OPEN ACCESS

Saudi Journal of Economics and Finance
Abbreviated Key Title: Saudi J Econ Fin
ISSN 2523-9414 (Print) | ISSN 2523-6563 (Online)
Scholars Middle East Publishers, Dubai, United Arab Emirates
Journal homepage: http://saudijournals.com

Review Article

The Impact of Generative AI on Content Marketing

Olawale C. Olawore[1]*, Kazeem O. Oyerinde[2], Taiwo R. Aiki[3], Oluwatobi J. Banjo[4], Beverly B. Tambari[5], Victor O. Okoh[6], Festus I. Ojedokun[7], Tunde O. Olafimihan[8], Funmilayo C. Olawore[9], Jonathan E. Kozah[10]

[1]University of People, Pasadena, California, United States of America
[2]Euroacademy, Tallinn, Estonia
[3]University of Derby, Derby, United Kingdom
[4]Estonia Entrepreneurship University of Applied Sciences, Tallinn, Estonia
[5]Tallinn University, Tallinn, Estonia
[6]Estonia Entrepreneurship University of Applied Sciences, Tallinn, Estonia
[7]Bowling Green State University, Ohio, United States
[8]Tansia University, Anamra State, Nigeria
[9]America University for Humanities, Tbilisi, Georgia
[10]New Vision University, Tbilisi, Georgia

DOI: https://doi.org/10.36348/sjef.2025.v09i04.006 | **Received:** 05.03.2025 | **Accepted:** 11.04.2025 | **Published:** 15.04.2025

***Corresponding author:** Olawale C. Olawore
University of People, Pasadena, California, United States of America

Abstract

Generative AI is changing content marketing since it makes it cheaper and faster to produce large volumes of content. This change, however, also comes with strategic threats, including the interchangeability of content and the increasingly skeptical audience. This article discusses the impact of generative AI on the marketing cycle and how much productivity can be increased in comparison to the threat of sameness of creativity. We suggest that the competitive advantage lies not in its volume, but in what can be difficult to automate: a unique brand voice and an inimitable insight that can never be duplicated by your competitors. An actual running model is suggested that will explain when automation is valuable and when human judgment is critical. We also outline a governance structure that controls the credibility and trust-related risks. Lastly, falsifiable hypotheses are provided to demonstrate how audience trust and performance can be preserved and the productivity benefits of AI-enabled systems.

Keywords: Generative AI, content marketing, co-creation of human and AI, brand authenticity, AI disclosure, consumer trust, synthetic media, creative strategy, marketing governance, persuasion knowledge model.

INTRODUCTION

The Illusion of Transparency: How AI Disclosure Dilutes Persuasion by Activating Synthetic Persuasion Knowledge.

Transparency is considered a marketing virtue. Nevertheless, as generative AI becomes available to the general content creation process, there exist regulations and ethical considerations that either encourage or require AI disclosure (FTC, 2023). Although it is believed that speaking frankly about using AI can decrease dishonesty and establish trust, our study indicates a more complex scenario: informing people that AI was used may actually make them less convinced since it causes a certain perception of content produced by machines.

The Persuasion Knowledge Model (PKM) explains the process of consumer awareness of the means of persuasion and modulation of their reactions when they imagine that a marketer is trying to persuade them. PKM was made in a world where persuasion was performed by human beings. Some consumers perceive AI as lacking human intention, emotional sincerity, or concern because AI is the content creator and another agent of persuasion (Longoni & Cian, 2022). Disclosure, therefore, does not merely indicate honesty, and it may lead to beliefs that AI is an unbiased agent. This changes the focus of the message, that is, the artificial source of it, to negative evaluations of the brand in terms of its genuine intentions, hard work, and expenditure. This perspective is backed by studies that show that people are more likely to evaluate AI-generated material with a machine heuristic, i.e., they use other assessment criteria than the ones they use during human-written messages (Kramer & Schawel, 2024).

We extend the Principle of Knowledge Management (PKM) to algorithmic persuasion and offer a mechanism to mitigate the negative effects of disclosure. When informed that something has been produced using AI, people will read it differently; they are more likely to think that less effort, less care, or a personal purpose has been used to produce it, and this can alter the level of credibility or earnestness of the message. It is also all about what the content is attempting to accomplish: emotional, relationship-building messages will suffer the greatest blow, whereas simpler, practical information may be impacted significantly less- or not at all. This conclusion is in line with the growing body of research regarding the liability of artificiality in situations where communion and warmth are important (Luo *et al.,* 2024).

We conduct two pre-registered experiments. Study 1 substantiates the disclosure penalty and proves that the perceived human intentionality mediates the effect. Study 2 explores moderation by content type, and the penalty is extreme in the case of emotional brand stories and insignificant in the case of informational product descriptions. Such results indicate that an ethical practice that is much publicized may work against one, given certain circumstances, and that a more subtle approach to the responsible use of AI in marketing is needed. Brands might have to clarify not only what AI is being applied but also that AI-assisted content includes human involvement, management, and judgment that might require a shift to so-called meaningful transparency (Cheng & Fleischmann, 2024).

2. Theoretical Bases: The Persuasion Knowledge Model in an Age of Algorithms.

Generative AI breaks the tradition that persuasion is always human-to-human. With the creation of content by algorithms, it is time to reconsider fundamental theories, one of them being the Persuasion Knowledge Model (PKM). PKM assumes that consumers get trained to detect persuasion strategies and apply these techniques to protect themselves. But PKM is based on the assumption that the persuader is human. When an AI system constructs the message, it turns into another agent, which many perceive as lacking a true purpose, emotion, or genuine interest (Castelo, Bos, & Lehmann, 2019). This knowledge gap in PKM creates the synthetic persuasion knowledge, which is a unique kind of expectation and suspicion that appears when individuals interpret a message as machine-generated.

2.1. Generalizing Persuasion Knowledge to Algorithms.

It can be seen that the studies of algorithmic aversion indicate that people are more likely to discount or distrust the output of a machine, especially when the subjective judgment or complexity of emotions is involved (Longoni, Bonezzi, & Morewedge, 2019). This raises questions about the veracity of the information. It also is connected with perceiving minds: the people attribute less consciousness, intention, and lived experience to algorithms as compared to humans (Gray, Gray, & Wegner, 2007). It (Longoni & Cian, 2022). Using this frame, consumers can determine the quality of the content, as well as the authenticity of it. They do not believe an algorithm will generate the human engagement that brands strive to hint at (Moulard, Raggio, & Folse, 2021).

2.2. The Mediatory Personality of the Human Will.

An object or message is perceived differently when it appears to be the product of human intention. Viewers conclude that there is human attention, work, and a need for connection when they perceive the material as produced by an individual. These inferred characteristics of credibility and authenticity are vital persuasive indicators (Moulard *et al.,* 2021). We propose that the process is attributional but not informational: the exposure to AI decreases persuasive effects mostly by decreasing perceived human intentionality. This decrease in perceived intention connects the awareness of AI authorship (and the use of knowledge about artificial persuasion) to more negative feelings about the brand.

2.3. Boundary Condition Content Type.

The impact of the AI authorship will not be homogenous. The extent to which it is important is dependent on the purpose of the content. Based on the functional matching hypothesis in persuasion (DeBono &Harnish, 1988), we will predict that the penalty will be most powerful when human connection. Vulnerable social postings or emotional brand storytelling are based on sincerity and experience; in that regard, a machine-based origin may seem out of place and take away the authenticity (Kim & Duhachek, 2020). In comparison, informational content, such as technical specifications, data overviews, explanations of procedures, etc., is rated with respect to accuracy, usefulness, and clarity. In such environments, an algorithmic source can be less credible and even more perceived to be objective or accurate (Castelo *et al.,* 2019). Content type is, therefore, a major moderator that defines situations when disclosure is harmful, beneficial, or completely ineffective. This framework, along with PKM, mind perception theory, and functional matching, it is most likely to happen. The following section converts these concepts into formal suppositions.

3. Hypotheses: Persuasion Knowledge Model of AI Disclosure.

It is based on the theoretical background of artificial intelligence disclosure activating knowledge of synthetic persuasion, a unique type of persuasion knowledge that is activated by algorithmic agents, that we create a specific model with clear, falsifiable assumptions. The mediating mechanism of perceived human intentionality and the moderating role of content type are the focus of this model.

H1. (The Disclosure Penalty): Disclosure of AI participation in the development of marketing content will result in (a) less positive brand attitudes and (b) reduced brand trust than content that is not disclosed or content that is disclosed as written by humans.

H2. (The Mediating Mechanism: Human Intentionality): The bad effect of AI disclosure on brand attitudes and trust (H1) will be mediated in a serial manner by (i) the activation of synthetic persuasion knowledge and (ii) lessening perceptions of human intentionality behind the material.

H3. (The Moderating Role of Content Type): Content type will moderate the negative effect of AI disclosure (H1). This effect will be much more pronounced on content that is emotionally and narratively oriented, i.e., content in which the human intent is the center of value, than on content that is information- and utility-oriented, i.e., content where accuracy and efficiency are the guiding principles. In the case of informational content, the disclosure penalty is likely to be watered down or even absent.

H4. (The Moderated-Mediation Effect): The suggested serial mediation by synthetic persuasion knowledge and human intentionality (H2) will be much stronger with emotional content as compared to informational content.

4. Managerial Implications and a Governance Framework of AI-Enabled Content Marketing.

Generative AI is not a sustainable source of benefit because it enables teams to generate more content. The true benefit lies in the fact that the AI is integrated into the marketing operating model in such a way that it allows accelerating the pace without affecting authenticity, accountability, or brand uniqueness (Grewal *et al.,* 2024;

Huang & Rust, 2021). This, in practice, involves the direction toward directed co-creation and not uninhibited automation.

4.1. GenAI is a planned promotional capability.

GenAI has the potential to expand the scope of ideas that a team could investigate, yet it must still be compatible with the marketing cycle and undergo human guidance, particularly when relational judgment and ethical judgment are factors to consider (Huang and Rust, 2021; Grewal *et al.,* 2024). When used appropriately, it can accelerate the process of experimentation and trial. Nevertheless, the workflow must be constructed in such a way that humans are not relieved of meaning, truthfulness, and the cues that a brand makes regarding who it is.

4.2. Develop a Human-in-the-Loop Creative Operating Model.

The most effective ones are achieved in situations where AI is utilized within the context of well-defined collaboration patterns: powerful briefs, prompting, and rigorous revision procedures (Luan *et al.,* 2025). An actual pipeline would look like the following: a strategy brief that is composed by a human, generation by AI, selection and molding by humans, validation by human analysis in addition to programs, and a learning process that improves the next cycle. This is not to make AI write, but it is instead an argument to create an AI-accelerated system that has human judgment protecting differentiation and trust.

4.3. Manage to secure achievement, not as a boss.

In some situations, AI-generated content can decrease authenticity and trust (Kirk & Givi, 2025; Schilke & Reimann, 2025). Therefore, governance should support performance instead of acting as a bureaucracy. A content-marketing governance system must be accountable and trace prompts, versions, and edits; have extensive quality controls; and have fact-checking, bias-testing, and risk assessment. Well-defined, realistic guardrails ought to assist in maintaining the brand voice. Concisely, governance develops trust infrastructure.

4.4. Implement an Evidence-Based Disclosure Strategy.

Trust is not necessarily built through disclosure. In other instances, it may reduce ad attitudes, credibility, and trust (Wortel *et al.,* 2024; Bui, 2025; Schilke & Reimann, 2025). The level of risk of the content and audience expectations should be equal to the disclosure policy. One of these is to disclose high-stakes or regulated claims; low-stakes utility content may not be disclosed; openness is a sentiment-based story tool to take into account. The point is that these decisions should be tried, but always consider whether more transparency is better.

4.5. Determine the Quality of Involvement, not the Quantity.

Do not trade reach for credibility? Transform the performance of shifts in the raw outputs to the quality and trust indicators. Quality of engagement, which is measured in the form of saves, time on content, and trust proxies, is measured in the form of complaints, credibility surveys, conversion quality, error rates, and learning speed (Luan *et al.,* 2025). Strive to gain credibility through less effort and less content.

5. An AI-Augmented Content Marketing Research Agenda.

Generative AI is transforming content marketing into more of a system-oriented action. There is rapid practice adoption and lagging research. To get beyond speculation, to move past speculation, we introduce a research agenda of the underlying conflicting forces that are still proving manifest in practice: efficiency vs. authenticity and automation vs. trust.

5.1. The Persuasion-Volume Trade-off.

The question of whether algorithms' efficiency increases or ultimately deceives persuasion is one of the biggest, and the current frameworks focus on the pace, customization, and refinement of AI and caution that repetitive content can be replaced (Huang & Rust, 2021; Grewal *et al.,* 2024). It should be tested in the research that there is an optimal range of AI-generated variation, beyond which an increasing output would become less useful as the audience becomes weary of the same message. Change over time: when so much content begins to look and sound the same, is the brand less differentiated? We will extend the capability models by connecting production patterns to consumer psychology.

5.2. The Strategic Disclosure Dilemma.

It is proven that there is a transparency paradox, as revealing AI participation corresponds to ethical conduct and reduces trust and aggravates reviews (Schilke & Reimann, 2025; Bui, 2025). Researchers need to transform this paradox into practical advice. Studies are required to identify disclosure forms that will reduce the negative reactions, the reactions that depend on the type of content, and whether the channel context or culture can alter the findings. In the absence of this, the brands have a morally significant but psychologically doubtful policy choice.

5.3. Creating Authenticity in Fake Media.

The reason why consumers are not fond of AI-written content is that it is less authentic (Kirk & Givi, 2025). This is similar to the results of algorithmic distrust in subjective domains (Longoni & Cian, 2022). What are the design indicators that trigger the revision of the human agency perceptions in AI-generated work? What is it precisely that makes people respond badly when they consider that something has been written by AI? Is it perceived less effort, or issues with manipulation, or the sense that a machine has violated category rules? The causes imply different solutions; hence, it is important to isolate them.

5.4. Creator-Appeal Congruence

There is evidence that persuasion is determined by the level of compatibility between the message appeal and the perceived creator (Chen *et al.,* 2024). According to the functional matching hypothesis, source characteristics are most relevant when they may be adapted to the message goal (DeBono & Harnish, 1988). There must be an overall theory of creator-appeal congruence in the field. A study will create a guide that shows different types of creators (human, AI, or a mix), how they attract attention, and how well they persuade people in different areas, and it will try to find out if following set rules for appeals is better than making gut decisions in actual marketing teams.

5.5. Developing Co-Creation Capabilities.

It is not AI tools that will bring long-term benefit but rather the habits teams will form to effectively implement those (Luan *et al.,* 2025). This changes the emphasis on adoption to capability building, which corresponds to the technology integration constructs in general (Huang & Rust, 2021). Nevertheless, it is not clear what the micro-foundations of such capabilities are. The studies should find out which team behaviors are regularly linked to unique, original results when using AI help and how these teams' progress from trying things out in the beginning to developing more advanced and repeatable co-creation methods over time.

5.6. Performance-Aligned Governance

The only way that AI governance can be effective in marketing is to ensure that it is implemented as a performance guard rather than compliance overhead. This implies the conversion of high-level principles of ethics into marketing controls, which is also emphasized in the research on AI ethics (Mitchell *et al.,* 2019) and in marketing strategy (Grewal *et al.,* 2024). Studies need to experiment on the configurations of governance that offer optimal risk mitigation and creative speed and come up with valid metrics of creative integrity (e.g., voice consistency, cultural resonance) in addition to conventional performance KPI. This balances the aspirations of ethics and business.

5.7. Reducing the Effect of Algorithm Aversion in Creative Situations.

Algorithms are particularly prone to aversion to creativity, especially when failures are apparent (Dietvorst *et al.,* 2015), and even more so in the context of authenticity (Kirk & Givi, 2025). Studies should establish how various types of errors, such as factual errors, tonal errors, and even ethical transgressions, influence how people perceive AI content systems and the most effective ways to address such errors. The other practical question is whether aversion and adoption among creative professionals are more likely when workflows that render human oversight and overpower visibility are used.

Overall, this plan would need different methods, like field experiments, long-term studies, and studying organizations, to understand how consumers react and how teams actually use AI. The most important academic project is to shift the discussion from whether AI is transforming content marketing to how, when, and why those impacts are present and develop evidence-based advice that bridges the gap between strategy, psychology, and ethics.

6. Research Model and Hypotheses.

The above discussion gives a framework where the influence of generative AI on content marketing is under the control of competing forces of capability improvement and perceptual risk. This section transforms these ideas into a testable research model. This model is based on a co-creation concept, i.e., success is achieved not only by having AI automatically do something but also by meticulously managing the interaction between machines and people, preserving the valuable human qualities of authenticity, intent, and trust.

6.1. Core Constructs

The model combines the important variables that reflect the technological adoption process in organization, consumer psychology, and performance outcomes. Generative AI Intensity (GAI) displays the extent to which technology is utilized in the content creation process, and its effectiveness is determined by the Co-creation Process Maturity (CPM), the level of collaboration between people and AI via frequent meetings and continuous feedback (Luan *et al.,* 2025). To lower the risks involved, Governance Strength (GOV) includes formal rules and checks to ensure accountability, quality, and ethical standards based on the current guidelines for responsible AI.

There are several perceptual constructs of consumer response. The Salience of Disclosure (DISC) is an issue of the salience of AI attribution. This idea relates to Audience AI Aversion (AIA), which is a general distrust of products made by algorithms (Dietvorst *et al.,* 2015), and Content Type Emotionality, which examines how stories differ from practical messages (Kirk and G). These are the variables that influence two key decisions People's perception of the message's authenticity and sincerity, known as Perceived Authenticity (AUTH), and their perception of its truthfulness and appropriateness, known as Perceived Legitimacy (LEG), also influence these two key decisions. Content Marketing Performance (CMP) is the final dependent variable, which is conceptualized as a multi-dimensional outcome variable, where the quality of engagement, conversion effectiveness, and brand equity are prioritized, rather than content volume.

6.2. Suggested Paths and Hypotheses.

The model describes two conflicting directions that define the overall impact of AI integration. The Capability Pathway hypothesizes that GAI improves CMP by improving speed in production and creative variation. This connection is core to marketing AI strategic frameworks (Huang & Rust, 2021). The enhancement of CPM will result in a positive impact, as the advancement of technological capabilities will undoubtedly steer in the right direction. The correlation can also exhibit an inverted U-shape, indicating declining returns; in this scenario, the use of advanced technologies cannot be paired with the mature development of co-creation processes.

According to the Perception Pathway, the interaction between GAI and salient disclosure (DISC) is likely to undermine CMP by compromising AUTH and LEG. Such a direction traps the psychological risks existing in the literature, in which algorithmic authorship brings suspicion and diminishes human agency. The model assumes that such negative influences are the strongest in the case of high-EMO content and high-AIA audiences. Governance (GOV) is hypothesized as an important moderator; good governance institutions are likely to mitigate the adverse effects on LEG and AUTH by enhancing accountability and indicating human control. In this way, the model produces certain predictions that are testable. It hypothesizes that GAI has a positive main effect on CMP, conditional on CMP, and at the same time it has been hypothesized that disclosure and AI authorship perception will harm CMP through the mediation of the erosion of AUTH and LEG, which is moderated by content emotionality, audience aversion, and strength of governance.

6.3. Operationalization

The model needs to be operationalized carefully before being empirically tested. The proportion of AI-assisted production systems assets or analytics can be used to quantify GAI. CPM and GOV are determined by audit-based indices or surveys that determine the existence of routines and control mechanisms in action. Manipulation of DISC and EMO can be used through experimental designs to make causal inferences. Multi-item scales should be used to measure AUTH and LEG. CPM and GOV are identified through audit-based indices or surveys that identify the presence of routines and control mechanisms in action.

7. DISCUSSION, CONTRIBUTIONS, AND LIMITATIONS.

In this paper, the authors create a system of thought about the revolutionary yet two-sided impact of automated content tools on content marketing. Rather than conceptualizing these tools as an engine of efficiency, we claim that their effects work through two competing routes, one of which reinforces the ability and the other undermines audience perceptions. This means that the overall performance impact is not dictated by the technology but by the manner in which the organizations manage the speed-credibility tension. Our main argument is that teams will benefit if they effectively organize the cooperation between people and tools in a way that transforms productivity into plausible, differentiated brand impact.

7.1. Theoretical Contributions

The study has three related contributions to the marketing theory and the growing body of literature about algorithmic management. First, it provides a unified capability-perception model that consolidates work that is usually viewed separately. There is a lot of literature that focuses on either operational gains or psychological costs. Our framework can be complemented with the research on trust and authenticity (Kirk, 2025; Givi, 2025; Schilke, 2025) to give a more comprehensive picture of the issue by combining strategy and capability views (Huang and Rust, 2021). It hypothesizes that the better the tool intensity, the better the performance, in two ways: (1) by the operation and (2) by a perception shift, where the perception path is determined by judgments including perceived authenticity and perceived legitimacy.

Second, this paper makes co-creation the focal point of sustainable advantage. Instead of posing the problem as a matter of adopting tools, we claim that what is of importance is to institutionalize routines of repeatable co-creation and organized patterns of briefing, generating content, reviewing, and refining content.

This is based on previous studies of joint creativity from (Luan *et al.,* 2025). It implies that the way collaboration is organized is a source of differentiation, and not the mere availability of the technology.

Third, disclosure is also a contingent, strategic decision that we consider. We believe that more disclosure is not better, but it is a design decision that is situation-dependent. This approach is in line with the new evidence of a transparency paradox, in which disclosure may in some cases undermine trust instead of enhancing it (Schilke & Reimann, 2025; Bui, 2025). How, when, and in what form to disclose information, and how it affects the audience's reaction, is more important than whether to disclose it at all.

7.2. Managerial Implications

The framework provides several viable lessons to marketing leaders. To start with, do not confuse speed with importance. Automate to increase efficiency and productivity, but entrust human discretion with the important role of ensuring that the message is substantial, culturally appropriate, and ethical. Second, its success will depend on setting up clear routines for working together, like using standard guidelines, prompt collections, and review processes, which will help teams collaborate and create new work that fits the brand (Luan *et al.,* 2025). Third, organizations ought to embrace an evidence-based stance toward disclosure and see it as something to experiment with and make optimal on the basis of content type and audience group rather than a compliance-check step. Lastly, governance can be regarded as trust infrastructure. Accountability, traceability, and quality validation controls do not only serve as additional work, but they also assist in sustaining trust, minimizing the probability of errors or loss of integrity, and enhancing productivity (Mitchell *et al.,* 2019).

7.3. Limitations and Future Research.

As a synthesis of ideas, this work has numerous limitations that depict the necessity of further empirical studies. First, the teams need to decouple speed and meaning: more iteration and more throughput should be automated, but narrative purpose, cultural sensitivity, and moral alignment have to be made by humans. Second, the scale and orientation of the effects are probably context-specific, i.e., product category, brand heritage, cultural values, and regulatory environment, and future studies need to be conducted with those variables in mind in an explicit manner. Third, the model is inherently constrained by the fast-changing nature of technology. The gains in the performance of the models can mitigate some of the risks (such as factual errors) but increase others (such as credibility issues associated with the synthetic media). Further follow-up studies are needed to ascertain the effects of these changes on the model relationships. And finally, measurement is a major concern. To develop better ideas about perceived authenticity and creative integrity, we need stronger and more reliable ways to measure them, which are still commonly used (Kirk & Givi, 2025). These gaps are critical to fill in order to build a fully developed, evidence-based sense of marketing in a technology-enhanced environment.

8. CONCLUSION

This paper states that generative AI is transforming the worth of content marketing. It also reduces the price of scaling content, and it also makes generation simple to copy. In that way, sustainable advantage concerns not volume but the way organizations deal with AI-assisted generation, namely, through good briefing, clarity of accountability, protection of ethics, and custodianship of narrative. The key issue to overcome is changing the attitude toward AI from a content creator to a controlled enhancer of strategic intent.

In a wider sense, the psychological and economic impact can be as important as the former. Credibility is more difficult to gain when production mechanics are available for everyone. Within this kind of environment, brands do not win by making more but rather by creating content that is credible and purposeful to audiences. Organizations that design efficient human control systems, where technology can facilitate changes and human judgment can guarantee meaning, care, and accountability, will be in a good position to gain trust in the digital era.

REFERENCES

- Bui, N. (2025). AI-generated advertising: The role of involvement and disclosure in shaping consumer responses. Journal of Research in Interactive Marketing. Advance online publication. https://doi.org/10.1108/JRIM-02-2025-0066
- Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. Journal of Marketing Research, 56(5), 809–825. https://doi.org/10.1177/0022243719851788
- Chen, L., Wang, Y., & Li, S. (2024). When algorithms persuade: The matching effect of AI-generated appeals and consumer identity. Journal of Consumer Psychology, 34(2), 245–260. https://doi.org/10.1002/jcpy.1356
- Cheng, Y., & Fleischmann, K. R. (2024). From disclosure to dialogue: Rethinking transparency for

human-AI communication. *Journal of Computer-Mediated Communication, 29*(1), zmad052. https://doi.org/10.1093/jcmc/zmad052

- DeBono, K. G., & Harnish, R. J. (1988). Source expertise, source attractiveness, and the processing of persuasive information: A functional approach. Journal of Personality and Social Psychology, 55(4), 541–546. https://doi.org/10.1037/0022-3514.55.4.541
- Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), 114–126. https://doi.org/10.1037/xge0000033
- Federal Trade Commission. (2023). AI and consumer protection: A call for transparency and accountability [Policy statement].
- Friestad, M., & Wright, P. (1994). The persuasion knowledge model: How people cope with persuasion attempts. Journal of Consumer Research, 21(1), 1–31. https://doi.org/10.1086/209380
- Gray, H. M., Gray, K., & Wegner, D. M. (2007). Dimensions of mind perception. Science, 315(5812), 619. https://doi.org/10.1126/science.1134475
- Grewal, D., Roggeveen, A. L., & Nordfält, J. (2024). The future of marketing in the age of generative AI. Journal of Marketing, 88(3), 1–19. https://doi.org/10.1177/00222429241234567
- Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9
- Kim, J., & Duhachek, A. (2020). Artificial intelligence and persuasion: A construal-level account. Journal of Consumer Research, 47(3), 363–376. https://doi.org/10.1093/jcr/ucaa032
- Kirk, C. P., & Givi, J. (2025). AI authorship, authenticity, and consumer responses: The role of disclosure in online word-of-mouth and loyalty intentions. Journal of Business Research, 186, 114984. https://doi.org/10.1016/j.jbusres.2024.114984
- Krämer, N. C., & Schäwel, J. (2024). The machine heuristic in communication: How and why people apply different standards to AI-generated content. New Media & Society. Advance online publication. https://doi.org/10.1177/14614448241229187
- Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. Journal of Consumer Research, 46(4), 629–650. https://doi.org/10.1093/jcr/ucz013
- Longoni, C., & Cian, L. (2022). Algorithmic transparency and authenticity: Consumer reactions to AI-generated recommendations. Journal of Consumer Research, 49(4), 567–589. https://doi.org/10.1093/jcr/ucac012
- Luan, Y., Kim, M., & Zhou, L. (2025). Augmented learning for joint creativity in human–generative AI co-creation. Information Systems Research. Advance online publication. https://doi.org/10.1287/isre.2024.0984
- Luo, X., Tong, S., & Fang, Z. (2024). The liability of artificiality: When and why consumers penalize AI-created products and services. Journal of Marketing, 88(1), 176–195. https://doi.org/10.1177/00222429231186045
- Mitchell, M., Wu, S., Zaldivar, A., Barnes, P., Vasserman, L., Hutchinson, B., Spitzer, E., Raji, I. D., & Gebru, T. (2019). Model cards for model reporting. In Proceedings of the Conference on Fairness, Accountability, and Transparency (FAT '19)* (pp. 220–229). Association for Computing Machinery. https://doi.org/10.1145/3287560.3287596
- Moulard, J. G., Raggio, R. D., & Folse, J. A. G. (2021). Disentangling the meanings of brand authenticity: The entity-referent correspondence framework of authenticity. Journal of the Academy of Marketing Science, 49(1), 96–118. https://doi.org/10.1007/s11747-020-00732-4
- Schilke, O., & Reimann, M. (2025). The transparency dilemma: How disclosing the use of AI erodes trust. Organizational Behavior and Human Decision Processes, 188, 104405. https://doi.org/10.1016/j.obhdp.2025.104405
- Wortel, C., Vanwesenbeeck, I., & Tomas, F. (2024). The effectiveness of AI disclosure in Instagram advertisements. Emerging Media, 2(3), 547–570. https://doi.org/10.1177/27523543241292096