FORSCHUNGSFORUM
DER ÖSTERREICHISCHEN
FACHHOCHSCHULEN
2024

University of
Applied Sciences

Labelling Generative AI: Investigating Consumer Preferences For AI-Generated vs. Human-Written Product Descriptions And Their Impact On Purchase Intention

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Abstract.
As generative artificial intelligence becomes more integral in digital marketing strategies, including tasks such as crafting product descriptions, AI is playing an increasingly important role in interacting with consumers. This research addresses a gap in understanding the consumer's perspective, particularly their preferences for human-written versus AI-generated product descriptions and their influence on the purchase decision process. On the one hand, product descriptions are becoming relevant due to the projected increase in online sales. On the other hand, trustworthy use of AI in marketing communications is becoming increasingly important due to the EU AI Act's emphasis on transparent labelling of AI-generated content. Using a between-subjects design, the initial study provides insights into attitudes towards the perceived quality and persuasiveness of information, as well as purchase intention. The preliminary results indicate that the source of the text (AI-generated vs. human-written) significantly affect the quality of information and purchase intention. The study aims to provide deeper insights into the role of AI in the consumer decision-making process. Data collection for a second study is ongoing, focusing on various product types.

Keywords: Generative AI, Purchase Decision, Consumer Behaviour, Digital Marketing, Labelling AI

1 INTRODUCTION

The retail industry is undergoing a transformation due to the integration of artificial intelligence (AI) and the growth of e-commerce. Digital marketers are revolutionising their approach with the help of AI, particularly generative AI. They are increasingly using AI for content creation such as creating product descriptions to enhance communication effectiveness. This technology is not only changing business operations but also improving consumer interactions, leading to increased customer engagement and satisfaction (Longoni & Cian, 2022; Zhu et al., 2022). This highlights the impact of generative AI on consumer interactions throughout their customer journey, which affects their purchase behavior (Jain, Wadhwani, & Eastman, 2023). Product descriptions play a crucial role in customer behavior in outlining product features, promoting items, complying with SEO standards, and evoking emotions. This is especially significant because online sales are projected to make up 25% of global sales by 2025 (Chevalier, 2022), emphasizing the increased significance of verbal product information in online shopping. The aim of these factors is to provide essential information that is relevant for purchasing decisions (Kollmann, 2019). According to initial research, the quality of product information is a crucial factor in customer trust and decision-making (Jain & Gandhi, 2021; Chen et al., 2021). The type of product also moderates consumer acceptance of descriptions, particularly for experience products that can only be evaluated post-purchase (Nelson, 1970; Zhu et.al., 2022). Verbal descriptions are crucial for e-commerce products as they cannot be physically examined (Manzano et al., 2016; Peck et al., 2013). Generative AI offers a practical solution for creating product descriptions, especially for short texts, that closely resemble human writing. However, the source of information significantly affects audience perception and product evaluation (Atkinson & Rosenthal, 2014; Walten & Wiedmann, 2023). While AI-generated information is generally considered trustworthy when accurate and comprehensive, there is a lack of research on the perceived credibility of AI vs. human-generated information. Initial findings suggest a trust deficit in AI suggestions for experience products, possibly due to the perceived lack of emotional intelligence in AI (Castelo et al., 2019). This research gap is especially relevant in light of the EU AI Act, which emphasizes the importance of transparent labelling AI-generated content to address consumer concerns about trust and credibility.

2 METHODS

For initial insights, a non-student quota sample of 256 participants (38% female, 62% male; average age 41.6, SD = 11.8) from an Austrian panel was used. They were randomly allocated to one of three experimental groups and compensated financially post-survey. In Study 1, a three-level between-subjects design was applied. Participants viewed a couch's description and image, with randomized and balanced stimulus allocation. The AI condition included a label indicating AI generation, the human condition had a human-generated label, and a baseline condition had no labels. Post-exposure, participants rated on a seven-point scale (1='strongly disagree' to 7='strongly agree') collected information

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about: information quality (Zhang et al., 2011; 3 items, $\alpha = 0.967$), persuasiveness of information (Le, 2023; 3 items, $\alpha = 0.904$), quality of information (semantic differential, 5 items, $\alpha = 0.851$), and purchase intention (Spears & Singh, 2004; 3 items, $\alpha = 0.953$).

3 RESULTS

3.1 *Manipulation Check*

First, we aimed to confirm the effectiveness of our experimental setup. For the manipulation check we used a single-item measure to determine whether participants could identify the label used ('AI-generated', 'Human-generated' or 'I can't find this information.'). The findings indicated that 70% accurately determined the source of the product descriptions. After excluding participants who did not pass the assignment, the revised sample size consisted of 178 respondents (37% female; 63% male, $M_{age} = 42{,}3$; $SD_{age} = 11{,}8$).

3.2 *Information quality – Persuasiveness of information*

The initial phase of our analysis involved conducting a Pearson correlation analysis to delve into the interrelationships between various indices of consumer perception. The results showed a strong positive correlation between the quality of product information and its persuasiveness ($r(178) = .821$, $p < .001$), indicating a significant link between these two aspects. Another strong correlation was found between information quality and persuasiveness ($r(178) = .837$, $p < .001$), highlighting the significant link between perceived information quality and its ability to persuade. These findings are illustrated in figure 1.

3.3 *Information source – Consumer Perception*

Additionally, the impact of the information source is a crucial factor in our study. To analyze the impact of the source (human vs. AI vs. unlabeled) on different consumer perception indices, we examined an analysis of variance. The study found that the quality of product information was affected by the information source ($F(2, 175) = 4.708$, $p = .010$). Additionally, significant differences were observed in the persuasiveness ($F(2, 175) = 7.611$, $p < .001$) and quality ($F(2, 175) = 10.292$, $p < .001$) of the information depending on the source.

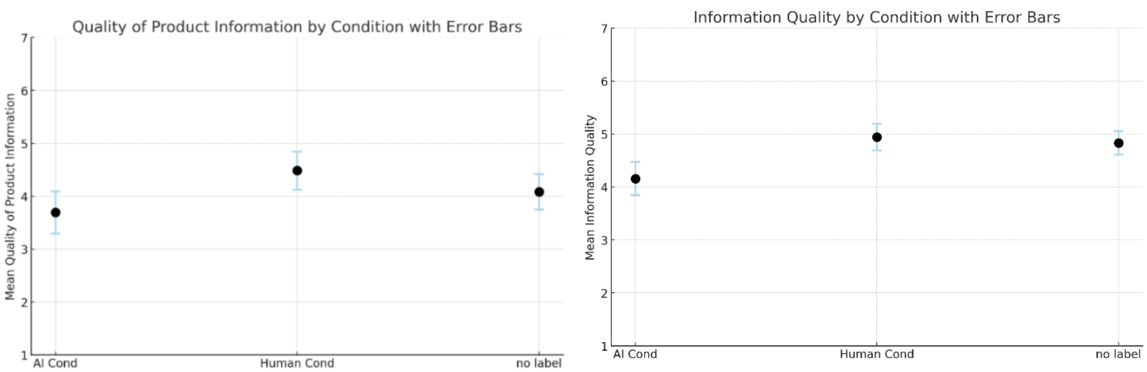

Figure 01: Mean rating of quality of product information(left)& information quality (right) across three conditions (AI generated- Human written– no Label). Error bars indicate standard error of the mean (SEM).

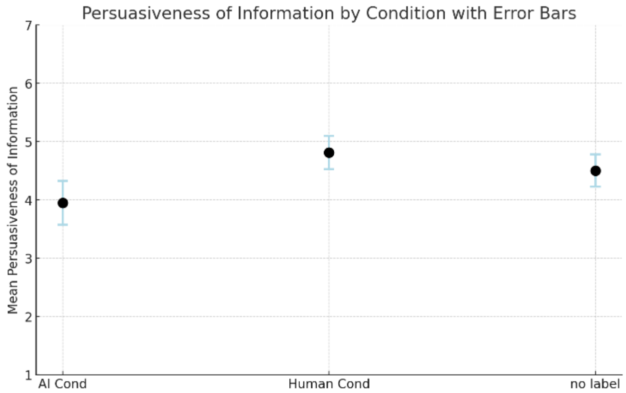

Figure 02: Mean rating Quality of Product information (left) and Persuasiveness (right) (y-axis) across three conditions (AI – generated - Human written– no Label). Error bars indicate standard error of the mean (SEM).

3.4 Purchase Intention

Regarding purchase intentions, a Pearson Correlation Analysis showed significant positive correlations between information quality (r (178) = .414, p < .001) and purchase intention, as well as between product information quality (r(178) = .411, p < .001) and purchase intention. This indicates that a higher perceived quality of information is associated with an increase in purchase intentions. Furthermore, the study found a positive correlation between the persuasiveness of product information and purchase intention (r(178) = .458, p < .001). This suggests that consumers are more likely to purchase a product when they perceive the information about it to be highly persuasive. The ANOVA analysis also revealed a significant difference in purchase intention among the groups (F(2, 175) = 3.392, p = .036), indicating that the source of product information has an impact on consumer purchasing behavior.

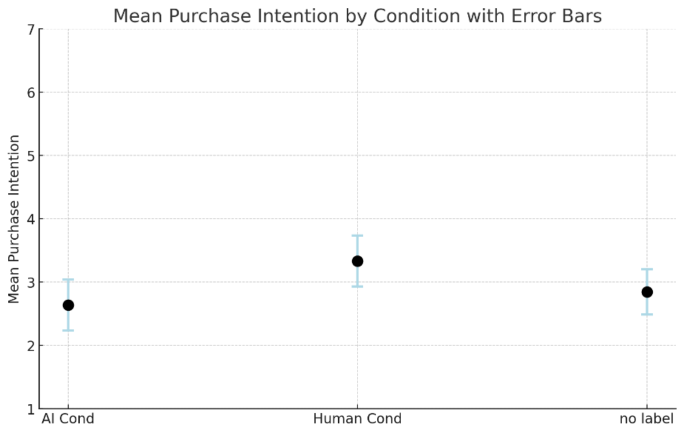

Figure 03: Mean rating of purchase intention (y-axis) across three conditions. Error bars indicate the standard error of the mean (SEM).

4 CONCLUSIO

Our study yielded several interesting highlights. Firstly, a strong positive correlation was identified between the quality and persuasiveness of product information, emphasizing the impact of content quality on consumer decision-making. Secondly, the study successfully demonstrated the significant effects of different sources of product information (AI-generated, human-generated, and unlabelled) on consumer perception, providing valuable insights for content strategy in e-commerce. This finding emphasises that the source of information, as well as the content, plays a crucial role in shaping consumer perceptions. Thirdly, the research established a positive effect between the quality and persuasiveness of product information and the consumers' purchase intentions, underscoring the role of effective content in driving sales. The findings underline the critical impact of information quality and persuasiveness on shaping consumer purchase decisions highlighting the need to adopt a balanced approach to AI, ensuring that technological efficiencies are utilized while not sacrificing consumer trust and engagement. This underscores the need for marketers and e-commerce platforms to carefully consider how they present product information, balancing the efficiency of AI-generated content with the trust and authenticity often associated with human-generated content. This is especially important in e-commerce, where product descriptions significantly influence consumer behaviour. It is worth noting that this study only focuses on one product category, sofas. The generalisability of the findings may be limited by this factor, particularly for products with varying levels of complexity and consumer involvement. To address this limitation, a follow-up study will examine different product types.

REFERENCES

[1] Atkinson& Rosenthal, S. (2014). Signaling the green sell: The influence of eco-label source, argument specificity, and product involvement on consumer trust. *Journal of Advertising, 43*(1), 33-45. https://doi.org/10.1080/00913367.2013.834803

[2] 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%2F0022243719851788

[3] Chen, H., Chan-Olmsted, S., Kim, J. & Sanabria, I. M. (2021). Consumers' perception on artificial intelligence applications in marketing communication. *Qualitative Market Research: An International Journal, 25*(1), 125-142. https://doi.org/10.1108/QMR-03-2021-0040

[4] Chevalier, S. (2022). *Global retail e-commerce sales 2014-2025. Retail e-commerce sales world-wide from 2014 to 2025*. Retrieved February 5, 2022, from https://www.statista.com/statistics/379046/world-wide-retail-e-commerce-sales/

[5] Jain, S. & Gandhi, A.V. (2021). Impact of artificial intelligence on impulse buying behaviour of Indian shoppers in fashion retail outlets. *International Journal of Innovation Science,*

13(2), 193-204. https://doi.org/10.1108/IJIS-10-2020-0181

[6] Jain, V., Wadhwani, K., Eastman, J. (2023). Artificial Intelligence consumer behavior: A hybrid review and research agenda. *Journal of Consumer Behavio*ur,1-22. DOI: 10.1002/cb.2233

[7] Kollmann, T. (2019). E-Business - Grundlagen elektronischer Geschäftsprozesse in der Digitalen Wirtschaft *(7th edition) [E-Business - Basics of electronic business processes in the digital economy]. Springer.* https://doi.org/10.1007/978-3-658-26143-6 (in German.)

[8] Longoni, C., & Cian, L. (2022). Artificial intelligence in utilitarian vs. hedonic contexts: The "word-of-machine" effect. Journal of Marketing, 86(1), 91-108. https://doi.org/10.1177/0022242920957347

[9] Manzano, R., Gavilan, D., Ferrán, M., Avello, M., & Abril, C. (2016). Autotelic and instrumental need for touch: Searching for and purchasing apparel online. *International Journal of Economics & Management Sciences, 5*(2), 1-7. http://dx.doi.org/10.4172/2162-6359.1000322

[10] Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy, 78*(2), 311-329. https://doi.org/10.1086/259630

[11] Peck, J., Barger, V. A., & Webb, A. (2013). In search of a surrogate for touch: The effect of haptic imagery on perceived ownership. *Journal of Consumer Psychology, 23*(2), 189-196. https://doi.org/10.1016/j.jcps.2012.09.001

[12] Walten, L., & Wiedmann, K. P. (2022). How product information and source credibility affect consumer attitudes and intentions towards innovative food products. *Journal of Marketing Communications, 29*(7), 637-653. https://doi.org/10.1080/13527266.2022.2061033

[13] Zhu, Y., Thang, R., Zou, Y., Jin, D. (2022). Investigating customers' responses to artificial intelligence chatbots in online travel agencies: the moderating role of product familiarity. *Journal of Hospitality and Tourism Technology, 14*(2), 208-224. https://doi.org/10.1108/JHTT-02-2022-004

[14] Zhu, Y., Zhang, J., Wu, J., Liu, Y. (2022). AI is better when I'm sure: The influence of certainty of need on consumers' acceptance of AI chatbots. J*ournal of Business Research, 150, 642-652.* https://doi.org/10.1016/j.jbusres.2022.06.044

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