in their country (United Kingdom), each on a 5-point Likert scale (1 = 'strongly disagree' to 5 = 'strongly agree'), with high agreement indicating low media skepticism and vice versa (adapted from Stroembaeck et al., 2020, and Tsfati, 2003). The media skepticism construct demonstrates adequate internal consistency (Cronbach's $\alpha = 0.89$) and substantial average inter-item correlation ($\bar{r} = 0.62$).

- We measure participants' *perceived news outlet reputation* using four items assessing whether they find a particular news outlet (which later presents the excerpt for the reading task) 'reliable', 'trustworthy', 'credible', and whether it has the 'necessary expertise to do the job' (adapted from Kim & Dennis, 2019). We quantify perceived news outlet reputation on a 5-point Likert scale (1 = 'strongly disagree' to 5 = 'strongly agree'). The perceived news outlet reputation construct demonstrates adequate internal consistency (Cronbach's $\alpha = 0.96$) and strong average inter-item correlation ($\bar{r} = 0.84$).

For the reading task and post-treatment questionnaire, we assign the participants randomly to one of two treatment groups and code the group assignment based on the condition (sensor-based condition versus non-sensor-based condition) as a dummy, with seeing an excerpt with evidence based on sensor data coded as 1 and seeing an excerpt without such evidence coded as 0. In the post-treatment questionnaire, we conduct a *treatment and attention check* and ask about participants' perceived *argument strength* and *content credibility*.

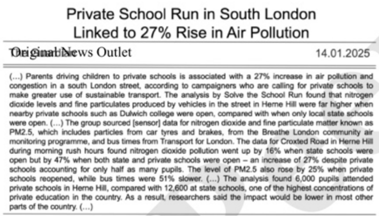
- In the treatment and attention check, we examine whether participants perceive the treatment as intended. We ask them to state which news outlet has published the presented excerpt and whether the excerpt includes evidence based on sensor data supporting the arguments in the excerpt.
- Furthermore, we measure *argument strength* on four items, according to whether participants find the presented arguments 'convincing', 'good', 'strong', and 'persuasive', each on a 5-point Likert scale (1 = 'strongly disagree' to 5 = 'strongly agree'), with high agreement indicating high strength of arguments and vice versa (adapted from Cheung et al., 2009). The argument strength scale shows sufficient internal consistency in both groups (sensor-based condition: Cronbach's $\alpha = 0.95$; non-sensor-based condition: Cronbach's $\alpha = 0.95$). Exploratory factor analysis supports a one-factor solution in each group, with strong loadings (0.89-0.93) and substantial explained variance (82-83%). These results indicate high reliability and unidimensionality across the two conditions.
- We measure *content credibility* on five items asking participants to evaluate the content according to whether they find it 'believable', 'accurate', 'biased', 'objective', and 'fair', each on a 5-point Likert scale (1 = 'strongly disagree' to 5 = 'strongly agree'), with high agreement indicating high content credibility and vice versa (adapted from Sundar, 1999). The content credibility scale shows internal consistency in both groups (sensor-based condition: Cronbach's $\alpha = 0.92$; non-sensor-based condition: Cronbach's $\alpha = 0.91$). Exploratory factor analysis supports a one-factor solution in each group, with strong loadings (0.73-0.91) and substantial explained variance (67-70%). These results indicate high reliability and unidimensionality across conditions.

4.3 Stimulus Material

In the reading task, we ask participants to read one of two approximately 200 or 240-word excerpts from an article featuring a traffic concern in London, United Kingdom. The excerpt reports on how traffic impacts air pollution during school journeys (see Figure 2). Across the two treatment groups, the publication date and the name of the news outlet remain constant. The content varies depending on whether it includes evidence on air pollution drawn from sensor data or from testimonies. In the excerpt containing evidence based on sensor data, the central claim and argument within the excerpt – that traffic causes higher pollution – are supported with data collected from sensors measuring nitrogen dioxide levels and fine particles (e.g., "nitrogen dioxide pollution went up by 16%"). In the excerpt without such evidence, the claim is supported with testimonies about stress due to congestion and figures on pupil attendance during school periods (e.g., "It feels like you can breathe again (…) there isn't the stress of noise and pollution. It's just a much calmer and more enjoyable journey to school."). Additionally, both excerpts contain a statistical figure as a form of additional, data-driven evidence well-established in journalistic reporting (e.g., "The analysis found 6,000 pupils attended private schools in Herne Hill, compared with 12,600 at state schools, one of the highest concentrations of private education in the country."). We included this element to ensure comparability, allowing us to examine whether evidence based on sensor data excerpts shows effects beyond 'conventional' data-driven evidence. Pre-tests confirm that participants can recognize sensor-based articles as such. The excerpt displays the original newspaper name, which is a well-known and, according to a ranking (YouGov, 2023), reputable newspaper in the United Kingdom.

Figure 2. Excerpts Across the Two Conditions (Sensor-Based versus Non-Sensor-Based).

Sensor-Based Condition

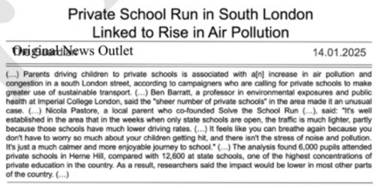


Private School Run in South London
Linked to 27% Rise in Air Pollution

Original News Outlet 14.01.2025

(…) Parents driving children to private schools is associated with a 27% increase in air pollution and congestion in a south London street, according to campaigners who are calling for private schools to make greater use of sustainable transport. The analysis by Solve the School Run found that nitrogen dioxide levels and fine particulates produced by vehicles in the street in Herne Hill were far higher when nearby private schools such as Dulwich college were open, compared with when only local state schools were open. (…) The group sourced [sensor] data for nitrogen dioxide and fine particulate matter known as PM2.5, which includes particles from car tyres and brakes, from the Breathe London community air monitoring programme, and bus times from Transport for London. The data for Croxted Road in Herne Hill during morning rush hours found nitrogen dioxide pollution went up by 16% when state schools were open but by 47% when both state and private schools were open – an increase of 27% despite private schools accounting for only half as many pupils. The level of PM2.5 also rose by 25% when private schools reopened, while bus times were 51% slower. (…) The analysis found 6,000 pupils attended private schools in Herne Hill, compared with 12,600 at state schools, one of the highest concentrations of private education in the country. As a result, researchers said the impact would be lower in most other parts of the country. (…)

Non-Sensor-Based Condition



Private School Run in South London
Linked to Rise in Air Pollution

Original News Outlet 14.01.2025

(…) Parents driving children to private schools is associated with a[n] increase in air pollution and congestion in a south London street, according to campaigners who are calling for private schools to make greater use of sustainable transport. (…) Ben Barratt, a professor in environmental exposures and public health at Imperial College London, said the "sheer number of private schools" in the area made it an unusual case. (…) Nicola Pastore, a local parent who co-founded Solve the School Run (…), said: "It's well established in the area that in the weeks when only state schools are open, the traffic is much lighter, partly because those schools have much lower driving rates. (…) It feels like you can breathe again because you don't have to worry so much about your children getting hit, and there isn't the stress of noise and pollution. It's just a much calmer and more enjoyable journey to school." (…) The analysis found 6,000 pupils attended private schools in Herne Hill, compared with 12,600 at state schools, one of the highest concentrations of private education in the country. As a result, researchers said the impact would be lower in most other parts of the country. (…)

4.4 Descriptive Statistics

We collected the data in July 2025. We recruited participants through convenience sampling on the crowdsourcing platform *Prolific*, through which we sent the experiment link to participants who voluntarily agreed to participate. Crowdsourcing platforms, such as *Prolific* or *Amazon Mechanical Turk,* are widely recognized for yielding reliable and high-quality data in behavioral research and experiments (Bhattacherjee, 2023). We targeted our sampling to adults who are fluent in English and reside in the United Kingdom.

From the initial sample of 1,041 participants, we first filter the data of 170 participants who failed the treatment and attention check, resulting in a sub-sample of 871 participants. To test whether failure of the treatment and attention check introduced systematic demographic bias, we conduct Chi-squared and Fisher's exact tests. We find a significant association between the age range and dropout status (Pearson's $\chi^2(5, N = 1{,}041) = 13.39$, $p < 0.05$), indicating a relationship between age range and dropout. However, the association with dropout and gender categories is non-significant (Fisher's exact, simulated p-value based on 2,000 replicates = 0.73) or educational level (Fisher's exact, simulated p-value based on 2,000 replicates = 0.42), suggesting that dropout due to failed treatment and attention check is random.

Additionally, we apply a median-based filtering rule to filter data from participants with implausible completion times, i.e., those who complete the task faster than one-third the median or slower than three times the median (Curran, 2016). This results in the filtering of data from 18 participants, reducing the sub-sample from 871 to 853 afterward, ensuring that only data of participants with plausibly attentive response times remain. To assess whether dropout due to filtering based on completion time introduced systematic demographic bias, we conduct Chi-squared and Fisher's exact tests. A Chi-squared test shows a non-significant association between age range and dropout (Pearson's $\chi^2(5, N = 871) = 2.35$, $p = 0.80$). A Fisher's exact test shows a non-significant association between gender categories and dropout (Fisher's exact, simulated p-value based on 2,000 replicates = 0.11). Similarly, we find a non-significant association between educational level and dropout (Fisher's exact, simulated p-value based on 2,000 replicates = 0.27). These results suggest that dropout due to filtering based on time criteria is random.

After filtering the data based on failed treatment and attention check and time criteria, the final, filtered sample [2]comprises data from a total of 853 participants assigned to two independent treatment groups: 443 participants assigned to the sensor-based condition and 410 participants assigned to the non-sensor-based condition. For covariance-based multi-group SEM with Maximum Likelihood (ML) and 18 indicators per group (four items measuring *perceived news outlet reputation*, five items measuring *media skepticism,* four items measuring *argument strength*, five items measuring *content credibility*), these per-group sizes exceed common adequacy guidelines (e.g., ≥ 200 per group; subject-to-parameter ratios ≥ 10:1) (Wolf et al., 2013). Our structural model estimates 66 parameters overall (including factor loadings, residual variances, latent variances, regression paths, and intercepts across the two groups), with N = 853, yielding a ratio of ≈ 13:1 (and >6:1 even when considered per group), which falls within recommended ranges. Power is sufficient to detect medium standardized paths (standardized regression weight $\beta \approx 0.30$) and indirect effects with bias-corrected bootstrapping. Thus, the filtered sample is well powered for the planned multi-group SEM and measurement-invariance tests.

The filtered sample consists of 53.2% female, 46.2% male, and 0.6% diverse participants. The median age range is 35 to 44 years, and the median educational level is a Bachelor's degree (see Table 1).

[2] Due to the nature of the research, supporting data is not available.

Table 1. Demographics.

Variable	*N*	%
Gender	853	100
Male	394	46.2
Female	454	53.2
Diverse	5	0.6
NA	0	0.0
Age Range	853	100
18 to 24	63	7.4
25 to 34	205	24.0
35 to 44	229	26.8
45 to 54	178	20.9
55 to 64	118	13.8
65 and older	60	7.0
Educational Level	853	100
No School Leaving Certificate	6	0.7
Secondary General School-Leaving Certificate	176	20.6
University Entrance Qualification	67	7.9
Apprenticeship	34	4.0
Bachelor's Degree	379	44.4
Master's Degree / Diploma	149	17.5
PhD	24	2.8
Other	18	2.1

We conduct Chi-squared and Fisher's exact tests to assess whether participants assigned to the sensor-based condition differ from those assigned to the non-sensor-based condition in terms of demographics (gender categories, age ranges, educational levels). We find no significant differences by gender categories (Fisher's exact, simulated p-value based on 2,000 replicates = 0.12), age range (Pearson's $\chi^2(5, N = 853) = 2.76$, $p = 0.74$), and educational level (Fisher's exact, simulated p-value based on 2,000 replicates = 0.26).

5. Results

5.1 Empirical Analysis

To test the hypothesized mediation model across two experimental conditions (sensor-based condition versus non-sensor-based condition), we perform a multi-group, covariance-based SEM because it allows for the simultaneous estimation of multiple relationships between latent and observed variables, accounts for measurement error, and enables testing whether structural paths differ across the two conditions. We conduct all analyses in *R* (Version 4.4.0) using *RStudio* (Version 2024.12.1+563). To run the SEM in *R*, we use the *lavaan* package (Version 0.6-19; Rosseel, 2012).

5.2 Measurement Model and Descriptive Statistics

As endogenous latent variables, we measure *argument strength* (Cheung et al., 2009) with four items and *content credibility* (Sundar, 1999) with five items, each rated on a 5-point Likert scale. Although such data from Likert scales are technically ordinal, simulation studies show that with five or more categories and approximately symmetric distributions, treating items as continuous yields negligible bias in parameter estimates, standard errors, and fit indices when using ML (Rhemtulla et al., 2012). Along with demographics (gender categories, age range, educational level), we measure *perceived news outlet reputation* (Kim & Dennis, 2019) and *media skepticism* (Stroembaeck et al., 2020; Tsfati, 2003) as control variables on 5-point Likert scales before treatment.

Descriptive statistics: At the construct level, means are comparable for *perceived news outlet reputation* (M = 3.33 in both conditions) and *media skepticism* (M ≈ 3.74-3.75). By contrast, participants in the sensor-based condition rate *argument strength* (M = 3.47, SD = 0.96) and *content credibility* (M = 3.32, SD = 0.86) higher than those in the non-sensor-based condition (*argument strength*: M = 2.78, SD = 1.01; *content credibility*: M = 2.82, SD = 0.83).

Reliability and convergent validity: A*rgument strength* shows in the sensor-based condition strong construct-level reliability (CR) of 0.95, and convergent validity (average variance extracted, AVE) of 0.83. These metrics are similar in the non-sensor-based condition (CR = 0.95, AVE = 0.82). *Content credibility* shows similar strong metrics (sensor-based condition: CR = 0.92, AVE = 0.70; non-sensor-based condition: CR = 0.91, AVE = 0.68). The control variables also show strong reliability and validity metrics (*perceived news outlet reputation*: CR = 0.96 (sensor-based condition), 0.95 (non-sensor-based condition); AVE = 0.85 (sensor-based condition), 0.84 (non-sensor-based condition); *media skepticism*: CR = 0.90 (sensor-based condition), 0.88 (non-sensor-based condition), AVE = 0.65 (sensor-based condition), 0.60 (non-sensor-based condition). We do not remove any measurement items during the confirmatory factor analyses (CFA), and we observe no substantial cross-loadings (> 0.30). Therefore, the hypothesized structural paths remain unchanged. All standardized factor loadings from the multi-group CFA range from 0.70 to 0.95 for both conditions. Thus, all constructs surpass the CR benchmark of 0.70 and the AVE benchmark of 0.50, indicating adequate convergent validity (Fornell & Larcker, 1981; Gefen et al., 2011). Squared multiple correlations (R^2) indicate that the latent variables account for between 48% and 91% of the variance in their respective indicators.

Appendix B displays the complete wording of all items, descriptive statistics (M, SD), standardized factor loadings, squared multiple correlations (R^2) for each indicator, and construct-level reliability (CR) and convergent validity (average variance extracted = AVE).

Discriminant validity: We further assess discriminant validity by applying the Fornell-Larcker criterion (Fornell & Larcker, 1981), in which the square root of each construct's AVE should exceed its correlations with other constructs. Tables 2a and 2b show that this criterion is met for all constructs in both the sensor-based and the non-sensor-based condition. Hence, these results show adequate discriminant validity for all latent endogenous and control variables across the two conditions.

Table 2a: Fornell-Larcker Discriminant Validity (Sensor-Based Condition).

Construct	AVE	PR	MS	AS	CC
Perceived News Outlet Reputation (PR)	0.850	0.922			
Media Skepticism (MS)	0.645	-0.600	0.803		
Argument Strength (AS)	0.828	0.422	-0.213	0.910	
Content Credibility (CC)	0.704	0.524	-0.338	0.764	0.839

Table 2b: Fornell-Larcker Discriminant Validity (Non-Sensor-Based Condition).

Construct	AVE	PR	MS	AS	CC
Perceived News Outlet Reputation (PR)	0.837	0.915			
Media Skepticism (MS)	0.602	-0.588	0.776		
Argument Strength (AS)	0.823	0.317	-0.132	0.907	
Content Credibility (CC)	0.676	0.408	-0.261	0.744	0.822

Measurement invariance: We then test configural, metric, scalar, and strict invariance across the two conditions (sensor-based vs. non-sensor-based). Establishing measurement invariance ensures that the latent constructs are conceptually and statistically comparable across different experimental conditions (Davidov et al., 2014). Results support full invariance at all levels before freeing structural paths (see Table 3), meaning that any observed differences in path coefficients can be attributed to structural rather than measurement differences. All models show adequate fit (Comparative Fit Index (CFI) $\approx$ 0.98; Root Mean Square Error of Approximation (RMSEA) $\leq$ 0.07; Standardized Root Mean Square Residual (SRMR) $\leq$ 0.03), with changes in fit indices across steps (ΔCFI $\leq$ 0.001; ΔRMSEA $\leq$ 0.004; ΔSRMR $\leq$ 0.006) within recommended thresholds (Chen, 2007). These results justify comparing latent relationships across the two conditions.

Table 3: Measurement Invariance Fit Indices.

Model	CFI	RMSEA	SRMR	ΔCFI	ΔRMSEA	ΔSRMR
Configural	0.9822	0.0727	0.0230	—	—	—
Metric	0.9821	0.0684	0.0284	0.0001	0.0042	0.0055
Scalar	0.9821	0.0646	0.0290	0.0001	0.0038	0.0005
Strict	0.9812	0.0622	0.0288	0.0010	0.0024	0.0002

ΔCFI $\leq$ 0.001 and ΔRMSEA $\leq$ 0.004 at each step indicate that invariance holds.

Robustness check: To validate these results, we conduct robustness checks by computing polychoric correlations for each of the two conditions and re-estimate the CFAs. The polychoric-based models, which are more appropriate than Pearson correlations for ordered categorical data (Holgado-Tello et al., 2010), produce nearly identical standardized loadings, factor correlations, and fit indices to the ML-based models. We retain ML with Full Information Maximum Likelihood (FIML) for the main analyses, as this approach both handles missing data and enables bootstrapping of indirect effects, which is unavailable under Weighted Least Squares Mean and Variance Adjusted (WLSMV) in *lavaan* (Rosseel, 2012). Together, these checks support the continuous treatment of our items, no evidence of multicollinearity among indicators, and the appropriateness of ML estimation in this context (see Appendix C for the polychoric correlation matrix, means, and standard deviations for all measurement items).

5.3 Structural Equation Model

Before conducting the SEM analyses, we examine the covariates for multicollinearity using variance inflation factors (VIFs) from an ordinary least squares (OLS) regression predicting the mediator variable (*argument strength*). VIF values range from 1.03 to 3.53, well below the common threshold of 10 (or the more conservative threshold of 5) (O'Brien, 2007). These results indicate no problematic multicollinearity among the predictors and no distortion of the estimated paths in the SEM due to excessive shared variance among covariates.

Because configural, metric, scalar, and strict measurement invariance all held, we can meaningfully compare latent constructs across the two conditions and conduct covariance-based multi-group SEM. We therefore estimate the structural model with all paths freely across the conditions without constraining any paths, consistent with our goal of examining potential differences in the mediation process between the two conditions.

Thus, through covariance-based multi-group SEM, we analyze whether perceptions of *argument strength* mediate the effect of seeing sensor-based articles versus non-sensor-based articles on *content credibility*, while controlling for *perceived news outlet reputation*, *media skepticism*, and demographics. We estimate model parameters with ML and use FIML for missing data. To assess indirect effects, we apply non-parametric bootstrapping with 5,000 resamples to obtain bias-corrected standard errors and 95% confidence intervals. All reported p-values reflect bootstrap-based estimates. We set the first loading of each factor to 1 to establish the metric and freely estimate residual covariances, unless cross-loadings are theoretically implausible or unsupported by modification indices. Because some educational level categories have very low frequencies (< 3% of the sample), we collapse "No school leaving certificate", "Other", and "PhD" into a single "Other" category. For dummy coding, we use "male", age range 18-24, and "Secondary general school-leaving certificate" as the reference categories.

For the key paths, we find that the *a*-path (*condition → argument strength*) is stronger in the sensor-based condition ($\Delta = 0.72$, $p < 0.05$) than in the non-sensor-based condition ($\Delta = 0.40$, $p < 0.05$) (see Table 4 and Figure 3). The *b*-path (*argument strength → content credibility*) is similar across the two conditions (sensor-based condition: $\beta = 0.57$, 95% CI [0.50, 0.65]; non-sensor-based condition: $\beta = 0.56$, 95% CI [0.49, 0.62]), indicating that stronger arguments are associated with higher perceived content credibility regardless of condition. The direct effect *c'*-path (*condition → content credibility*) is non-significant in both conditions. Indirect effects via *argument strength* are significant in both conditions (sensor-based condition: $\beta = 0.41$, $p < 0.05$; non-sensor-based condition: $\beta = 0.40$, $p < 0.05$).

The model further includes *perceived news outlet reputation*, *media skepticism*, and demographics (gender categories, age range, educational level) as controls (see Table 5a and 5b). *Perceived news outlet reputation* shows a significant positive effect on both *argument strength* (sensor-based condition: $B = 0.41$, $p < 0.001$; non-sensor-based condition: $B = 0.30$, $p < 0.001$) and *content credibility* (sensor-based condition: $B = 0.18$, $p < 0.001$; non-sensor-based condition: $B = 0.16$, $p < 0.001$). The effect of *media skepticism* on *argument strength* is non-significant in either condition. Its effect on *content credibility* is small but significant in the sensor-based condition ($B = -0.10$, $p < 0.05$), but non-significant in the non-sensor-based condition. The effects of selected demographics are also significant. Identifying as female in the non-sensor-based condition predicts higher *argument strength* ($B = 0.20$, $p < 0.05$) and lower *content credibility* ($B = 0.13$, $p < 0.05$) in the sensor-based condition. Identifying as diverse predicts lower *argument strength* ($B = -0.59$, $p < 0.01$) in the sensor-based condition; however, this result should be interpreted with caution due to the small sample size of this demographic category ($n = 5$). Respondents aged 35 years and older rated *argument strength* significantly lower in the sensor-based condition (B = -0.53 to -0.48, $p < 0.05$). In contrast, younger participants aged 25-34 in the sensor-based condition rate *content credibility* higher than older participants (B = 0.26, $p < 0.01$). Respondents aged 55-64 rated *argument strength* significantly lower in the non-sensor-based condition (B = -0.42, $p < 0.05$). Having a PhD, no school leaving certificate, and other educational levels (summarized as "other") increases *argument strength* in the sensor-based condition (B = 0.58; $p < 0.01$). In the non-sensor-based condition, having a Master's degree decreases *argument strength* (B = -0.33, $p < 0.05$).

The fully unconstrained multi-group SEM fits the data sufficiently, $\chi^2(0) = 0.000$, $p = 1.00$, CFI = 1.000, Tucker-Lewis-Index (TLI) = 1.000, RMSEA = 0.000, SRMR = 0.000. We explain these unusually high fit indices by the sufficient fit and full invariance of the measurement model, and that the SEM's measurement portion is saturated relative to the CFA, leaving minimal residual misfit for the structural paths.

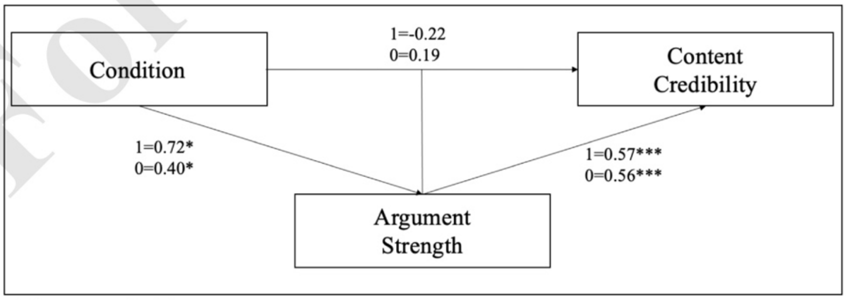
The model explains 21.3% of the variance in *argument strength* in the sensor-based condition and 15.1% in the non-sensor-based condition. For *content credibility*, the model accounts for 60.1% of the variance in the sensor-based condition and 56.7% in the non-sensor-based condition.

Table 4: Multi-Group Mediation Analysis Results, by Condition.

	Sensor-Based Condition			**Non-Sensor-Based Condition**		
Path	**$\beta(SE^{boot})$**	**z**	**p**	**$\beta(SE^{boot})$**	**z**	**p**
a: Condition → Argument Strength	0.722 (0.340)	2.12	0.034 *	0.401 (0.191)	2.10	0.036 *
b: Argument Strength → Content Credibility	0.573 (0.039)	14.69	<0.001 ***	0.556 (0.034)	16.55	<0.001 ***
c': Direct Effect (Condition → Content Credibility)	-0.216 (0.221)	-0.98	0.330	0.185 (0.304)	0.61	0.540
Indirect Effect (Condition → Argument Strength → Content Credibility)	0.413 (0.196)	2.11	0.035 *	0.401 (0.191)	2.10	0.036 *
Total Effect	0.197 (0.314)	0.63	0.530	0.185 (0.304)	0.61	0.540

*: P ≤ 0.05; **: P ≤ 0.01; ***: P ≤ 0.001.
Standardized coefficients, standard errors (SEs), z-, and p-values from bootstrapped estimates (5,000 draws).

Figure 3: Path Diagram with SEM Results.



1=Sensor-Based Article
0=Non-Sensor-Based Article
*: P ≤ 0.05; **: P ≤ 0.01; ***: P ≤ 0.001.

Table 5a: Multiple Regression on Argument Strength, by Condition.

	Sensor-Based Condition				Non-Sensor-Based Condition			
Predictor	**B (SE)**	**β**	**95% CI**	**p**	**B (SE)**	**β**	**95% CI**	**p**
Media Skepticism	0.059 (0.061)	0.050	[-0.064, 0.179]	0.332	0.040 (0.077)	0.031	[-0.113, 0.190]	0.603
Perceived News Outlet Reputation	0.408 (0.053)	0.441	[0.302, 0.508]	<0.001 ***	0.300 (0.061)	0.294	[0.177, 0.417]	<0.001 ***
Age: 25-34	-0.293 (0.154)	-0.138	[-0.588, 0.010]	0.058	0.211 (0.181)	0.092	[-0.155, 0.558]	0.243
Age: 35-44	-0.493 (0.160)	-0.234	[-0.802, -0.169]	0.002 **	-0.019 (0.184)	-0.009	[-0.380, 0.338]	0.917
Age: 45-54	-0.478 (0.155)	-0.212	[-0.785, -0.169]	0.002 **	-0.144 (0.185)	-0.060	[-0.502, 0.214]	0.436
Age: 55-64	-0.614 (0.181)	-0.234	[-0.969, -0.271]	0.001 **	-0.422 (0.210)	-0.148	[-0.828, -0.008]	0.045
Age: 65+	-0.532 (0.232)	-0.136	[-0.994, -0.076]	0.022 *	0.101 (0.217)	0.029	[-0.326, 0.524]	0.642
Gender: Diverse	-0.590 (0.197)	-0.030	[-1.016, -0.152]	0.003 **	-0.835 (0.554)	-0.085	[-1.875, 0.357]	0.132
Gender: Female	-0.092 (0.081)	-0.050	[-0.248, 0.068]	0.255	0.199 (0.093)	0.103	[0.018, 0.382]	0.031 *
Edu: Univ. Entrance Degr.	-0.002 (0.178)	-0.001	[-0.361, 0.342]	0.991	-0.011 (0.203)	-0.003	[-0.406, 0.387]	0.956
Edu: Apprenticeship	0.276 (0.250)	0.054	[-0.243, 0.741]	0.270	-0.272 (0.238)	-0.059	[-0.736, 0.204]	0.252
Edu: Bachelor's Degree	-0.030 (0.116)	-0.016	[-0.261, 0.203]	0.797	-0.091 (0.124)	-0.047	[-0.328, 0.161]	0.464
Edu: Master's Degree	-0.099 (0.140)	-0.042	[-0.382, 0.172]	0.481	-0.325 (0.152)	-9.122	[-0.627, -0.021]	0.033 *
Edu: Other	0.576 (0.193)	0.123	[0.198, 0.953]	0.003 **	-0.198 (0.199)	-0.053	[-0.581, 0.199]	0.319
R^2	0.213				0.151			

*: $P \leq 0.05$; **: $P \leq 0.01$; ***: $P \leq 0.001$.

Table 5b: Multiple Regression on Content Credibility, by Condition.

	Sensor-Based Condition				Non-Sensor-Based Condition			
Predictor	**B (SE)**	**β**	**95% CI**	**p**	**B (SE)**	**β**	**95% CI**	**p**
Argument Strength	0.573 (0.039)	0.616	[0.497, 0.649]	<0.001 ***	0.556 (0.034)	0.648	[0.488, 0.620]	<0.001 ***
Media Skepticism	-0.099 (0.041)	-0.090	[-0.181, -0.019]	0.015 *	-0.075 (0.048)	-0.068	[-0.170, 0.017]	0.118
Perceived News Outlet Reputation	0.175 (0.044)	0.204	[0.090, 0.264]	<0.001 ***	0.156 (0.036)	0.178	[0.085, 0.229]	<0.001 ***
Age: 25-34	0.264 (0.093)	0.133	[0.084, 0.443]	0.004 **	-0.071 (0.101)	-0.036	[-0.270, 0.125]	0.483
Age: 35-44	0.084 (0.100)	0.043	[-0.112, 0.278]	0.396	-0.176 (0.097)	-0.095	[-0.368, 0.017]	0.069
Age: 45-54	0.123 (0.096)	0.059	[-0.065, 0.311]	0.200	-0.300 (0.109)	-0.146	[-0.515, -0.086]	0.006 **
Age: 55-64	-0.033 (0.101)	-0.013	[-0.229, 0.162]	0.747	-0.237 (0.112)	-0.097	[-0.460, -0.013]	0.035 *
Age: 65+	-0.244 (0.150)	-0.067	[-0.535, 0.064]	0.104	-0.416 (0.148)	-0.139	[-0.710, -0.137]	0.005 **
Gender: Diverse	-0.046 (0.147)	-0.003	[-0.373, 0.282]	0.752	-0.079 (0.336)	-0.009	[-0.914, 0.514]	0.813
Gender: Female	-0.113 (0.054)	-0.065	[-0.220, -0.005]	0.038 *	-0.015 (0.059)	-0.009	[-0.128, 0.104]	0.794
Edu: Univ. Entrance Degree	-0.066 (0.140)	-0.020	[-0.346, 0.214]	0.637	-0.205 (0.116)	-0.070	[-0.425, 0.027]	0.077
Edu: Apprenticeship	-0.192 (0.159)	-0.040	[-0.518, 0.111]	0.228	0.213 (0.150)	0.054	[-0.069, 0.516]	0.155
Edu: Bachelor's Degree	-0.048 (0.073)	-0.028	[-0.189, 0.093]	0.510	-0.108 (0.078)	-0.065	[-0.254, 0.050]	0.167
Edu: Master's Degree	-0.011 (0.086)	-0.005	[-0.185, 0.152]	0.899	-0.107 (0.098)	-0.047	[-0.293, 0.087]	0.273
Edu: Other	0.019 (0.121)	0.004	[-0.217, 0.266]	0.877	-0.099 (0.136)	-0.031	[-0.360, 0.173]	0.468
R^2	0.601				0.567			

*: $P \leq 0.05$; **: $P \leq 0.01$; ***: $P \leq 0.001$.

To ensure the robustness of the main findings, we replicate the analysis with the initial sample before filtering the data (N = 1,041). The *b*-path (*argument-strength → content credibility*) remains large and significant in both conditions (sensor-based condition: $\beta = 0.64$; non-sensor-based condition: $\beta = 0.68$; both $p < 0.001$), and the direct effect *c*'-path (*condition → content credibility*) remains non-significant. The *a*-path (*condition → argument strength*) is positive but attenuated and non-significant ($\beta = 0.49$). Consequently, indirect effects are smaller and imprecisely estimated. These results indicate that our main conclusions are robust in direction and that filtering data from participants based on failed treatment and attention check and time criteria primarily affects the size and precision of the *a*-path (and hence the indirect effect). The attenuation of the *a*-path in the initial sample is expected, as participants who failed the treatment and attention check or showed implausible completion times likely did not process the treatment as intended. Thus, filtering increases measurement validity by ensuring that the analysis reflects participants who engaged with the treatment, while the overall pattern of mediation (a strong *b*-path, and a non-significant *c*'-path) remains consistent.

Summarizing, we confirm our three hypotheses, namely that the effect of seeing a sensor-based article on argument strength and subsequently content credibility is significantly higher compared to seeing non-sensor-based articles. The enhanced relationship between seeing a sensor-based article (in comparison to a non-sensor-based article) and content credibility is primarily mediated by argument strength, but not directly. See Table 6 for a summary of the hypothesis testing results.

Table 6. Results of Hypothesis Testing.

No.	Hypothesis	Supported / Not Supported
1	Sensor-based articles increase argument strength more than non-sensor-based articles.	✓
2	The positive effect of argument strength on content credibility is stronger when seeing sensor-based articles in comparison to when seeing non-sensor-based articles.	✓
3	Sensor-based articles increase content credibility through stronger arguments more than non-sensor-based articles.	✓

6. Discussion

In this study, we examined whether sensor-based articles increase argument strength and, subsequently, content credibility more than non-sensor-based articles. By applying multi-group covariance-based SEM, we find that comparisons between the two experimental groups (sensor-based condition versus non-sensor-based condition) reflect structural differences, showing greater effects when seeing sensor-based articles compared to when seeing non-sensor-based articles.

Our results suggest four issues for discussion.

Technology-enabled origin of evidence as a differentiating factor in shaping content credibility: Beyond the hypothesis testing using multi-group covariance-based SEM, initial analyses indicate that the two groups differ substantially in their mean levels of argument strength and content credibility, with higher values observed in the sensor-based condition than in the non-sensor-based condition. The moderation analysis further supports these findings, showing that the effect on argument strength is significantly stronger in the sensor-based condition. This result suggests that evidence based on sensor data with its technology-enabled origin plays a differentiating role in the persuasion process, consistent with prior IS and organizational research (Kitchin, 2014; Newell & Marabelli, 2015; O'Leary, 2013; Shim et al., 2020). Our results further show that argument strength increases content credibility slightly more in the sensor-based condition than in the non-sensor-based condition. This finding reinforces the notion that argument strength is a key predictor of content credibility. However, since the difference between the two conditions is marginal, the technology-enabled origin of evidence appears to be rather a differentiator in shaping perceptions of argument strength, but less so in shaping content credibility.

Positive effect of perceived news outlet reputation. Perceived news outlet reputation emerges as a robust positive predictor of both argument strength and content credibility in both conditions, consistent with prior work highlighting the positive effect of a reputable news outlet on content credibility (anonymized for review). This finding points to the central role of news outlet reputation as a source-related factor offering mental shortcuts that shape persuasion.

Inconsistent effects of media skepticism. Media skepticism shows no effect on argument strength and only a small negative effect on content credibility in the sensor-based condition. This suggests that perceptions of argument strength in this context are relatively robust to skeptical readers. Such robustness aligns with prior research indicating that data-driven evidence conveys factuality and precision, thereby enhancing persuasiveness (Koetsenruijter, 2011; Porter, 1995; Van Dijk, 1988). The non-significant effect on argument strength may be attributed to the inclusion of traditional data-driven evidence in both conditions, which likely contributed to sufficient robustness against media skepticism. Consequently, additional evidence derived from a technology-enabled origin may not have been necessary to further buffer against skeptical perceptions. Further possible explanations relate to the rigorous nature of the topic presented in the excerpts or the reputation of the well-known news outlet displayed in the excerpts, both of which may have mitigated the effect of media skepticism. Nevertheless, the small negative association between media skepticism and content credibility in the sensor-based condition remains unexplained and is therefore open to further investigation.

Lower perceived argument strength of sensor-based articles among older readers: Among the various marginal effects of demographic factors, our results indicate that the age range is a significant factor in shaping *argument strength* and *content credibility*, with older participants rating *argument strength* lower in the sensor-based condition. While younger participants relate to higher ratings of *content credibility* in the sensor-based condition, older participants relate to lower *content credibility* ratings in the non-sensor-based condition. One possible explanation is that the design or presentation of evidence based on sensor data in quantified form may reduce understandability for older audiences. As sensor-based articles often present information in numerical values, they can make it harder for readers, especially those used to consuming testimonial-based journalistic content, to interpret and positively evaluate the argument strength and content credibility (Liao & Fu, 2014; Thaesler-Kordonouri et al., 2024). For older audiences, the unfamiliarity of this data-driven reporting style and the lack of established skills for interpreting such data may lead to increased doubt. In contrast, younger readers appear to prefer such data-driven reporting. These findings highlight the importance of considering demographic factors such as age, skills, or other individual differences when investigating or publishing sensor-based articles in an inclusive manner (Faik et al., 2024; Liao & Fu, 2014; Trauth, 2017).

7. Limitations and Suggestions for Future Research

We acknowledge that our study has several limitations, each of which leads to a suggestion for future research.

Unobserved content-related factors: Although we observe significant differences in content credibility ratings through mediating relationships with argument strength based on the evidence type, the direct effect of exposure to either sensor-based or non-sensor-based articles on content credibility is non-significant. Hence, our results suggest that argument strength predicts content credibility, both when seeing sensor-based articles and when seeing non-sensor-based articles. Therefore, we acknowledge the limited generalizability, as beyond testing the mediating role of argument strength, we did not examine additional content-related factors (Metzger et al., 2003) that may shape content credibility and the extent to which the technology-enabled origin of evidence acts as a differentiator. For example, the topic displayed in the excerpt may play a role. While we randomized the treatment group assignment to strengthen causal inference, we exposed participants in both conditions to an excerpt on the same topic on air pollution. For example, Woelker and Powell (2021) find that different topics act as moderators, shaping the effect of various factors on credibility ratings. Hence, future studies could present participants multiple articles covering different topics to minimize topic-specific effects. In the context of sensor-based journalism, evidence based on sensor data may be 'advantageous' for certain topics, such as environmental issues, but less advantageous, or even inapplicable, for others, such as politics. Besides the topic, the tone may also play a role.

Because the excerpts did not vary in tone, future research may want to investigate how emotional versus neutral presentations shape the effect of different evidence types on content credibility (Thaesler-Kordonouri et al., 2024). This could help determine whether evidence based on sensor data can counterbalance the polarising effects of emotionally framed reporting.

Unobserved individual factors beyond demographics. While age emerged as a significant factor predicting argument strength in the context of sensor-based journalism, other individual-level factors may also play a crucial role. For instance, the effects of cognitive and affective mechanisms, such as novelty effects, comprehensibility, cognitive load, issue involvement, or expertise, remain unclear (Thaesler-Kordonouri et al., 2024). Future research could therefore integrate process-tracing methods (e.g., eye-tracking, think-aloud protocols, or physiological measures) to identify which cognitive factors further drive content credibility. In addition, applying cognitive analysis frameworks, such as the Elaboration Likelihood Model (Petty & Cacioppo, 1986), could help explain how readers process multiple content-related and source-related factors simultaneously, depending on their issue involvement and expertise, and how this interplay ultimately shapes the content credibility of sensor-based articles compared to non-sensor-based articles.

Effect of reputable news outlets: Showing the participants an article presented by a reputable news outlet may have overemphasized the effect of news outlet reputation in our analysis, thereby limiting the generalizability of our results. Future research may want to extend the experimental design by adding articles presented by less reputable news outlets to compare the strength of the effect of different news outlets when evaluating the content credibility of sensor-based articles in comparison to non-sensor-based articles.

Country- and context-dependency of media skepticism: While the effect of media skepticism appears small and inconsistent in our findings, we acknowledge that the construct itself may vary considerably across countries and contexts (Stroembaeck et al., 2020). As trust in institutions varies across cultural contexts (Davidov et al., 2014), the effect of media skepticism may likewise differ depending on cultural setting. Future research could examine the role of media skepticism on argument strength and content credibility in the context of sensor-based journalism across different countries. Such an approach would help clarify whether media skepticism functions as a more salient factor in specific cultural environments and how it interacts with content credibility perceptions in the context of sensor-based journalism compared to other types of journalism.

8. Conclusion

In this study, we find that sensor-based articles enhance argument strength and, in turn, content credibility more strongly than non-sensor-based articles. We demonstrate that the technology-enabled origin of evidence acts as a differentiator in credibility formation in the journalism context. With these findings, we extend journalism and communication research on argument strength as a content-related factor shaping content credibility and contribute to the emerging literature on sensor-based journalism. For media organizations, we highlight sensor-based data collection as a strategic lever to strengthen arguments and content credibility, while pointing to that news outlet reputation, media skepticism, and demographic differences may also play a role.

Theoretical implications: First, our findings contribute to prior literature on the role of argument strength in shaping perceptions and particular content credibility (Beisecker et al., 2024; Boller et al., 1990; Cheung et al., 2009; Nicolaou & McKnight, 2006; Sussman & Siegal, 2003; Wathen & Burkell, 2002; Yi et al., 2013). Furthermore, our findings parallel the superiority of evidence based on technology-enabled data collection techniques for decision making, as indicated in prior IS and organizational research (Loebbecke & Picot, 2015; McAfee & Brynjolfsson, 2012; Newell & Marabelli, 2015; O'Leary, 2013; Shim et al., 2020). Further, we extend journalism and communication research, which remains inconclusive on the persuasive effects of data-driven evidence, by suggesting that the technology-enabled origin of evidence may serve as a key differentiating factor (Chinn & Weeks, 2020; Godler et al., 2020; Henke et al., 2019; Kazmierczak et al., 2025; Thaesler-Kordonouri et al., 2024). Moreover, our findings also extend research on content credibility formation in journalism contexts by contextualizing sensor-based journalism as a still underexplored journalistic practice (anonymized for review). Furthermore, the direct, positive effect of perceived news outlet reputation on content credibility in both conditions suggests that, regardless of the evidence type, pre-existing perceptions about the reputation of a news outlet continue to shape content credibility (Kim & Dennis, 2019; Metzger et al., 2010; anonymized for review). The comparatively weaker role of media skepticism indicates that it may operate more selectively, potentially exerting stronger effects when readers see sensor-based articles (Stroembaeck et al., 2020; Tsfati, 2003; anonymized for review).

Practical implications: For media organizations, these results suggest that investing in sensor-based data collection may strengthen arguments, which in turn may enhance content credibility and ultimately increase sales (Zhang et al., 2014). Especially in times of content abundance (Diakopoulos, 2019; Shirky, 2008), collecting and leveraging sensor data for reporting may help establish strong, convincing, and verifiable argumentation. However, the consistent, yet limited, effect of news outlet reputation shows that using evidence based on sensor data alone does not replace the importance of maintaining a strong media brand (Kim & Dennis, 2019). Furthermore, media organizations should account for perceptual differences across different demographic segments when creating and publishing sensor-based articles, with particular focus on age, as evaluations of argument strength and content credibility vary substantially across different age groups (Liao & Fu, 2014).

Acknowledgements

The authors report there are no competing interests to declare.

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Appendices

Appendix A: Measurement Items

Part 1. Pre-Treatment Questionnaire:

1. Demographics:
   - 1.1 Gender: female, male, diverse, prefer not to disclose
   - 1.2 Age range: 18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, 65 or older
   - 1.3 Education: What is your highest level of education completed? No school leaving certificate; Secondary general school-leaving certificate; University entrance qualification; Apprenticeship; Bachelor's Degree; Master's Degree / Diploma; PhD; Other.
2. Perceived news outlet reputation (Kim & Dennis, 2019): State your agreement on the following statements related to the newspaper (1 = 'strongly disagree' to 5 = 'strongly agree'; 5-point Likert scale):
   - 2.1 Do you know the newspaper [newspaper name displayed in the excerpt for the reading task]? (Yes / No)
   - 2.2 I find the newspaper [newspaper name displayed in the excerpt for the reading task] reliable.
   - 2.3 I find that the newspaper [newspaper name displayed in the excerpt for the reading task] is trustworthy.
   - 2.4 I find the newspaper [newspaper name displayed in the excerpt for the reading task] has the necessary expertise to do its job.
   - 2.5 I find the newspaper [newspaper name displayed in the excerpt for the reading task] credible.
3. Media skepticism (Stroembaeck et al., 2020; Tsfati, 2003): State your agreement on statements about the media in your country, that is, newspapers, magazines, television, and radio (Reversed) (1 = 'strongly disagree' to 5 = 'strongly agree'; 5-point Likert scale):
   - 3.1 The media are fair.
   - 3.2 The media are unbiased.
   - 3.3 The media tell the whole story.
   - 3.4 The media are accurate.
   - 3.5 The media separate facts from opinions.

Part 2. Post-Treatment Questionnaire:

1. Treatment and Attention Check:
   - 1.1 Which of the following news outlets published the excerpt you just read? ([newspaper name displayed in the excerpt for the reading task], Other)
   - 1.2 Does the excerpt say that information based on sensor data supports the claim? (Yes / No)
2. Argument Strength (Cheung et al., 2009): State your agreement on the statements related to the content of the excerpt (1 = 'strongly disagree' to 5 = 'strongly agree'; 5-point Likert scale):
   - 2.1 The arguments provided in the article are convincing
   - 2.2 The arguments provided in the article are strong.
   - 2.3 The arguments provided in the article are good.
   - 2.4 The arguments provided in the article are persuasive.

1. Content Credibility (Sundar, 1999): State your agreement on adjectives related to the content of the excerpt (1 = 'strongly disagree' to 5 = 'strongly agree'; 5-point Likert scale):
   - 1.1 Believable
   - 1.2 Accurate
   - 1.3 Unbiased
   - 1.4 Objective
   - 1.5 Fair

Appendix B: Measurement Items, Descriptive Statistics, Standardized Loadings, Squared Multiple Correlations (R^2), Construct Reliability (CR), and Average Variance Extracted (AVE) by Group.

		Sensor-Based Condition					Non-Sensor-Based Condition				
Construct / Item	**Item Wording**	**M (SD)**	**Load-ing**	**R²**	**CR**	**AVE**	**M (SD)**	**Load -ing**	**R²**	**CR**	**AVE**
Perceived News Outlet Reputation	I find the newspaper ….	3.33 (1.00)			0.958	0.850	3.33 (0.94)			0.953	0.837
Reliable (NR1)	… reliable.	3.34 (1.01)	0.946	0.896			3.32 (0.97)	0.934	0.872		
Trustworthy (NR2)	…trustworthy.	3.32 (1.00)	0.940	0.882			3.31 (0.95)	0.953	0.909		
Expertise (NR3)	… has the necessary expertise to do the job.	3.35 (0.97)	0.860	0.740			3.37 (0.92)	0.835	0.696		
Credible (NR4)	… credible.	3.32 (1.00)	0.940	0.883			3.33 (0.94)	0.933	0.871		
Media Skepticism (reverse-cc)	The media …	3.75 (0.78)			0.900	0.645	3.74 (0.75)			0.883	0.602
Fair (MS1)	… are fair.	3.75 (0.79)	0.869	0.755			3.72 (0.74)	0.811	0.656		
Unbiased (MS2)	… are unbiased.	3.74 (0.78)	0.696	0.484			3.73 (0.77)	0.702	0.492		
Whole Story (MS3)	… tell the whole story.	3.76 (0.77)	0.777	0.605			3.75 (0.75)	0.804	0.647		
Accurate (MS4)	… are accurate.	3.77 (0.78)	0.861	0.742			3.76 (0.74)	0.812	0.659		
Separation Facts from Opinions (MS5)	… separate facts from opinions.	3.74 (0.78)	0.799	0.639			3.73 (0.76)	0.744	0.554		
Argument Strength	The arguments provided in the excerpt are…	3.47 (0.96)			0.951	0.828	2.78 (1.01)			0.949	0.823
Convincing (AS1)	…convincing.	3.46 (0.95)	0.916	0.839			2.77 (1.00)	0.898	0.806		
Good (AS2)	… strong.	3.47 (0.96)	0.913	0.834			2.79 (1.02)	0.914	0.835		
Strong (AS3)	… good.	3.47 (0.96)	0.927	0.859			2.78 (1.01)	0.925	0.855		
Persuasive (AS4)	… persuasive.	3.47 (0.96)	0.884	0.781			2.77 (1.00)	0.892	0.796		
Content Credibility	The content of the excerpt is …	3.32 (0.86)			0.922	0.704	2.82 (0.83)			0.912	0.676
Believable (CC1)	… believable.	3.31 (0.86)	0.752	0.565			2.81 (0.84)	0.729	0.531		
Accurate (CC2)	… accurate.	3.32 (0.85)	0.810	0.656			2.82 (0.83)	0.786	0.618		
Unbiased (CC3)	… unbiased.	3.33 (0.85)	0.833	0.695			2.82 (0.83)	0.829	0.687		
Objective (CC4)	… objective.	3.32 (0.86)	0.872	0.760			2.82 (0.83)	0.845	0.714		
Fair (CC5)	… fair.	3.33 (0.86)	0.919	0.845			2.81 (0.83)	0.912	0.832		

Items rated on 1-5-point Likert scales (1 = strongly disagree, 5 = strongly agree). Loadings are standardized (std.all); SMC = squared multiple correlation (R^2); CR = composite reliability; AVE = average variance extracted.

Appendix C: Polychoric Correlation Matrix, Means, and Standard Deviations for All Measurement Items.

Table C.I: Polychoric Correlation Matrix, Means, and Standard Deviations for All Measurement Items (Sensor-Based Condition)

Item	*M*	*SD*	NR1	NR2	NR3	NR4	MS1	MS2	MS3	MS4	MS5	AS1	AS2	AS3	AS4	CC1	CC2	CC3	CC4	CC5
NR1	3.25	1.01	1.000	0.896	0.784	0.877	-0.477	-0.391	-0.461	-0.488	-0.424	0.377	0.367	0.383	0.376	0.332	0.429	0.444	0.430	0.467
NR2	3.19	1.05	0.896	1.000	0.794	0.881	-0.473	-0.396	-0.456	-0.475	-0.414	0.336	0.348	0.359	0.324	0.323	0.423	0.452	0.389	0.460
NR3	3.51	1.02	0.784	0.794	1.000	0.818	-0.444	-0.330	-0.400	-0.484	-0.431	0.313	0.341	0.344	0.324	0.333	0.393	0.359	0.361	0.394
NR4	3.36	1.06	0.877	0.881	0.818	1.000	-0.455	-0.362	-0.410	-0.485	-0.397	0.357	0.360	0.373	0.371	0.341	0.428	0.425	0.394	0.456
MS1	3.61	0.91	-0.477	-0.473	-0.444	-0.455	1.000	0.627	0.661	0.688	0.656	-0.171	-0.184	-0.168	-0.169	-0.176	-0.236	-0.271	-0.249	-0.261
MS2	4.05	0.89	-0.391	-0.396	-0.330	-0.362	0.627	1.000	0.587	0.534	0.518	-0.128	-0.144	-0.111	-0.139	-0.148	-0.196	-0.263	-0.252	-0.242
MS3	3.97	0.88	-0.461	-0.456	-0.400	-0.410	0.661	0.587	1.000	0.676	0.572	-0.160	-0.173	-0.189	-0.195	-0.195	-0.235	-0.221	-0.242	-0.248
MS4	3.51	0.93	-0.488	-0.475	-0.484	-0.485	0.688	0.534	0.676	1.000	0.688	-0.163	-0.171	-0.181	-0.160	-0.232	-0.232	-0.238	-0.249	-0.270
MS5	3.58	0.96	-0.424	-0.414	-0.431	-0.397	0.656	0.518	0.572	0.688	1.000	-0.138	-0.130	-0.122	-0.990	-0.161	-0.217	-0.236	-0.214	-0.221
AS1	3.52	1.01	0.377	0.336	0.313	0.357	-0.171	-0.128	-0.160	-0.163	-0.138	1.000	0.823	0.852	0.812	0.637	0.607	0.593	0.608	0.655
AS2	3.46	1.01	0.367	0.348	0.341	0.360	-0.184	-0.144	-0.173	-0.171	-0.130	0.823	1.000	0.852	0.819	0.581	0.597	0.555	0.589	0.632
AS3	3.49	1.03	0.383	0.359	0.344	0.373	-0.168	-0.111	-0.189	-0.181	-0.122	0.852	0.852	1.000	0.811	0.577	0.603	0.53	0.613	0.632
AS4	3.43	1.07	0.376	0.324	0.324	0.371	-0.169	-0.139	-0.195	-0.160	-0.990	0.812	0.819	0.811	1.000	0.538	0.554	0.515	0.571	0.592
CC1	3.54	0.96	0.332	0.323	0.333	0.341	-0.176	-0.148	-0.195	-0.232	-0.161	0.637	0.581	0.577	0.538	1.000	0.776	0.569	0.613	0.663
CC2	3.35	0.93	0.429	0.423	0.393	0.428	-0.236	-0.196	-0.235	-0.232	-0.217	0.607	0.597	0.603	0.554	0.776	1.000	0.646	0.657	0.727
CC3	3.04	1.04	0.444	0.452	0.359	0.425	-0.271	-0.263	-0.221	-0.238	-0.236	0.593	0.555	0.530	0.515	0.569	0.646	1.000	0.764	0.778
CC4	3.31	0.99	0.430	0.389	0.361	0.394	-0.249	-0.252	-0.242	-0.249	-0.214	0.608	0.589	0.613	0.571	0.613	0.657	0.764	1.000	0.821
CC5	3.34	1.00	0.467	0.460	0.394	0.456	-0.261	-0.242	-0.248	-0.270	-0.221	0.655	0.632	0.632	0.592	0.663	0.727	0.778	0.821	1.000

Table C.II: Polychoric Correlation Matrix, Means, and Standard Deviations for All Measurement Items (Non-Sensor-Based Condition)

Item	*M*	*SD*	NR1	NR2	NR3	NR4	MS1	MS12	MS3	MS4	MS5	AS1	AS2	AS3	AS4	CC1	CC2	CC3	CC4	CC5
NR1	3.25	1.01	1.000	0.896	0.784	0.877	-0.477	-0.391	-0.461	-0.488	-0.424	0.243	0.278	0.252	0.264	0.266	0.296	0.308	0.304	0.342
NR2	3.19	1.05	0.896	1.000	0.794	0.881	-0.473	-0.396	-0.456	-0.475	-0.414	0.287	0.294	0.284	0.295	0.264	0.325	0.326	0.316	0.357
NR3	3.51	1.02	0.784	0.794	1.000	0.818	-0.444	-0.330	-0.400	-0.484	-0.431	0.181	0.185	0.181	0.207	0.270	0.266	0.291	0.287	0.317
NR4	3.36	1.06	0.877	0.881	0.818	1.000	-0.455	-0.362	-0.410	-0.485	-0.397	0.260	0.293	0.260	0.302	0.300	0.319	0.321	0.308	0.359
MS1	3.61	0.91	-0.477	-0.473	-0.444	-0.455	1.000	0.627	0.661	0.688	0.656	-0.109	-0.870	-0.940	-0.116	-0.134	-0.207	-0.181	-0.136	-0.147
MS2	4.05	0.89	-0.391	-0.396	-0.330	-0.362	0.627	1.000	0.587	0.534	0.518	-0.620	-0.610	-0.070	-0.850	-0.123	-0.166	-0.155	-0.82	-0.154
MS3	3.97	0.88	-0.461	-0.456	-0.400	-0.410	0.661	0.587	1.000	0.676	0.572	-0.870	-0.830	-0.830	-0.134	-0.146	-0.201	-0.185	-0.163	-0.195
MS4	3.51	0.93	-0.488	-0.475	-0.484	-0.485	0.688	0.534	0.676	1.000	0.688	-0.128	-0.104	-0.114	-0.144	-0.234	-0.235	-0.200	-0.164	-0.241
MS5	3.58	0.96	-0.424	-0.414	-0.431	-0.397	0.656	0.518	0.572	0.688	1.000	-0.690	-0.540	-0.060	-0.104	-0.122	-0.151	-0.136	-0.121	-0.176
AS1	2.90	1.10	0.243	0.287	0.181	0.260	-0.109	-0.620	-0.870	-0.128	-0.690	1.000	0.798	0.850	0.795	0.584	0.561	0.548	0.558	0.615
AS2	2.78	1.05	0.278	0.294	0.185	0.293	-0.870	-0.610	-0.830	-0.104	-0.540	0.798	1.000	0.844	0.834	0.582	0.601	0.549	0.581	0.616
AS3	2.70	1.05	0.252	0.284	0.181	0.260	-0.940	-0.070	-0.830	-0.114	-0.060	0.850	0.844	1.000	0.814	0.572	0.544	0.541	0.558	0.570
AS4	2.73	1.12	0.264	0.295	0.207	0.302	-0.116	-0.850	-0.134	-0.144	-0.104	0.795	0.834	0.814	1.000	0.568	0.580	0.503	0.527	0.591
CC1	3.17	1.00	0.266	0.264	0.270	0.300	-0.134	-0.123	-0.146	-0.234	-0.122	0.584	0.582	0.572	0.568	1.000	0.731	0.529	0.549	0.652
CC2	2.82	0.89	0.296	0.325	0.266	0.319	-0.207	-0.166	-0.201	-0.235	-0.151	0.561	0.601	0.544	0.580	0.731	1.000	0.594	0.633	0.702
CC3	2.51	1.01	0.308	0.326	0.291	0.321	-0.181	-0.155	-0.185	-0.200	-0.136	0.548	0.549	0.541	0.503	0.529	0.594	1.000	0.757	0.776
CC4	2.74	0.97	0.304	0.316	0.287	0.308	-0.136	-0.820	-0.163	-0.164	-0.121	0.558	0.581	0.558	0.527	0.549	0.633	0.757	1.000	0.780
CC5	2.83	0.95	0.342	0.357	0.317	0.359	-0.147	-0.154	-0.195	-0.241	-0.176	0.615	0.616	0.570	0.591	0.652	0.702	0.776	0.780	1.000

2.6 Deploying online experiments to investigate content credibility in sensor-based journalism (Extended Abstract)

Reproduction from:

Boboschko, I., & Loebbecke, C. (2026). Deploying online experiments to investigate content credibility in sensor-based journalism (Extended Abstract), German Society for Online Research Conference (GOR), Cologne, Germany.

My contributions to this paper include the co-development of the research idea, literature review, experiment design, data collection, data analysis, manuscript draft, and revision based on the comments from the co-author.

Deploying online experiments to investigate content credibility in sensor-based journalism (Extended Abstract)

Relevance & Research Question:

The emerging field of sensor-based journalism relies on data beyond human reach collected by sensors (Diakopoulos, 2019; Loebbecke & Boboschko, 2020). Earlier works on sensor-based journalism study the impact of identity cues and outlet reputation on content credibility (Sundar, 1999). Communication and media studies investigate testimonial-based argument strength as driver of content credibility (Boller et al., 1990; Wathen & Burkell, 2002). To fill the gap, we ask how argument strength influences content credibility in the context of sensor-based journalism.

Methods & Data

This study deploys a between-subjects online experiment (N= 853) followed by multi-group covariance-based structural equation modeling. Two treatment groups read an article on traffic affecting air pollution in London, one drawing evidence from sensor data, the other from testimonials. As endogenous latent variables, we measure argument strength with four items and content credibility with five items. Measurement items, wording of all items, descriptive statistics, standardized factor loadings, squared multiple correlations for each indicator, construct-level reliability, and convergent validity are available upon request.

Results

Sensor-based journalism fosters argument strength and credibility formation; statistical details and interpretations are available upon request. Controlled online experiments (McCroskey, 1969) allow for realistically simulating (journalistic) media consumption.

Added Value

Promoting research in sensor-based journalism – in times of AI-based hallucinations, increasingly relevant phenomena in today's democracies.

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3. Technology-Enabled Offerings Enhancements, Platform Use, and Divestments

3.1 Mass media deploying digital personalization: an empirical investigation

Loebbecke, C., Oberschulte, F., & Boboschko, I. (2021). Mass media deploying digital personalization: an empirical investigation, International Journal on Media Management, 23(3-4), 176-203 [VHB: C], doi.org/10.1080/14241277.2022.2038605.

My contribution to this paper includes the revision based on the comments from the co-authors and reviewers.

3.2 Towards AI-based thumbnail design for fostering consumption on digital media platforms

Loebbecke, C. Obeng-Antwi, A., Boboschko, I., & Cremer, S. (2024). Towards AI-based thumbnail design for fostering consumption on digital media platforms, International Journal of Information Management, 78, 1-12 [VHB: B], doi.org/10.1016/j.ijinfomgt.2024.102801.

My contribution to this paper includes the revision based on the comments from the co-authors and reviewers.

3.3 The double-edged sword: empowerment and risks of platform-based work for women

Hoedl, T., & Bobsochko, I. (2025). Empowerment and risks of platform-based work for women, International Conference 'Wirtschaftsinformatik', Muenster, Germany [VHB: B], https://ais-insights.ai/pdf/Contribution_115_final_a.pdf.

My contribution to this paper includes the co-development of the research idea, literature review, and revision based on the comments from the co-author and reviewers.

3.4 IT-driven divestments: towards theoretical multiplicity through a configurational approach

Boboschko, I. (2022). IT-driven divestments: towards theoretical multiplicity through a configurational lens, European Conference on Information Systems (ECIS), Timisoara, Romania [VHB: A], aisel.aisnet.org/ecis2022_rp/154.

My contributions to this paper include the development of the research idea, literature review, manuscript draft, and revision based on the comments from the reviewers.

4. Conclusion

4.1 Summary

Considering sensor-based journalism with regard to its potential, its impact on decision making, and associated ethical concerns, the dissertation finds that sensor-based journalism enables evidence-based insights into previously inaccessible phenomena and supports decision making under uncertainty. It further shows that sensor-based journalism introduces ethical concerns related to privacy, accountability, and surveillance. The findings extend across individual, organizational, and societal levels [Paper #1].

Regarding the credibility formation in sensor-based journalism, the dissertation finds that contributor names do not impact credibility, while individual factors, such as issue involvement and expertise, and source-related factors, such as contributor jobs and news outlet reputation, slightly enhance it [Papers #2 – #5]. Compared to source-related and individual factors, argument strength as a content-related factor is the primary credibility driver in sensor-based journalism [Papers #4 – #5]. In this context, argument strength and, hence, credibility are perceived as higher in journalistic articles containing evidence based on sensor data compared to articles without such evidence [Paper #5]. Furthermore, the dissertation indicates that online experiments are well-suited for investigating credibility formation in the context of sensor-based journalism. Thereby, it particularly highlights the value of experiments for studying emerging, technology-enabled phenomena for which real-world data are not yet available [Paper #6].

Referring to technology-enabled enhancements of media offerings, the dissertation identifies little use of personalization among German legacy newspapers that go online [Paper #7]. Moreover, it finds that an AI-based imagery analysis enables automated classification of visual cues and customized thumbnail design for fostering consumption of hedonic media goods on video and e-commerce platforms [Paper #8]. Based on data from an AI-based imagery analysis, thumbnails containing faces with negative emotions and less text are associated with increased consumption of hedonic media goods on video and e-commerce platforms.

Concerning platform use, the dissertation derives four propositions conceptualizing how women with caregiving responsibilities use platforms for work processes. It shows that such platform use can empower women by fostering occupational flexibility and financial independence, while simultaneously disempowering and exposing them to financial, employment, mental health, and privacy risks that may reinforce patriarchal power structures [Paper #9].

Considering divestment strategies, the dissertation suggests two causal configurations that theoretically ground strategic divestments in response to digitization and technological advancements for enhancing organizational and innovation performance. These causal configurations propose that divestment reconfigurability alone (1) or together with a high level of organizational separation via divestments (2) leads to higher organizational and innovation performance [Paper #10].

4.2 Discussion

The findings offer several issues for discussion.

- Sensor-based journalism as a socio-technical phenomenon

  The findings regarding the potential and impact of sensor-based journalism on decision making confirm earlier work highlighting efficiency gains from data-driven practices for managerial decision making (Loebbecke & Picot, 2015; McAfee & Brynjolfsson, 2012; Miles et al., 2018; O'Leary, 2013). At the same time, ethical concerns related to privacy, accountability, and surveillance at individual, organizational, and societal levels underline the socio-technical nature of sensor-based journalism through the interdependence of technologies, organizations, and social systems (Loebbecke & Picot, 2015; Mumford, 2006). By shaping decision making beyond organizational contexts, sensor-based journalism operates within the broader institutional role of journalism as a fourth pillar of democratic societies. It links technologies, organizations, and social systems and enables public deliberation for a vital and inclusive pluralistic democracy (Diakopoulos, 2019; Loebbecke et al., 2025).

- Sensor-based journalism as a differentiator in credibility formation and persuasion

  The finding that argument strength is the primary driver of credibility in sensor-based journalism extends earlier persuasion research (Hoeken & Hustinx, 2009; Sussman & Siegal, 2003; Yalch & Elmore-Yalch, 1984). While prior studies indicate that data-driven evidence increases cognitive load and diminishes the influence of content-related factors while increasing the impact of peripheral, source-related factors (Thaesler-Kordonouri et al., 2024; Yalch & Elmore-Yalch, 1984), sensor-based journalism acts as a differentiating context. When evaluating the credibility of content based on evidence drawn from sensor data, individuals scrutinize arguments thoroughly rather than relying on peripheral, source-related factors.

- Mismatch between the potential of deploying technology to enhance offerings and actual deployment

  Building on prior work on the potential of deploying technologies to enhance media offerings (Diakopoulos, 2019), the dissertation finds that this potential is not fully realized in practice. Although technological capabilities to customize and enhance media offerings, such as through algorithm-based personalization and AI-based imagery analysis, are increasing, legacy newspapers in Germany use only limited personalization. While these insights are based on one journalistic genre and a single geographical context, the observed mismatch points to underlying organizational, strategic, legal, and societal barriers. For example, the findings indicate that legacy newspapers are aware of the need to weigh potential gains in engagement or sales against the risks of reduced content diversity, increased costs, and heightened data protection and privacy concerns. These trade-offs tend to result in a conservative approach to personalization. Furthermore, overly intensive personalization may be perceived as intrusive by users (Sutanto et al., 2014) or erode brand equity (Keller, 2013). Moreover, in a context of declining credibility in news media (Newman et al., 2019), even the perception of small manipulation can undermine journalistic credibility (Carroll, 2020). These barriers highlight the need to contextualize investigations of technology-enabled offerings enhancements within their specific organizational, regulatory, and societal settings.

- Persuasion patterns in utilitarian versus hedonic media contexts

  The dissertation shows that persuasion patterns in sensor-based journalism differ from those observed on video and e-commerce platforms. Identity cues play only a limited role in credibility formation in sensor-based journalism, whereas faces and emotional expressions drive consumption of hedonic media goods on video and e-commerce platforms. Additionally, quantitative evidence based on sensor data enhances argument strength and credibility in sensor-based journalism, whereas more text decreases consumption of hedonic media goods on video and e-commerce platforms. A likely explanation for these persuasion divergences lies in the nature of the contexts investigated (Deng & Poole, 2010; Jones et al., 2004; Li et al., 2022; Thaesler-Kordonouri et al., 2024). The dissertation examines persuasion patterns in sensor-based journalism from a utilitarian media perspective (e.g., traffic-related news). In contrast, it studies persuasion patterns on video and e-commerce platforms from a hedonic media perspective (e.g., videos, books, music, movies, and games).

Consequently, this dissertation adds to prior research that emphasizes the context-dependence of persuasion processes (Pornpitakpan, 2004).

- Temporal dynamics of studying technology deployment in the media

  Investigations of technology deployment in the media should be interpreted and built upon through a time-sensitive lens, given the rapid evolution of both technologies and regulatory frameworks. The deployment of algorithm- and AI-based systems is increasingly shaped by legal constraints associated with data protection, transparency, and accountability – particularly in efforts to safeguard democracy-relevant journalism (Diakopoulos, 2016; Zanker et al., 2019). In addition, media organizations' growing restrictions on access to content for AI-based systems further complicate the scalability of automated media analysis, and hence AI-driven product enhancements (Fletcher, 2024). Consequently, research on technology deployment in the media requires ongoing contextualization, and future replications should account for shifting technological, regulatory, and institutional conditions when building on prior findings.

- Terminological and conceptual inconsistency in credibility research

  By examining the concept of credibility, the dissertation addresses a terminological and conceptual inconsistency in research (Appelman & Sundar, 2015). With regard to the terminology, the distinction between 'credibility' and 'trust' remains inconclusive. Some scholars use the terms interchangeably (Self, 1996), while others distinguish between them (Tseng & Fogg, 1999). Further disagreement exists regarding their causal ordering, with credibility conceptualized as an antecedent of trust (Pavlou, 2002) or, conversely, trust viewed as an antecedent of credibility (Hovland & Weiss, 1951). The dissertation adapts the terminology from Hovland and Weiss (1951) and focuses on the term 'credibility' determined by trust. Similarly, prior research is also inconclusive about the measurement of credibility as different measurement constructs exist for different types of media and outlets, additionally distinguished through both online and offline contexts (Appelman & Sundar, 2015). Hence, the diversity of definitions and measurement constructs limits cross-study comparisons. Accordingly, the comparability of the dissertation's findings is bounded by the specific conceptual framing and measurement constructs employed. This constraint underscores the conceptual plurality and context dependency in credibility research (Appelman & Sundar, 2015; Henrich et al., 2010).

- Multiperspectivity of technology-enabled phenomena in the media and beyond

  The dissertation draws on critical perspectives, such as women's empowerment (Kabeer, 1999), and approaches emphasizing theoretical multiplicity, such as the configurational approach (Meyer et al., 1993). Thereby, it highlights the potential of applying underutilized research perspectives when studying technology-enabled phenomena in the media context and beyond. It extends dominant IS research perspectives, which have long overlooked dynamics related to interdisciplinary, critical, and diversity-aware perspectives (Henrich et al., 2010; Trauth, 2017).

- Methodological pluralism for studying technology deployment in the media

  In the context of a fast-evolving media environment, the dissertation underlines how methodological pluralism facilitates the investigation of complex and context-dependent dynamics of technology deployment. Further, it allows for capturing a diverse empirical view of the phenomenon of technology deployment in the media (Agerfalk, 2013). Combining qualitative and quantitative approaches enables both exploratory insights and systematic testing, thereby opening new, complementary research opportunities for scholars in IS research and beyond.

4.3 Contribution

Contribution to Theory

The dissertation contributes to behavioral economics research, particularly prospect theory (Kahneman & Tversky, 1979). While prior IS research has primarily examined how technology deployment supports individual and organizational decision making under uncertainty (Loebbecke & Picot, 2015; McAfee & Brynjolfsson, 2012; Miles et al., 2018; O'Leary, 2013), the dissertation extends these insights to decision making processes beyond the individual or organizational scope, namely to journalistic and societal contexts. It extends the applicability of prospect theory to the context of sensor-based journalism. It highlights that sensor-based journalism enables evidence-based insights into previously inaccessible real-world phenomena, thereby supporting decision making under uncertainty.

Furthermore, the dissertation contributes to dual-process theories and especially the concepts of heuristic-based information processing and the Elaboration Likelihood Model (Chaiken, 1980; Evans, 2008; Gigerenzer et al., 1999; Petty & Cacioppo, 1986; Sundar, 2008). It challenges established assumptions about how social presence, reputation, and recognition heuristics impact persuasion and credibility (Gigerenzer et al., 1999; Erickson & Kellogg, 2000). Whereas earlier studies grounded in heuristic-based information processing suggest that source-related factors increase credibility (Chaiken & Maheswaran, 1994; Gigerenzer et al., 1999; Kim & Dennis, 2019), the dissertation shows that such factors often have a limited impact in sensor-based journalism. This research challenges core assumptions of the Elaboration Likelihood Model (Petty & Cacioppo, 1986) and argumentation-based persuasion literature (Hoeken & Hustinx, 2009). Despite the higher cognitive demands associated with quantitative content based on data-driven evidence (Thaesler-Kordonouri et al., 2024; Yalch & Elmore-Yalch, 1984), individuals do not shift toward the peripheral route of information processing in sensor-based journalism. Instead of relying on news outlet reputation, argument strength remains the primary credibility driver in sensor-based journalism. Additionally, the dissertation confirms prior research on context-dependence in persuasion processes (Pornpitakpan, 2004) by highlighting that content containing numerical, data-driven insights persuades individuals in utilitarian media contexts, while more text does not in hedonic media contexts (Deng & Poole, 2010; Jones et al., 2004; Li et al., 2022; Thaesler-Kordonouri et al., 2024).

The dissertation extends experimental design research (McCroskey, 1969) by demonstrating the applicability of experimental methods to study credibility formation in the emerging context of sensor-based journalism. It also corroborates prior IS studies on experimental design research (Maruping et al., 2025; Schwenk, 1982). It shows that experiments represent a suitable methodological approach for studying underexplored, technology-enabled phenomena in the media context whose insights may serve as a foundational step for future research.

The dissertation contributes to research on personalization in online contexts (Tam & Ho, 2006) as it provides contextual insights and boundaries for applying personalization in the mass media. It adds to prior work on mass media and news personalization across devices and journalistic genres (Chung et al., 2016; Gershon, 2017; Jesse & Jannach, 2021; Thorson & Wells, 2016).

Moreover, the dissertation contributes to theories of visual information processing and framing in the context of hedonic media consumption (Tversky & Kahneman, 1981). It confirms prior research on how insights from AI-based imagery analysis may enhance consumption on digital media platforms (Li et al., 2022). It extends literature on AI-based design (Gregor & Hevner, 2013; Yoon & Kim, 2019) by pointing to the potential of AI-based support to reconceptualize thumbnails as persuasive, customized, decomposable micro-level recommendation entities.

The dissertation advances prior IS research on the platform use for work processes (Deng & Galliers, 2024) as it integrates gendered perspectives in the media context and beyond. It extends the concept of women's empowerment (Kabeer, 1999) to IS research. Thereby, it shows that platform use for work processes, such as social media blogging, can simultaneously empower and disempower women with caregiving responsibilities and, hence, reinforce gendered power relations.

Finally, the dissertation contributes to IS research by applying the resource-based view (Penrose, 1995; Wernerfelt, 1984; Wade & Hulland, 2004) and the concept of organizational ambidexterity (Montealegre et al., 2019; Zhang et al., 2018) to theoretically ground the underexplored phenomenon of strategic divestments in response to digitization and technological advancements. It demonstrates how the deployment of emerging technologies in the media and beyond necessitates not only resource accumulation, as a dominant research stream in IS (Hess et al., 2016), but also strategic withdrawal and reconfiguration. Thereby, it provides a perspective of theoretical multiplicity underlying the phenomenon of how media organizations may respond to emerging technologies.

Recommendations for Practice

In light of the findings on the potential of sensor-based journalism, its impact on decision making, and the associated ethical concerns, media organizations should consider deploying sensors to support journalistic reporting. Besides providing insights into phenomena that are difficult to observe by humans, evidence based on sensor data can strengthen arguments and increase credibility. However, media organizations should pursue strategies that balance the potential of deploying sensors with their accompanying risks. When deploying sensors, ethical data practices remain essential to sustain readership and economic viability (Loebbecke & Picot, 2015; Zuboff, 2015).

Given the distinct persuasion patterns observed across various technology-enabled contexts in the dissertation, media organizations should adapt context-dependent content strategies (Diakopoulos, 2019). For utilitarian media goods, such as news, they should deploy sensors to strengthen arguments and, hence, credibility. For hedonic media goods, they may consider an AI-based customized thumbnail design to align visual cues with individuals' preferences and, for instance, avoid excessive use of text or include faces with strong emotions. However, media organizations should balance economic incentives for deploying sensors, algorithm-based personalization, or AI-based imagery analysis with the risks of reduced content diversity, increased costs, and heightened data protection and privacy concerns. This balance is critical in utilitarian media contexts, such as news, where content diversity carries greater societal relevance in safeguarding democracy-relevant journalism than in hedonic media contexts.

Furthermore, platform-based media organizations should offer more inclusive work arrangements. They should account for power distributions and adopt practices that mitigate financial, employment, privacy, and mental health risks for women with caregiving responsibilities.

Finally, media organizations should remain flexible and adaptive and view technology-driven divestments as a strategic lever to actively rebalance resources when responding to emerging technology developments and market shifts.

4.4 Limitations and Suggestions for Future Research

The dissertation has limitations that open multiple paths for future research.

- Selected settings

  The selected settings for investigating technology deployment in the media are illustrative. The exemplary cases of sensor-based journalism [Paper #1] do not capture the heterogeneity of deploying sensors in the media. They do not consider technologies such as drones, satellite imagery, or blockchain-based sensing infrastructures, which may entail distinct implications for journalistic practices, regulatory frameworks, and societal outcomes (Kazmierczak et al., 2025). Likewise, restricting the analyses to a small set of empirical settings, such as personalization practices among five German legacy newspapers or platform use in one setting, may constrain the generalizability of the findings. Future research may therefore study a broader range of technology deployments. Moreover, future research may assess whether and how the findings from the selected settings may translate to other media-related contexts.

- Theoretical groundings

  The dissertation may overlook additional theoretical perspectives that may further explain technology deployment in the media and its role in safeguarding an inclusive, democracy-relevant journalism. The configurational approach is inherently limited in capturing the full range of relevant attributes and theoretical interdependencies (Fink, 2010; Meyer et al., 1993). Hence, future research may broaden the theoretical scope by drawing on both well-established and underutilized IS perspectives. Future research could incorporate insights from the Technology Acceptance Model (Davis, 1989) or the concept of socio-technical systems (Mumford, 2006). Critical or inclusion-oriented perspectives may also enrich analyses of technology deployment in media contexts (Faik et al., 2024; Oreglia & Srinivasan, 2016; Zuboff, 2019).

- Online experiments

  The online experiments [Papers #2 – #6] are subject to limitations in generalizability for several reasons:

  1) Sampling and temporal scope: The experimental studies applied convenience sampling to collect the data. Although convenience sampling is common in behavioral research, it limits the generalizability of the findings. Moreover, the one-shot design captures perceptions at a single point in time, which limits conclusions about longer-term effects. Future research should consider random sampling and longitudinal or repeated-measures designs to assess longer-term effects and increase external validity.
  2) Unobserved factors: The limited explanatory power of some models suggests that individuals' perceptions may depend on additional unobserved factors beyond those explicitly varied and observed. Such unobserved factors may include content features, such as topic, tone, or contextual framing. Woelker and Powell (2021) find that, particularly in sports articles, identity cues decreased credibility. In this regard, the impact of the evidence drawn from sensor data on credibility could vary in different topical contexts, such as environmental reporting versus political journalism. Future research could extend the experimental models by explicitly controlling for additional content-related factors that may shape individuals' perceptions. Varying emotional versus neutral framing could clarify whether evidence drawn from sensor data can counterbalance the polarizing effects of emotionally framed reporting (Thaesler-Kordonouri et al., 2024). Accounting for gender or racial bias related to the identity cues may yield additional insights. Furthermore, applying within-subjects designs with multiple stimuli across diverse topics and tones would help control for topic- and tone-specific effects. In addition, future research may want to combine multiple stimuli within the same condition to test their interaction effects on individuals' perceptions.
  3) Simplified operationalizations: The operationalizations of source- and content-related factors examined in the dissertation are simplified representations used for the experimental treatments. News outlet reputation, as a key source-related factor, was varied by assigning participants to an article from either a reputable and well-known or a less reputable and unknown news outlet, according to a ranking (YouGov, 2023). Even though the categorization of the news outlet reputation was verified in pre-treatment checks, source-related factors in the real world extend beyond binary news outlet reputation categories (reputable versus less reputable). Similarly, the variation of the two evidence types (evidence based on sensor data and evidence that is not based on

sensor data) may not fully reflect the diverse ways in which sensor-based journalism can be implemented in journalistic practice. Hence, the operationalizations reflect rather superficial and prototypical features of source- and content-related factors. Future research could apply more variations. Operationalizations of source-related factors may involve additional dimensions, such as partisan leanings of news outlets. Operationalizations of content-related factors may extend to mixed formats of evidence based on sensor data (numerical values versus visualizations). Future research may implement more realistic treatments, which could provide richer insights into how individuals perceive and evaluate journalistic content related to sensor-based journalism. In this context, future research may also consider utilizing alternative operationalizations for measuring the inconsistent construct of credibility.

4) Artificiality of experimental settings: The experiments were conducted in a controlled but simplified and artificial environment, whereby the participants were exposed to journalistic content in a forced and decontextualized manner. Such artificial experimental media consumption settings differ from natural consumption of journalistic content, characterized by content abundance and selective exposure. Thus, it remains unclear to what extent increased credibility perceptions translate into actual consumption behavior or economic outcomes. Also, the journalism industry has historically depended on readers' credibility perceptions (Appelman & Sundar, 2015). In today's media markets, increasingly relying on indirect revenue models and shifting consumption patterns, it is more difficult to derive actionable implications from insights into credibility perceptions for financial outcomes. Future research could therefore apply more naturalistic experimental designs, such as field experiments or observational studies, to better capture real-world media consumption and strengthen external validity.
5) Unobserved individual factors beyond demographics*:* While individual factors, such as issue involvement, expertise, and age, emerged as significant factors impacting credibility perceptions in sensor-based journalism, other unobserved individual-level factors may also play a role. The effects of cognitive and affective mechanisms, such as novelty effects, comprehensibility, or cognitive load, remain unobserved (Thaesler-Kordonouri et al., 2024). Besides extending questionnaires to these factors, future research could integrate process-tracing methods (e.g., eye-tracking, think-aloud protocols, or physiological measures) to identify which additional individual factors drive credibility perceptions in sensor-based journalism.

6) Filtering criteria: Before analyzing the experimental data, a notable proportion of participants' data was filtered according to failed treatment and attention checks and time criteria. Although robustness checks indicate that results remain substantively unchanged when including the data of filtered participants, filtering the data may still introduce selection biases. In some models, younger participants were more likely to fail the treatment and attention checks. Future research could explore whether the treatment design needs adjustment in terms of clarity or whether certain participant groups require additional assistance.
7) Interpretation challenges of experimental findings: In the dissertation, multiple findings in the experimental studies diverge from prior research, such as the limited influence of news outlet reputation or identity cues. While this is not a limitation per se, experimental research appears to serve here primarily as an entry point for future research rather than offering an exhaustive explanation of the phenomena. Given the complexity of emerging technology-enabled phenomena, future research may benefit from complementary qualitative approaches. Interviews or ethnographic research could deepen the understanding of the underlying processes through which individuals perceive and evaluate content related to sensor-based journalism.

- Observational data

The insights based on observational data [Papers #7 – #8] are subject to limitations in measurement depth and external validity, which also affect their generalizability.

1) The observational data from the web-based simulation of newspaper consumption on legacy newspaper websites is limited to desktop usage only, constraining insights into mobile and cross-device personalization. Short data collection periods and dynamic website content positioning limit conclusions about personalization deployment and its evolution over time. Future research could apply longitudinal and large-scale designs, longer exposure periods, and mobile and cross-device usage contexts to enhance generalizability.
2) The observational data from the AI-based imagery analysis, performed through third-party software, may be affected by classification errors. Furthermore, the focus on only focal thumbnails may overlook the influence of adjacent visual cues. Future research could validate automated classifications through human coding or alternative imagery analysis models and examine the effects of visual cues within full visual environments.

- Geographical and cultural contexts

  The findings from all thirteen papers are dependent on geographical and cultural contexts, thereby limiting their generalizability to those particular contexts. Investigating credibility relies on perceptual credibility judgments, which are socially learned and sensitive to cultural norms, prior experience, and situational context (Henrich et al., 2010). Hence, perceptual measures based on convenience samples face limitations with regard to external validity and generalizability. Polarized media systems, societies with low institutional trust, or contexts where technology-enabled attributes are perceived differently may act as additional confounders (Davidov et al., 2014). Also, technology deployment or platform use may differ across countries or geographical regions as they may depend on different legal constraints, subsidiaries, or innovation mentalities. Therefore, future research may consider conducting more cross-cultural comparisons of technology deployment in the media (Davidov et al., 2014).

- Economic effects

  While the AI-based imagery analysis captures actual consumption effects, the remaining studies do not provide direct insights into the financial outcomes of technology deployment in the media. Future research could explicitly examine the economic implications associated with such deployments. In addition, analyzing regulatory, institutional, and societal constraints or competitive dynamics may help explain why certain technologies are adopted or resisted in practice.

4.5 Outlook

The dissertation investigates technology deployment in the media as an underexplored phenomenon in IS research. It focuses on sensor-based journalism, including its potential, its impact on decision making, the associated ethical concerns, and credibility formation. In addition, it studies the broader deployment of emerging technologies in the media, such as algorithm-based personalization, AI-based imagery analysis for enhancing offerings, platform use, and divestment strategies in response to digitization and technological advancements. It concludes with multiple paths for complementary research endeavors to refine the present insights.

Beyond these paths and especially in the context of a fast-evolving media environment, future IS research may broaden the research scope when studying technology deployment in the media. It may want to explore the deployment of other emerging technologies, such as extended reality, generative AI, or blockchain technology across additional media genres. Furthermore, it may also deepen the understanding of changing media consumption patterns, including convergence dynamics across devices. In rapidly shifting geopolitical and regulatory contexts, media, technologies, organizations, society, and politics are increasingly intertwined, calling for future IS research to situate technology deployment in the media within broader socio-technical structures.

Overall, the dissertation underpins the growing need for continued investigations into the deployment of emerging technologies in the media to safeguard healthy, democracy-relevant journalism and a resilient media industry in increasingly challenging times (Loebbecke et al., 2025).

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