

Made by a Machine, Liked by a Human?**AI-Generated vs. Human-Created Content in Social Media Marketing and the Effect of Disclosing “Made with AI”**Author: Georgio Nader¹*Affiliation:*

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Abstract:

Scroll through Instagram today and there is a good chance that at least one of the posts you liked was not made by a person. Brands are turning to generative AI tools such as ChatGPT, Midjourney and Canva's Magic Studio to produce captions and visuals faster and cheaper, but we still know very little about how consumers actually react to this content, especially when they are told it was made by AI. In this study I tested whether AI-generated social media posts perform differently from human-created ones, and whether a “Made with AI” label changes the picture. I ran a between-subjects experiment with 120 USEK students who were randomly shown one of three versions of the same Instagram campaign for a fictional Lebanese coffee brand: human-created, AI-generated without disclosure, and AI-generated with disclosure. I measured four outcomes: engagement intention, perceived authenticity, brand trust and purchase intention, and compared the groups using one-way ANOVA. The results show that when participants did not know the content was AI-made, they rated it almost the same as the human-made posts, and even slightly higher on engagement (3.66 vs. 3.58). Once the label was added, however, every score dropped, with perceived authenticity falling the most (from 3.81 to 2.74). In other words, the problem is not the AI content itself but what people think when they find out. These findings suggest that marketers can use AI to support content creation, but that transparency rules, such as the EU AI Act, will force brands to think carefully about how they communicate AI use to their audience.

Keywords:

Generative AI, Social Media Marketing, AI Disclosure, Perceived Authenticity, Brand Trust, Consumer Behavior

Introduction:

A few years ago, making one good Instagram post for a brand meant a photographer, a graphic designer, a copywriter and at least a couple of days of back-and-forth with the client. Today, a single marketing intern can produce a full week of posts in one afternoon using generative AI. Tools like ChatGPT write the captions, Midjourney or Adobe Firefly create the visuals, and scheduling platforms publish them automatically. For small businesses, and especially Lebanese businesses that have been operating on tight budgets since the economic crisis, this is a very attractive deal.

But marketing has never been only about producing content, it is about building a relationship with people. Social media in particular is supposed to be the “human” face of the brand, the place where customers feel they are talking to real people behind the logo. This raises an uncomfortable question: if consumers discover that the post they liked was written and designed by a machine, do they still feel the same about the brand?

This question is becoming more urgent because disclosure is no longer optional. Meta now adds “AI info” labels to certain images on Instagram and Facebook, TikTok labels AI-generated content, and the European Union’s AI Act (Regulation (EU) 2024/1689) includes transparency obligations for AI-generated content. So brands are moving toward a world where their audience will often know when content is AI-made.

Most of the existing research looks either at AI in marketing in general, or at how people react to algorithms making decisions for them. Much less is known about everyday social media content, and almost nothing has been done with Lebanese or Middle Eastern consumers, who are some of the heaviest social media users in the region. This is the gap that my study tries to fill.

The main research question is: Does AI-generated social media content perform differently from human-created content, and does disclosing that the content is “Made with AI” change how consumers respond to it?

To answer this question, my study aims to:

- Compare engagement intention (liking, commenting, sharing) between AI-generated and human-created posts.
- Measure whether consumers perceive AI-generated content as less authentic.
- Evaluate the effect of an AI disclosure label on brand trust.
- Assess whether any of these differences carry over to purchase intention.
- Provide practical recommendations for marketers in Lebanon on how to use AI content without damaging their brand.

Literature Review:

2.1 AI in marketing: from hype to daily tool

Researchers have been predicting for a while that artificial intelligence would change marketing. Davenport et al. (2020) argued that AI would reshape almost every part of marketing, from customer targeting to sales and customer service. Huang and Rust (2021) went further and proposed a framework where AI moves through three levels: mechanical AI for repetitive tasks, thinking AI for analysis, and feeling AI for tasks involving emotions and interaction. Content creation used to be considered a “human” task, since it requires creativity and emotional understanding, but the release of ChatGPT in late 2022 changed the discussion very quickly.

Dwivedi et al. (2023) collected the views of dozens of experts and concluded that generative AI would have a major impact on marketing, while also raising concerns about authenticity, accuracy and ethics.

2.2 AI in Finance and the unexpected effects of AI technology on sustainability

Many scholars argue that one of the main advantages of American large firms is technology (Beainy & Kamel, 2025), data analytics and better knowledge management has significantly improved the performance of firms in general (Subrahmanyam et al., 2024) and SMEs in particular (Khalife et al., 2024) also increasing financial transparency (Saber & Sassine, 2022). Furthermore, technology has allowed more accurate pricing (Khalife et al., 2023) positively attributing to an increase in market efficiencies. In the scale of national-wide economy, AI has enabled better prediction of economic quadrants (Nasser et al., 2025). Finally, one of the leading scholars on sustainability in finance has highlighted multiple times the positive impact of technology on non-financial metrics such as sustainability and ESG (Kaspard et al., 2025 ; Kaspard et al., 2026), but this is dependent on other variables such as proper country governance (Athari et al., 2023).

2.3 Do people trust machines? Algorithm aversion vs. appreciation

A big part of the literature looks at how people feel about algorithms. On one side, Dietvorst et al. (2015) found “algorithm aversion”: people lose confidence in an algorithm very quickly after seeing it make a mistake, even when it performs better than a human. Longoni et al. (2019) found that patients resist medical AI because they feel it cannot understand their unique situation. On the other side, Logg et al. (2019) found “algorithm appreciation”, where people actually follow advice more when they believe it comes from an algorithm. Castelo et al. (2019) helped explain this contradiction by showing that it depends on the task: people accept algorithms for objective tasks but resist them for subjective tasks that seem to require human feeling and intuition. Creative marketing content is clearly on the subjective side, which suggests that people may react negatively when they know AI is involved.

2.4 Authenticity and the “made by AI” label

Authenticity is one of the most valuable things a brand can have on social media. Morhart et al. (2015) describe brand authenticity through continuity, credibility, integrity and symbolism, basically, whether the brand feels real and true to itself. A recent study by Brüns and Meißner (2024) found that when followers learned that a brand used generative AI to create its social media content, perceived brand authenticity dropped and so did follower reactions. This is very close to my study, but it was done with European consumers, and it did not compare the same content with and without disclosure in a Lebanese context.

2.5 Theoretical framework

Two theories help explain why disclosure might matter. The first is the Persuasion Knowledge Model (Friestad & Wright, 1994). It says that when consumers recognize that someone is trying to persuade them, they activate a kind of “defense mode” and become more skeptical. An “AI-

generated” label can act as a trigger that reminds people this content was manufactured to influence them. The second is the Elaboration Likelihood Model (Petty & Cacioppo, 1986), which explains that people often judge messages using quick cues rather than careful thinking. On a fast-scrolling platform like Instagram, a small label can become a strong peripheral cue that shapes the whole judgment. Finally, the Theory of Planned Behavior (Ajzen, 1991) supports the use of purchase intention as a reasonable predictor of actual buying behavior.

2.6 The gap and hypotheses

Putting all of this together, most studies focus on AI in general or on algorithmic decisions, and the few that test AI-generated content come from Western markets. My study tests the same campaign in three versions with Lebanese university students, which allows me to separate the effect of the content from the effect of the label. Based on the literature, I propose:

- H1: When AI use is not disclosed, AI-generated content will perform similarly to human-created content.
- H2: Disclosing AI use will reduce perceived authenticity and brand trust compared to human-created content.
- H3: Disclosing AI use will reduce engagement intention and purchase intention.

Methodology:

3.1 Research design

I used a quantitative, between-subjects experimental design with three conditions. Each participant saw only one version of the campaign, so their answers were not influenced by comparing versions. The three conditions were:

- **Group A – Human-created:** posts designed and written by a student graphic designer and myself.
- **Group B – AI-generated, not disclosed:** posts created with ChatGPT (captions) and an AI image generator (visuals), with no label.
- **Group C – AI-generated, disclosed:** exactly the same posts as Group B, with a small “Made with AI” label under the post, similar to the one Instagram uses.

To make the test fair, I created a fictional Lebanese coffee brand called “Bunn & Co.” so that no participant had previous feelings about it. Each version included three Instagram posts with the same theme (a new iced coffee launch), the same colors, the same product and similar caption length. Only the creator (human or AI) and the label changed.

3.2 Sample and data collection

Data were collected through an online survey on Google Forms, shared through USEK student WhatsApp groups and class group chats between October and November 2026. Participants were randomly assigned to one of the three groups by their birth month. After removing incomplete answers and participants who failed the attention check, the final sample was 120 respondents (40 per group), aged 18 to 25, with 58% female and 42% male respondents. All participants were active Instagram users and participation was anonymous and voluntary.

3.3 Variables and measurement

The independent variable is the content condition (A, B or C). The four dependent variables were measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree), with items adapted from previous studies. The full questionnaire is in the Appendix.

Table 1: Variables and measurement

Variable	Example item	Items	Adapted from
Engagement intention	"I would like or comment on this post."	3	Brüns & Meißner (2024)
Perceived authenticity	"This post feels genuine and real."	3	Morhart et al. (2015)
Brand trust	"I feel I can trust this brand."	3	Morhart et al. (2015)
Purchase intention	"I would consider buying this product."	3	Ajzen (1991)

Note: Internal reliability was checked with Cronbach's alpha; values above 0.70 are considered acceptable (Nunnally, 1978).

3.4 Statistical analysis

The data were analyzed in SPSS / JASP. First, I calculated the mean score for each variable per participant and checked reliability using Cronbach's alpha. Then I used a **one-way ANOVA** to test whether the mean scores differ significantly between the three groups, followed by **Tukey's post-hoc test** to see exactly which groups differ from each other. The significance level was set at $p < 0.05$, and effect sizes were reported using eta squared (η^2) following Hair et al. (2019).

Results:

4.1 Reliability

All four scales showed acceptable reliability, with Cronbach's alpha ranging from 0.78 (purchase intention) to 0.89 (perceived authenticity), so the items were averaged into one score per variable.

4.2 Group comparison

Table 2 shows the mean scores and standard deviations for each group, together with the ANOVA results.

Table 2: Mean scores by condition and one-way ANOVA results

Variable	A: Human	B: AI (no label)	C: AI (labelled)	F (2,117)	p
Engagement intention	3.58 (0.71)	3.66 (0.68)	3.09 (0.80)	6.52	.002
Perceived authenticity	3.81 (0.64)	3.52 (0.73)	2.74 (0.82)	23.10	<.001
Brand trust	3.70 (0.66)	3.57 (0.70)	2.96 (0.77)	11.84	<.001
Purchase intention	3.39 (0.75)	3.44 (0.72)	2.91 (0.84)	5.61	.005

Note: Values are means with standard deviations in parentheses, on a 1–5 scale. n = 40 per group.

The ANOVA showed a significant difference between the groups for all four variables ($p < 0.05$). The biggest difference was in perceived authenticity ($F = 23.10$, $n_2 = 0.28$), while the smallest was in purchase intention ($F = 5.61$, $n_2 = 0.09$).

4.3 Post-hoc comparisons

Tukey's test showed a clear pattern. Between Group A (human) and Group B (AI, no label), there was **no significant difference** on any variable (all $p > 0.05$). Group B actually scored slightly higher than Group A on engagement intention (3.66 vs. 3.58) and purchase intention (3.44 vs 3.39). However, Group C (AI, labelled) scored significantly lower than both Group A and Group B on all four variables. Compared to the human-created posts, perceived authenticity dropped by 28% (from 3.81 to 2.74), brand trust by 20%, engagement intention by 14% and purchase intention by 14%.

Table 3: Summary of hypothesis testing

Hypothesis	Statement	Result
H1	Undisclosed AI content performs similarly to human content	Supported
H2	Disclosure reduces authenticity and brand trust	Supported
H3	Disclosure reduces engagement and purchase intention	Supported

Discussion and Conclusion:

5.1 Key findings

The most interesting finding of this study is that people could not really tell the difference. When the AI-generated posts had no label, participants rated them just as well as the human-made posts, and in some cases slightly better. The drop only happened when they were told the content was “Made with AI”. This means the negative reaction is not about the quality of the content, it is about the idea of AI being behind it. The fact that authenticity dropped the most confirms that social media users still expect a human touch from brands, even if they cannot actually see it.

5.2 Theoretical implications

The results support the Persuasion Knowledge Model (Friestad & Wright, 1994): the label seems to have activated participants’ skepticism, making them feel the content was more “manufactured”. They also match the idea of task-dependent algorithm aversion (Castelo et al., 2019), because creative content is a subjective task where people prefer humans. Finally, they extend the findings of Brüns and Meißner (2024) to a Lebanese sample, suggesting that this reaction is not limited to Western consumers.

5.3 Practical implications

For marketers, the message is not “stop using AI”. AI clearly produces content that people like. The real challenge is disclosure, which is becoming a legal and platform requirement anyway. Based on my results, I would suggest that brands use AI as an assistant rather than a replacement, keeping a human voice in captions and community replies; that they frame disclosure positively, for example “designed by our team with AI tools” instead of a cold “AI-generated” label; and that they avoid using AI for content that is supposed to be emotional or personal, such as founder stories or customer testimonials, where authenticity matters the most.

5.4 Limitations

This study has some limitations. The sample was made only of USEK university students, who are young and familiar with technology, so the results may not apply to older consumers. The brand was fictional, which helped control the experiment but does not reflect the loyalty people have with real brands. I also measured intentions and not real behavior, since participants did not actually like, share or buy anything. Finally, the sample size of 120 is enough for a student experiment but still relatively small.

5.5 Future research

Future research could test the same design with older age groups and with real brands, use real Instagram engagement data instead of survey answers, and compare different types of disclosure wording to find which one hurts brands the least. It would also be interesting to study whether the

negative effect of the label gets smaller over time, as people become more used to AI content in their daily feeds.

References

- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211.
- Athari, S. A., Saliba, C., Khalife, D., & Salameh-Ayanian, M. (2023). The role of country governance in achieving the banking sector's sustainability in vulnerable environments: New insight from emerging economies. *Sustainability*, 15(13), 10538.
- Brüns, J. D., & Meißner, M. (2024). Do you create your content yourself? Using generative artificial intelligence for social media content creation diminishes perceived brand authenticity. *Journal of Retailing and Consumer Services*, 79, 103790.
- Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. *Journal of Marketing Research*, 56(5), 809–825.
- Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24–42.
- 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.
- Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... Wright, R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642.
- European Parliament and Council of the European Union. (2024). Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). *Official Journal of the European Union*.
- Friestad, M., & Wright, P. (1994). The persuasion knowledge model: How people cope with persuasion attempts. *Journal of Consumer Research*, 21(1), 1–31.
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
- 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.
- Kamel, C., & Beainy, R. (2025). USA Versus China from an Equity Perspective. *International Journal of Research and Innovation in Social Science*, 9(10), 8191-8201.
- Kaspard, J. A., Khalil, F. C., & Kamel, C. A. (2025). Factors contributing to non-financial performance of companies. In *Sustainable Economic Development: Utilizing Non-Financial Performance, Sustainability Reporting, and Corporate Governance* (pp. 413-442). Cham: Springer Nature Switzerland.

- Kaspard, J., Kamel, C., Khalil, F., & Beainy, R. (2026). Financial Performance, Risk, and Market Integration of Sustainability-Oriented Equity Indices: Implications for the Sustainability Transition (2010–2025). *Risks*, 14(5), 99.
- Khalife, D., Subrahmanyam, S., & Farah, A. (2024). A Sustainable Circular Business Model to Improve the Performance of Small and Medium-sized Enterprises Using Blockchain Technology. *J. Wirel. Mob. Networks Ubiquitous Comput. Dependable Appl.*, 15(2), 240–250.
- Khalife, D., Yammine, J., Rahal, S., & Freiha, S. (2023). Pricing Asian and Barrier Options Using a Combined Heston Model and Monte Carlo Simulation Approach with Artificial Intelligence. *Mathematical Modelling of Engineering Problems*, 10(5), 1690.
- Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, 151, 90–103.
- Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research*, 46(4), 629–650.
- Morhart, F., Malär, L., Guèvremont, A., Girardin, F., & Grohmann, B. (2015). Brand authenticity: An integrative framework and measurement scale. *Journal of Consumer Psychology*, 25(2), 200–218.
- Nasser, A., Yammine, J., Harouny, J., & Khalife, D. (2025). Predicting Economic Quads Through Asset Returns Using Ensemble Machine Learning. *IEEE Access*.
- Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). McGraw-Hill.
- Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. *Advances in Experimental Social Psychology*, 19, 123–205.
- Saber, A. M., & Sassine, M. E. (2022). Reflections on internal control and internal audit roles for ensuring financial transparency toward Lebanese NGOs financial donors. *EuroMed Journal of Management*, 4(3), 186–198.
- Saber, A. M., & Sassine, M. E. (2022). Reflections on internal control and internal audit roles for ensuring financial transparency toward Lebanese NGOs financial donors. *EuroMed Journal of Management*, 4(3), 186–198.
- Subrahmanyam, S., Aishwaryalaxmi, N. S., Khalife, D., Shaikh, I. A. K., Faldu, R., & Asthana, N. (2024, April). Impact of knowledge management and big data analytics capabilities on firm performance. In *2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM)* (pp. 1–5). IEEE.