RED
MARKA
Revista de Marketing Aplicado
Vol. 29, No. 2 (2025), 180-199
ISSN: 1852-2300
DOI: https://doi.org/10.17979/redma.2025.29.2.12593

Received: September 03, 2025
Accepted: December 01, 2025

Communicative effectiveness of artificial intelligence-generated graphic design

Eficacia comunicativa del diseño gráfico generado por inteligencia artificial

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Abstract

This study systematically reviews the scientific production (2010-2025) on graphic design generated by artificial intelligence (AI), assessing its communicative effectiveness in terms of attention, persuasion, and recall. Based on a corpus of 250 documents indexed in WoS and Scopus, it applies a mixed methodology grounded in PRISMA and structural bibliometric analysis. The analysis reveals a shift from isolated computational approaches toward interdisciplinary frameworks integrating computer vision, persuasive communication, and media cognition. Stable semantic patterns, collaborative networks, and persistent methodological gaps are identified, particularly concerning the empirical evaluation of visual impact on users. Findings also show that AI reshapes aesthetics and alters perceptions of authenticity. The study's contribution lies in constructing an integrative conceptual framework linking computational and psychocognitive metrics, offering replicable guidelines and a critical reading of automated design.

Keywords: algorithmic image generation, artificial intelligence, automated graphic design, persuasive communication, visual attention, visual neurocognition

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How to cite this article: Braza Delgado, R. (2025). Communicative effectiveness of artificial intelligence-generated graphic design, *Redmarka. Revista de Marketing Aplicado*, Vol 29, No. 2, 180-199. https://doi.org/10.17979/redma.2025.29.2.12593

Resumen

Este estudio revisa sistemáticamente la producción científica (2010-2025) sobre diseño gráfico generado por inteligencia artificial (IA), evaluando su eficacia comunicativa en atención, persuasión y recuerdo. Con un corpus de 250 documentos indexados en WoS y Scopus, se aplica una metodología mixta sustentada en PRISMA y análisis bibliométrico estructural. El análisis evidencia un tránsito de enfoques computacionales aislados hacia marcos interdisciplinares que integran visión computacional, comunicación persuasiva y cognición mediática. Se identifican patrones semánticos, núcleos de colaboración y vacíos metodológicos, especialmente en la evaluación empírica del impacto visual en usuarios. Asimismo, se observa que la IA redefine la estética y modifica la percepción de autenticidad. El aporte consiste en un marco conceptual integrador que vincula métricas computacionales y psicocognitivas, ofreciendo lineamientos replicables y una lectura crítica del diseño automatizado.

Palabras clave: atención visual, comunicación persuasiva, diseño gráfico automatizado, generación algorítmica de imágenes, inteligencia artificial, neurocognición visual

1. INTRODUCTION

In the last decade, graphic design has undergone a structural transformation mediated by artificial intelligence (Hwang & Wu, 2025), which has reconfigured notions such as authorship and creative agency (Laba, 2024; McCormack et al., 2019). Tools such as DALL·E, Midjourney, or Stable Diffusion democratize the production of complex visualities (Hwang & Wu, 2025). Their presence is growing in advertising, institutional communication, and branding, although their impact on attention, persuasion, and recall still lacks systematic study. The literature is characterized by methodological fragmentation: computer vision focused on classification (Li et al., 2022), consumer psychology on aesthetic responses (Chan, 2025), and cultural studies on symbolic meanings (Laba, 2024). This dispersion limits the ethical, media-related, and epistemological understanding of the phenomenon. In response, a systematic review based on PRISMA (Page et al., 2021) is proposed, with an interdisciplinary approach and convergence between bibliometrics and communication, integrating persuasive and cognitive metrics (Zhou & Kawabata, 2023). The article follows the IMRyD model and proposes a frame of reference to evaluate AI design in attention, emotion, and memory.

2. STUDY JUSTIFICATION

The expansion of generative tools has shifted design toward conceptual ideation (Hwang & Wu, 2025), without an equivalent methodological consolidation. Although their use is increasing in advertising and communication, the persuasive impact on attention, memory, or behavior remains scarcely studied (Yun, 2025; Sands et al., 2025). The literature shows fragmentation: formal classification, aesthetic exploration, or symbolic analysis without communicative metrics (Grassini, 2024; Chan, 2025). In addition, a gap persists between technical sophistication and the absence of validated instruments for real audiences. Despite similarities in aesthetic responses, a negative bias toward AI works persists (Lin et al., 2024; Zhou & Kawabata, 2023). The article is justified because: (1) it addresses an empirical gap with a PRISMA review; (2) it articulates computational metrics and media cognition; and (3) it proposes a replicable framework to guide research and evaluation. Its contribution seeks to consolidate a theoretical foundation for graphic design with AI as a persuasive communicative practice.

3. GENERAL AND SPECIFIC OBJECTIVES OF THE STUDY

3.1. General objective

To analyze the scientific output (2010-2025) on graphic design generated by artificial intelligence through a systematic review with a bibliometric approach, identifying thematic patterns, trends, collaboration networks, and empirical indicators of communicative effectiveness in attention, persuasion, and recall.

3.2. Research question

How has the communicative effectiveness of graphic design generated by artificial intelligence been evaluated in the scientific literature (2010-2025), and what thematic, collaborative, and methodological patterns characterize it?

3.3. Thematic scope and analysis corpus

The corpus comprises 250 documents published between 2010 and 2025 in 190 academic sources, with an annual growth of 28,09% and an average age of 2,32 years. The average citation rate is 5,456. The data were obtained through Biblioshiny and Bibliometrix (Biblioshiny, 2025; Aria & Cuccurullo, 2017). A total of 884 author keywords and 1.730 indexed terms were identified. The analysis reveals 769 authors, with an average of 3,4 co-authors per document and low international collaboration (6,8%).

3.4. Specific objectives

To systematize the literature on graphic design generated by AI (2010-2025), in relation to attention, persuasion, and recall.

- To analyze the temporal, typological, and geographical evolution of the field.
- To identify authors, institutions, journals, and co-authorship and co-citation networks.
- To evaluate empirical studies on communicative effectiveness and methodological gaps.

4. THEORETICAL FRAMEWORK

4.1. Transformations of visual design mediated by artificial intelligence

The incorporation of algorithmic architectures such as convolutional neural networks and Vision Transformers (ViTs) has brought about a structural transformation of graphic design, shifting the focus from artisanal execution toward the automated and scalable generation of visualities. This technological turn reconfigures the epistemological foundations of design by introducing formal operations based on aesthetic classifiers, semantic segmentation, and algorithmic evaluation of compositional principles such as symmetry, balance, or visual harmony (Li et al., 2022; Yun, 2025).

From this perspective, AI-generated design not only automates procedures, but also redefines key notions such as visual authorship and creative agency, shifting the role of the designer toward curatorial functions and algorithmic oversight (Laba, 2024). This shift demands new frameworks of critical literacy, as proposed by recent educational models such as TPCACK or IDEE, aimed at integrating visual thinking, technology, and cultural agency (Hwang & Wu, 2025).

4.2. Historical evolution and discursive consolidation

Between 2015 and 2025, the field has experienced an accelerated discursive consolidation. From the first experiments with artistic GANs and symbolic auctions such as that of Edmond de Belamy (Rani et al., 2024), to the proliferation of generative systems in advertising, education, and digital visual culture, AI has gone from being a marginal resource to a structuring actor in visual production.

This trajectory has not been exempt from controversies over originality, intellectual property, and visual ethics, issues that have given rise to a growing need for interdisciplinary critical analysis.

A diachronic reading of the incorporation of AI in visual design reveals an accelerated progression in the last decade:

- 2015-2017: proliferation of neural style algorithms such as DeepArt and first generative networks (GANs) for visual art (Goodfellow et al., 2014).
- 2018: sale of Edmond de Belamy, the first AI-generated work auctioned at Christie's, which reopens the debate on authorship (Rani et al., 2024).
- 2020-2022: widespread adoption of generative AI in educational and advertising environments; improvement in classification models and computational aesthetics (Li et al., 2022).
- 2023-2025: consolidation of models such as ViTs and emergence of pedagogical approaches TPCACK/IDEE in design (Hwang & Wu, 2025; Yun, 2025).

In this evolution, tensions have also emerged regarding originality, copyright, and ethical responsibility in automated visual production, issues that continue to demand sustained critical reflection.

4.3. Media cognition and persuasive principles

The persuasive effectiveness of AI-generated designs is analyzed from dual cognitive models that combine bottom-up processing (based on automatic visual stimuli) and top-down processing (modulated by the recipient's expectations and prior knowledge) (Chan, 2025). Studies from computational neuroaesthetics have shown that attributes such as symmetry, the center of gravity, or negative space influence aesthetic appraisal and ocular fixation time (Lin et al., 2024).

Likewise, it has been documented that perceptions of authenticity, semantic congruence, or perceptual fluency modulate communicative effectiveness, especially in contexts of symbolic consumption or affective decision-making (Zhou & Kawabata, 2023). These findings support the empirical analysis of indicators such as spontaneous recall, intention to act, or credibility attributed to the sender (Grassini, 2024).

4.4. Epistemological gaps and justification of the review

Despite technological and empirical development, relevant theoretical gaps persist. Many aesthetic models operate without considering the recipient's affective or symbolic dimension, which leads to excessively formalist approaches. In addition, an implicit bias toward AI-generated works remains, even when their aesthetic evaluation is positive (Zhou & Kawabata, 2023).

In this context, the concept of "algorithmic imagination" (Laba, 2024) makes it possible to interpret AI visualities as ideological constructions, traversed by dominant narratives and normalized aesthetics. In the face of this conceptual and methodological heterogeneity, a systematic review is justified that synthesizes empirical evidence, identifies analytical gaps, and proposes theoretical guidelines for future studies.

5. METHODOLOGY

This study adopts a systematic review methodology with a mixed bibliometric approach, aimed at analyzing the evolution, structure, and thematic patterns of the academic output on graphic design generated by artificial intelligence (AI), with an emphasis on its communicative effectiveness (attention, persuasion, and recall). The methodological strategy combines scientific performance analysis and structural analysis of semantic and collaboration networks, in accordance with replicable protocols and international standards for systematic reviews (Donthu et al., 2021).

The review was conducted following the PRISMA 2020 guidelines (Page et al., 2021) and supported by validated tools for structural bibliometric analysis (Aria & Cuccurullo, 2017).

5.1. Selection and processing of the corpus

The documentary corpus was constructed from the Web of Science – Core Collection (WoS) and Scopus databases, selected for their high scientific reliability and coverage in the relevant fields. The query, conducted in May 2025, applied structured search equations with Boolean operators, which articulated four key semantic dimensions: generative technologies ("artificial intelligence", "machine learning"), visual design ("graphic design", "visual communication"), persuasive effectiveness ("persuasion", "attention"), and cognitive variables ("impact", "consumer perception").

Inclusion criteria: peer-reviewed articles in English or Spanish, published between 2010 and 2025, with full text available. Theses, grey literature, and documents without empirical or systematic content were excluded. After removing duplicates, the final corpus included 250 documents (74 from WoS and 228 from Scopus). It should be noted that, although the publication range considered extends through the year 2025, the data corresponding to that year include only documents published up to June 1, 2025. This temporal limitation must be taken into account when interpreting analyses of annual evolution or emerging trends.

5.2. Analytical tool used: Biblioshiny

Biblioshiny, the graphical interface of the Bibliometrix package in R, was used to import and unify metadata, and to apply standard bibliometric analysis metrics. This tool makes it possible to generate replicable analyses on collaboration networks, conceptual structures, and thematic maps. However, it is acknowledged that reliance on metadata may limit interpretive depth in qualitative analyses.

5.3. Performance analysis

Scientific productivity was evaluated through indicators such as the annual volume of publications, the most productive authors and institutions, the average number of citations per document, and the degree of international collaboration. These data make it possible to quantitatively contextualize the evolution of the field.

5.4. Content analysis

The semantic analysis was structured in two phases:

- Phase 1: generation of keyword co-occurrence networks using the Walktrap algorithm (Pons & Latapy, 2005), using the association index as a normalizer (Wagner & Leydesdorff, 2005).
- Phase 2: construction of two-dimensional thematic maps (Cobo et al., 2011 model), classifying clusters according to their density and centrality.

Both phases made it possible to detect stable semantic cores and relevant research gaps.

5.5. Delimitation and function of the documentary corpora

Three differentiated sets were used:

- Bibliographic corpus: 250 analyzed articles.
- Referential corpus: selected theoretical literature according to disciplinary areas indexed in WoS and Scopus.
- Methodological corpus: technical sources on bibliometrics and network analysis.

5.6. Terminological and linguistic considerations

Although the article is written in Spanish, key terms are kept in English, respecting the original indexed semantic labels and preserving the lexical coherence of the analyses.

5.7. Nature of the study and epistemological approach

This study is exploratory and descriptive in nature. It does not seek to test causal hypotheses, but rather to map existing knowledge, identify patterns and gaps, and offer an empirical basis for future theoretical or experimental research.

6. RESULTS

6.1. Evolution of scientific production (2010-2025)

The annual evolution of scientific production on graphic design generated by artificial intelligence (AI) and its impact on communicative effectiveness reveals sustained growth, with a notable acceleration from the year 2020 onward. The bibliometric analysis, based on 250 peer-reviewed academic documents published between 2010 and 2025, makes it possible to identify three differentiated chronological stages, characterized by thematic, methodological, and lexical transformations that shape the emergence of a consolidating subfield.

- Phase I: Dispersed emergence and computational foundations (2010–2017)

  Between 2010 and 2017, academic production was virtually null. Only two documents were identified across the entire period—one in 2010 and another in 2014—which, according to the titles and recorded keywords, focused on technical foundations of visual automation and general digital visualization, without explicitly addressing image generation through AI models or addressing communicative or persuasive dimensions. In this pre-paradigmatic stage, concepts such as graphic design or persuasive effectiveness are absent, and the predominant terms are visualization and machine learning, in contexts unrelated to applied visual communication. This thematic scarcity justifies classifying this period as a stage of fragmentary emergence.

- Phase II: Thematic configuration and methodological consolidation (2018–2021)

  From 2018 onward, sustained growth begins in the volume of publications: 9 documents in 2018, 10 in 2019, 20 in 2020, and 19 in 2021. This initial upturn coincides with relevant milestones in the history of AI-generated art, such as the auction of the work Edmond de Belamy—created using generative adversarial networks (GANs)—at Christie's, an event that reactivated the debate on authorship, algorithmic creativity, and aesthetic legitimacy (Rani et al., 2024).

  During this phase, studies focus on the formal evaluation of visual compositions produced by AI, the development of segmentation, classification, and morphological image analysis models, as well as automated aesthetic computation (Li et al., 2022; Lin et al., 2024). Although technical-computational approaches persist, works begin to emerge that link visual generation with the recipient's cognitive and emotional reactions, laying the groundwork for a future communicative articulation.

  The dominant lexicon during this stage includes terms such as visual communication, machine learning, artificial intelligence, and image processing, with a growing frequency of expressions such as graphic design and visual analytics, which anticipate the field's communicational turn.

- Phase III: Communicative expansion and interdisciplinary maturity (2022–2025)

  The third phase is characterized by quantitative acceleration and unprecedented thematic sophistication. The number of publications rises to 31 in 2022, 44 in 2023, and reaches its maximum in 2024 with 74 documents, representing 29,6% of the total corpus. This boom coincides with the mass adoption of generative AI platforms such as DALL·E 2, Midjourney, Stable Diffusion, and Adobe Firefly, as well as their systematic implementation in advertising, institutional, and educational environments (Hwang & Wu, 2025).

  The 2025 data, corresponding only to the January–June period, record 41 publications, representing an increase of 36,6% compared to the same interval in 2024 (30 articles between January and June). This methodological clarification makes it possible to avoid a distorted interpretation of the annual volume and suggests a possible stabilization of the production rate at high levels.

  From a terminological standpoint, the specialized vocabulary reflects a consolidation of interdisciplinary frameworks. In addition to the terms already established, expressions such as visual communication design, deep learning, visual design, and adversarial machine learning are strongly incorporated, indicating both the computational maturity of generative models and their evaluation in contexts of communicative reception. Likewise, keywords such as electroencephalography, brain-computer interface, or attention reveal the growing adoption of neurocognitive approaches to evaluate the impact of these images on processes of attention, emotion, and memory (Chan, 2025; Grassini, 2024; Zhou & Kawabata, 2023).

This lexical shift is not only a reflection of a thematic expansion, but also of an epistemological redefinition: from the AI-generated image as a technical artifact to the image as a communicative act, susceptible to empirical evaluation from cognitive psychology, visual rhetoric, and persuasive communication.

The chronological and semantic evolution of scientific production between 2010 and 2025—this last year being considered up to June 1, according to WoS and Scopus data—confirms the transition from a technical-formal approach toward an interdisciplinary communicative agenda, centered on the analysis of the visual effectiveness of algorithmically generated images. The field is thus configured as an emerging space of high productivity, with increasing theoretical and methodological density, which justifies the need for a rigorous systematic review such as the one proposed here.

6.2. Most prolific journals

Production is distributed across 157 sources, although some key journals stand out. IEEE Access leads with 10 articles, moving from technical to communicative approaches (Li et al., 2022; Yun, 2025). It is followed by ACM International Conference Proceeding Series (8 documents), focused on creative and persuasive computing. With 5 articles each, CEUR Workshop Proceedings, IEEE Transactions on Visualization and Computer Graphics, Journal of Physics: Conference Series, and Proceedings of SPIE have evolved from algorithmic analysis toward cognitive metrics (Lin et al., 2024). Mobile Information Systems and Journal of Network Intelligence also contribute (3 each), as do international forums such as IASDR 2021 and Lecture Notes in Computer Science.

From 2022 onward, journals such as International Journal of Art & Design Education and Visual Communication have been incorporated, linking visual generation, aesthetic expression, and persuasive effectiveness (Hwang & Wu, 2025; Laba, 2024). Overall, the sources reflect a transition from the technological toward interdisciplinary consolidation in AI-generated design. Table 1 presents the ten authors with the highest total production volume, together with their fractionalized score.

6.2.1. Patterns of scientific collaboration

The average fractionalization index is 1,79 authors per article, reflecting open but not intensive collaboration, in line with what was noted by Wagner & Leydesdorff (2005) for emerging interdisciplinary fields. Studies on deep visual modeling show a higher number of co-authors, while those on aesthetic reception present a lower density. The analysis of titles, abstracts, and journals suggests a combination of computer engineering centers and design or communication departments, although without complete affiliation data. This hybridization favors integrated models for analyzing communicative effectiveness, such as those proposed by Hang Li and Guomin Huang through machine learning applied to visual semantic evaluation.

Table 1. Total, and fractional authorship contribution (source: authors' own elaboration based on Biblioshiny and Scopus (2025))

Author	Total publications	Fractional publications
Li, Yixuan	5	1,5
Lee, Sungyoung	4	1,39
Li, Jianjun	4	1,2
Wang, Jing	4	2,33
Huang, Guomin	3	0,7
Huang, Gang	3	1,31
Li, Fang	3	0,89
Li, Hang	3	0,67
Lin, Cheng	3	0,7
Lin, Jiawei	3	0,57

6.2.2. Productivity, trajectory, and impact

The most cited authors were identified on the basis of h, g, and m indices, together with total citation volume and year of first publication. Table 2 summarizes these indicators.

Table 2. Impact and trajectory indicators of prominent authors (source: authors' own elaboration based on Biblioshiny (2025); data cutoff June 1, 2025)

Author	h-index	g-index	m-index	Total citations	No. publications	Start year
Lee, Sungyoung	3	4	0,25	64	4	2014
Wang, Jing	3	3	0,6	41	3	2021
Wu, Yuchen	3	3	0,75	37	3	2022
Tang, Yu	3	3	0,5	26	3	2020
Ancau, Mihai	2	2	0,5	12	2	2022

Four authorship profiles are identified:

• Consolidated trajectories (Lee, Sungyoung), active since 2014.
• High recent performance (Wu, Yuchen), with a high m index.
• Technical leadership (Wang, Jing), with high fractionalization and impact.
• Emerging profiles (Ancau, Mihai), with a brief but coherent trajectory.

This diversity shows that leadership combines volume, specialization, co-authorship, and methodological orientation.

6.3. Productivity by affiliation

The institutional analysis shows that the University of Coimbra and the University of North Carolina lead production with 9 publications each, followed by Politecnico di Milano and the Chinese Academy of Sciences with 8. With 7 documents, the University of Technology Sydney and Nanjing University stand out, while with 6 appear the University of California System, Hong Kong Polytechnic University, and Huazhong University of Science and Technology. Finally, MIT records 5 contributions (Biblioshiny, 2025).

Leading universities focus on visual computing and human–computer interaction, progressively incorporating communicative objectives. In Asia, institutions such as the Chinese Academy of Sciences, Nanjing University, and Huazhong University of Science and Technology stand out in computer vision. For their part, Politecnico di Milano and Hong Kong Polytechnic University contribute from generative design and visual communication. After 2020, centers such as the University of Technology Sydney and MIT increased their output, while the University of California System maintains a stable presence linked to semiotic and communicational approaches.

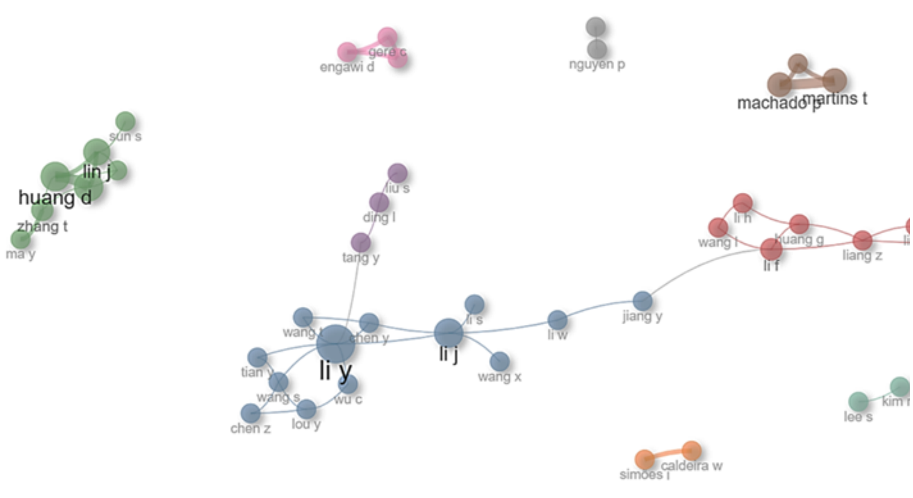
6.4. Authors' collaboration network

The co-authorship network analysis makes it possible to assess disciplinary consolidation and the emergence of scientific communities in AI-generated graphic design (Aria & Cuccurullo, 2017). Betweenness, accessibility, and impact (PageRank) metrics were applied, classifying authors into six structural roles. Profiles were identified with high accessibility (Caldeira W., Simões J., Nguyen P.), high betweenness (Tang Y., Ding L., Li J.), low betweenness and impact (Li H., He X., Tao J.), intermediate influence (Lin J., Zhang T., Huang D.), and moderate influence (Lou Y.). For example, Lin J. has worked on visual attention and aesthetic perception (Lin et al., 2024), while Tang Y. acts as a bridge between technical and communicative clusters.

6.4.1. Analysis of the subnetwork of the top 50 collaboration nodes

The subnetwork with the 50 authors with the highest PageRank, the most active collaborative core, was examined. This subnetwork (Image 1) presents 50 nodes, 1.225 possible links, a density of 0.0196, an average betweenness of 52.71, and an average accessibility of 0.1988, values higher than the full network (density 0.0083), which indicates greater cohesion and efficiency in information flow (Glänzel & Schubert, 2004). The analysis reveals moderate fragmentation and clusters defined by institutional and epistemological affinities, configuring a polycentric but integrated structure, typical of emerging fields.

Image 1. Distribution of authors by cluster (source: Biblioshiny (2025); data cutoff June 1, 2025)



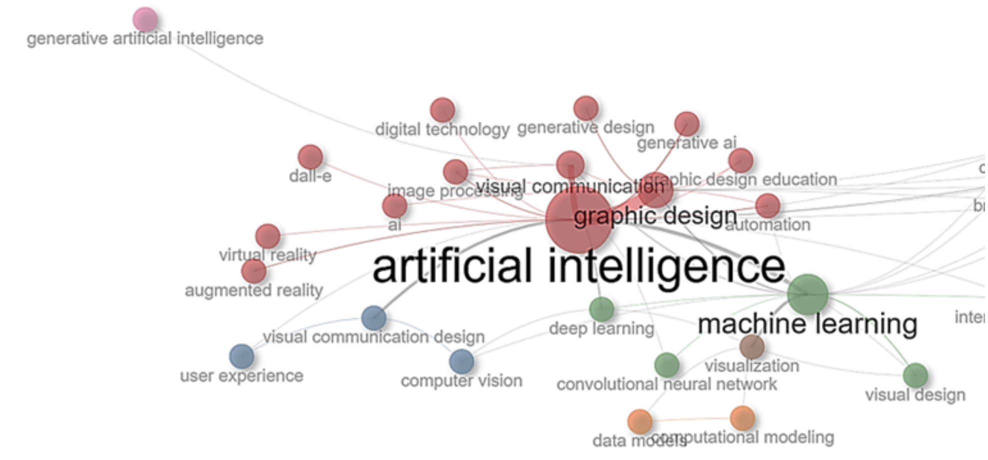
The structural analysis made it possible to identify emerging thematic lines in the most active clusters: computational aesthetics and visual perception (Zhou & Kawabata, 2023), education and pedagogical transition through models such as TPCACK (Hwang & Wu, 2025), visual representation and symbolic critique from "algorithmic imagination" (Laba, 2024), and technical infrastructure with Vision Transformers applied to communicative effectiveness (Yun, 2025). These trends, linked to central nodes, show methodological and conceptual diversity, and underscore the need for integrative approaches in future research.

6.5. Co-occurrence network of key terms

Based on 135 articles (2018–2025), a co-occurrence network with 52 nodes and 114 links was constructed, applying the Walktrap algorithm (Pons & Latapy, 2005; Aria & Cuccurullo, 2017) to declared and indexed terms (Callon et al., 1983; van Eck & Waltman, 2010), as observed in Image 2. Four clusters were identified: a visual-communicational one (graphic design, visual communication, DALL·E), another of computational infrastructure (machine learning, deep learning, convolutional neural networks), a third of interaction and experience (user experience, virtual reality), and a fourth of discursive applications (branding, co-design, algorithms). The network density (0,085) reflects medium cohesion and a balance between integration and diversity;

peripheral nodes (augmented reality, co-design) indicate incipient lines (Chen, 2006). The field appears structured around a robust core of interaction between AI and visual design, with still fragmentary areas that justify further research.

Image 2. Co-occurrence network of key terms (source: Biblioshiny (2025); data cutoff performed on June 1, 2025)



6.5.1. Communities in the semantic network

The complementary semantic categorization grouped six communities (Biblioshiny, 2025): generative modeling in design (automation through AI), evaluation of persuasive effectiveness (cognitive and emotional impact), user perception processes (attention, emotion, response), empirical validation methods (surveys, experiments), ethical and aesthetic controversies (authorship, biases, legitimacy), and communicative applications (advertising, social media, branding). These communities offer a cross-cutting reading that confirms three research vectors: algorithmic production, communicative-psychocognitive evaluation, and media-ethical applications. The network shows an expanding interdisciplinary ecosystem with technical, communicational, and critical convergence, but also with peripheral zones that require systematic and empirical integration.

6.6. Thematic areas

The analysis of thematic areas using Biblioshiny (Aria & Cuccurullo, 2017) makes it possible to classify conceptual cores according to centrality and density. Four categories are identified: motor themes, such as Persuasive AI visuals (AI design, attention, branding), a central line expanding on persuasive communication; basic themes, represented by Communication theory base (communication, message, audience), which constitute the foundational framework of the field; emerging themes, such as Ethics of automation (bias, authorship, deepfake), linked to incipient debates on ethics and authorship; and specialized themes, such as Cognitive theory cluster (memory, cognitive load, retention), consolidated but with low structural connection (Biblioshiny, 2025).

The conceptual evolution between 2010–2023 and 2024–2025 reveals a transition from thematic dispersion toward a technical hierarchization, articulated around GANs and machine learning. The consolidation of artificial intelligence as a macroconcept is observed, the transition from generative design toward GAN, and the fusion of visual design and user experience under machine learning. This convergence indicates a new epistemological regime in which algorithmic models not only produce images, but also mediate processes of signification, interaction, and visual persuasion.

7. CONCLUSIONS AND DISCUSSION

7.1. General conclusions

The bibliometric analysis of 250 documents (2010–2025) confirms a transition from technical-computational approaches toward an interdisciplinary configuration that articulates computer vision, persuasive communication, and media cognition (Chan, 2025; Lin et al., 2024). This process is corroborated by an annual growth of 28,09% and by the lexical and methodological diversification observed in the co-occurrence structures and thematic maps derived from Bibliometrix/Biblioshiny (Aria & Cuccurullo, 2017; van Eck & Waltman, 2010), with semantic communities detected through Walktrap (Pons & Latapy, 2005) and trends interpreted in accordance with scientific mapping frameworks (Chen, 2006; Donthu et al., 2021).

AI-generated design is thus emerging as a communicative practice that can be evaluated in attention, persuasion, and memory, although its consolidation is asymmetric: advances in algorithmic infrastructure and classification (Li et al., 2022; Yun, 2025) coexist with deficits in the integration of cognitive, affective, and contextual frameworks for a holistic evaluation of the recipient's experience (Zhou & Kawabata, 2023; Grassini, 2024; McCormack et al., 2019). The literature converges on three interdependent axes—algorithmic production, psychological/semiotic evaluation, and communicational applications—that structure an expanding transdisciplinary field (Laba, 2024; Hwang & Wu, 2025).

At the structural level, the co-authorship network exhibits low density and polycentrism with international collaboration of 6,8%, which limits the consolidation of integrative frameworks and the replicability of findings (Wagner & Leydesdorff, 2005). Overall, a sustained advance is observed in the empirical evaluation of the communicative effectiveness of AI design, together with the need for integrative models and mixed methodologies of high scientific rigor to articulate attentional, emotional, and mnemonic processes in real contexts of use (Lin et al., 2024; Zhou & Kawabata, 2023; Grassini, 2024; McCormack et al., 2019).

7.2. Theoretical implications

The results make it possible to outline an emerging theoretical framework of AI design as a communicative practice technologically mediated and cognitively modulated. First, a hybrid co-creation paradigm is consolidated that integrates algorithmic generation, human curation, and computational evaluation, questioning the human creation/automation dichotomy (Chan, 2025; Grassini & Koivisto, 2024). Second, the evidence suggests the co-occurrence of bottom-up (sensory perception) and top-down (contextual judgment) processes, which demands a multimodal approach to explain persuasive effectiveness (Lin et al., 2024).

Third, semantic mappings and co-occurrence show three structuring domains—generation, reception, and application—that legitimize the field's transdisciplinary anchoring (Aria & Cuccurullo, 2017; van Eck & Waltman, 2010; Laba, 2024). Fourth, terminological inconsistencies persist (e.g., "persuasion", "visual impact"), which calls for conceptual standardization and ecological validity of constructs and indicators (Donthu et al., 2021; McCormack et al., 2019). Finally, the incorporation of neurocognitive metrics—eye tracking, EEG, and cognitive load—articulates computational aesthetics with visual neuroscience, opening explanatory and predictive possibilities (Zhou & Kawabata, 2023; Grassini, 2024).

7.3. Practical implications

In professional applications, the results suggest that AI-generated compositions may show favorable metrics of attention and aesthetic judgment under specific experimental conditions, when principles of computational aesthetics (symmetry, hierarchy, balance) are optimized (Lin et al., 2024). The recipient's attitude toward what is generated by AI—including possible implicit attitudes—must be considered in communicative planning (Zhou & Kawabata, 2023). In branding and strategic communication, effectiveness depends not only on the sophistication of the model, but on the work of conceptual curation and the prompt architecture by the designer, who serves as a strategic mediator (Hwang & Wu, 2025; Laba, 2024).

AI can facilitate aesthetic personalization, automated A/B testing, and preference modeling; however, these capabilities require empirical validation with users through rigorous experimental designs and traceability between stimulus, response, and communicative outcome (Li et al., 2022; Chan, 2025; Grassini & Koivisto, 2024). In the fields of advertising and attitudes toward AI ads, the recent literature proposes frameworks to mitigate aversion and improve acceptance, an aspect relevant to responsible implementation (Sands et al., 2025).

7.3.1. Practical applicability of the theoretical framework

The study framework can be transferred to practice through specific procedures that guide the generation, evaluation, and professional use of graphic designs produced with

AI. First, the compositional principles identified—visual hierarchy, balance, figure–ground clarity, or semantic congruence—can be transformed into operational instructions integrated into prompts. Indications such as “focal point centered”, “balanced negative space”, or “coherent iconography” help obtain results more aligned with communicative objectives and with a project’s visual identity.

Second, bottom-up and top-down cognitive models make it possible to structure accessible and replicable communicative evaluations. Through A/B tests, small user groups can compare AI-generated variants by responding to specific questions about comprehension, credibility, or message clarity. This approach does not require specialized equipment and makes it possible to preliminarily validate communicative effectiveness prior to implementation.

With regard to optimizing visual effectiveness, AI enables rapid cycles of generation and selection. Brands, institutions, or creative teams can produce multiple versions of the same material with controlled variations in color, composition, or style. The designer, as a curatorial agent, identifies those options that can contribute to improving clarity, recall, or emotional impact, applying criteria derived from the theoretical framework.

Finally, these principles are operational in real professional environments. In agencies, AI is incorporated as an ideation and visual exploration phase; in institutions, it facilitates the consistent production of templates and graphic assets; and in education, it enables comparative exercises that strengthen visual literacy and critical evaluation. In this way, theory is translated into applicable procedures that can contribute to reinforcing coherence, efficiency, and communicative quality in AI-based projects, as synthesized in the following Table 3:

Table 3. Synthesis of the practical applicability of the theoretical framework (source: authors’ own elaboration)

Application axis	Practical action derived from the theoretical framework	Expected outcome
AI design generation	Incorporate compositional principles into prompts (hierarchy, balance, clarity)	Images more coherent with communicative objectives
Communicative evaluation	A/B tests with questions aimed at comprehension and credibility	Preliminary validation of communicative effectiveness
Visual optimization	Iterative generation–selection cycles with controlled variations	Potential improvement in clarity, recall, and impact
Professional production	Integration of AI into ideation, templates, and visual protocols	Greater coherence and efficiency in workflows
Educational environments	Critical comparison of AI-generated variants	Development of visual literacy and evaluative judgment

7.3.2. Integration of AI-generated graphic design in the marketing field

The evidence analyzed makes it possible to directly link AI-generated graphic design with key processes of strategic marketing. In the field of branding, generative models are integrated into the construction and management of visual identities by facilitating the rapid and coherent creation of stylistic variations aligned with positioning and with the brand's symbolic values, always under the designer's curatorial supervision as a strategic mediator (Hwang & Wu, 2025; Laba, 2024). Likewise, the ability to produce multiple visual alternatives increases the efficiency of A/B testing and favors the persuasive optimization of advertisements, promotional pieces, and conversion-oriented content.

From the consumer behavior perspective, recent research shows that aesthetic response, perceived authenticity, and attitudes toward AI-generated images influence message credibility and intention to interact, especially in contexts where affective decisions or symbolic consumption predominate (Zhou & Kawabata, 2023; Sands et al., 2025). This underscores the need to consider audience acceptance and possible cognitive biases in campaign planning.

The strategic use of AI in marketing makes it possible to personalize visual stimuli, adjust content according to segments, and generate more relevant communications, provided that criteria of conceptual coherence, professional control, and continuous empirical validation are maintained.

7.4. Study limitations

The study is limited to WoS and Scopus, with the consequent risk of coverage biases and anglophone taxonomies, in addition to reliance on metadata for structural analyses (Aria & Cuccurullo, 2017; Donthu et al., 2021). Disciplinary asymmetry is detected in favor of engineering and machine learning, while communicational and psychological approaches have lower representation (Li et al., 2022). Added to this are the collaborative fragmentation already indicated (Wagner & Leydesdorff, 2005) and the fact that the 2025 temporal cutoff includes only documents up to June 1, which conditions the reading of trends.

7.5. Future lines of research

(1) User experiments in ecologically valid contexts to evaluate attention, emotion, and memory; (2) hybrid evaluative models that integrate semantics, psychophysiology, and neurocognition (eye-tracking, EEG, cognitive load) (Lin et al., 2024; Grassini, 2024; Zhou & Kawabata, 2023); (3) ethical-sociosemiotic approaches in sensitive domains and in advertising to mitigate aversion and improve legitimacy (Sands et al., 2025; Laba, 2024); (4) study of the role of the designer as a strategic co-author (curation, prompts, style) (Hwang & Wu, 2025; McCormack et al., 2019); and (5) geographical and cultural

expansion of the empirical base, with attention to local visual capital and to international collaboration (Wagner & Leydesdorff, 2005).

7.6. Implications for a research agenda

An agenda is proposed that integrates (a) hybrid evaluation systems—persuasive indicators and neurocognitive metrics—for formative tests during visual generation (Aria & Cuccurullo, 2017; van Eck & Waltman, 2010; Pons & Latapy, 2005); (b) transdisciplinary programs that articulate generative AI, computational aesthetics, visual rhetoric, and design ethics (Laba, 2024; McCormack et al., 2019); and (c) lines on authorship, originality, and responsibility in human–machine co-creation, including criteria for the attribution of intentionality and legitimacy by audiences (Rani et al., 2024). In advertising, institutional communication, and experience design, it is advisable to incorporate evidence on attitudes toward AI-generated content to guide decision-making (Sands et al., 2025; Zhou & Kawabata, 2023).

8. AUTHORSHIP DECLARATION ACCORDING TO THE CRediT TAXONOMY

Rafael Braza Delgado: conceptualization; methodology; software; validation; formal analysis; investigation; resources; data curation; writing—original draft; writing—review and editing; visualization; supervision; project administration.

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