29th International Congress on Project Management and Engineering
Ferrol, 16th-17th July 2025

03-002 – Analysis of the use of Artificial Intelligence tools in industrial design – Análisis del uso de las herramientas de Inteligencia Artificial en el diseño industrial

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This study examines the capabilities, needs, and knowledge of designers regarding the use of artificial intelligence (AI) tools as support in the conceptual design phase. The research is grounded in the growing impact of AI on various creative disciplines, highlighting its potential to optimize and enrich the idea-generation process. Data collection involved the design of surveys targeting both professional designers and students, aiming to capture a broad and representative perspective. The surveys explore key aspects such as the level of familiarity with AI tools, specific areas of conceptual design where greater utility is perceived, primary barriers or limitations to their implementation, attitudes toward the integration of these technologies into the workflow, and the competencies deemed necessary for their effective use. The results aim to provide a detailed insight into how designers value and utilize AI in conceptual design, identifying opportunities for its development and integration into professional practice. This study seeks to serve as a foundation for developing strategies and tools that address the real needs of designers, fostering synergy between human creativity and technology.

Keywords: *Conceptual design; Artificial intelligence; Computer-aided design*

Este estudio analiza las capacidades, necesidades y conocimientos de los diseñadores respecto al uso de herramientas de inteligencia artificial (IA) como apoyo en la fase de diseño conceptual. La investigación parte del creciente impacto de la IA en diversas disciplinas creativas, destacando su potencial para optimizar y enriquecer el proceso de generación de ideas. Para recopilar datos, se diseñaron encuestas dirigidas tanto a diseñadores profesionales como a estudiantes, buscando abarcar una perspectiva amplia y representativa. Las encuestas exploran aspectos clave como el nivel de familiaridad con herramientas de IA, las áreas específicas del diseño conceptual donde perciben mayor utilidad, y las principales barreras o limitaciones para su implementación, así como las actitudes hacia la integración de estas tecnologías en el flujo de trabajo y las competencias que consideran necesarias para utilizarlas de manera efectiva. Los resultados esperan proporcionar una visión detallada de cómo los diseñadores valoran y emplean la IA en el diseño conceptual, identificando oportunidades para su desarrollo e integración en la práctica profesional. Este estudio busca servir como base para desarrollar estrategias y herramientas que respondan a las necesidades reales de los diseñadores, fomentando la sinergia entre creatividad humana y tecnología.

Palabras claves: *Diseño conceptual; Inteligencia artificial; Diseño asistido por ordenador*

Acknowledgments:

La investigación presentada en este artículo ha sido financiada por la Universitat Jaume I, con el proyecto GACUJIMC/2024/11. Agradecemos a Silvia Crespo la elaboración de los cuestionarios para la obtención de la información.

1. Introduction

Product design is a complex and iterative engineering process that involves numerous decisions at each stage. It begins with the identification of a need or problem and is structured into various activities that lead to a detailed optimal solution (Hsu & Woon, 1998). Pahl et al. (2007) define three main phases: conceptual design, embodiment design, and detailed design. The conceptual phase is where the product's function is established, solution principles are explored, and combined into various alternatives (Takala, 1989). The initial stage of design is considered one of the most critical, as it sets the foundation for key product-related decisions (Raymer, 1999) and determines approximately 70–80% of the final product cost (Corbett, 1986). According to Briggs and Reining (2007), this is the phase in which relevant ideas and concepts are developed.

To support these decisions and reduce development time, pioneering companies have begun to adopt Artificial Intelligence (AI) (Cooper & McCausland, 2024). AI has experienced rapid growth, revolutionizing traditional workflows across numerous fields and industries (Bordas et al., 2024). It has been described as the ability of a system to accurately interpret external data, learn from it, and apply that knowledge to achieve specific goals and tasks through flexible adaptation (Haenlein & Kaplan, 2019). The emergence of AI has also had a significant impact on design engineering. Its rapid advancement has led designers to consider it an additional method for generating creative ideas (Oktradiksa et al., 2021). Yüksel et al. (2023) highlight that the emergence and swift evolution of AI tools provide designers with a broad range of options from which to choose. Chen et al. (2024) propose the integration of generative models to enrich conceptual design and interpret creative combinational designs.

Brem et al. (2021) analyze the role of AI and distinguish between its function as an enabler and as an originator of innovation. The originator role is based on the notion of AI as a method of invention, particularly in the context of classification and prediction tasks. It combines the generative and creative potential of AI, enabled by advances in machine learning and deep learning. This role supports the early stages of innovation by identifying problems or uncovering potential market-aligned solutions (Cockburn et al., 2019). It enhances the ability to explore a vast range of possible solutions, thereby helping to mitigate uncertainty and reduce the complexity faced by decision-makers (Townsend and Hunt, 2019).

In contrast, the enabling function is grounded in AI's capacity to integrate and combine data in novel ways, made possible by recent technological advancements (Dinov, 2018). It relies on leveraging AI to identify opportunities for improving the processes that drive innovation (Balasubramanian et al., 2020), to redesign how we identify and engage with key users (Kakatkar et al., 2020), and to determine which changes to implement in services to increase their success (Verganti et al., 2020). This enabling role is data-driven—the more data, the better (Gregory et al., 2020). Generative AI, in particular, stands out for its ability to create novel content by learning from large datasets. It can produce diverse outputs such as text, images, videos, high-quality graphics, and even 3D designs (Kılınç and Keçecioğlu, 2024).

Cooper and McCausland (2024) develop a framework that maps various applications of AI in new product development, based on the type of function involved—originator or enabler. In the concept development phase, key activities include the generation of novel ideas through generative AI, internet-based mapping, and concept evaluation, among others.

Several studies have highlighted the use of AI-based design tools (Arda, 2024; Ghorbani, 2023; Gmeiner et al., 2023; Guo et al., 2023; Ying et al., 2023; Chulvi, 2025), as well as current designers' attitudes toward the adoption of AI tools in design practice (Kalving et al., 2024; Saadi & Yang, 2023) and the benefits for companies (Cooper, 2024). Research has also explored the use of AI during the conceptual phase of the design process (Khanolkar et al., 2023). Authors such as Verganti et al. (2020) argue that experience and creativity from engineers and designers are essential in the innovation and design process involving AI. Therefore, the present study aims to analyze designers' knowledge and use of generative AI tools in the design process, as well as their perspectives on the limitations they have identified and the improvements they believe should be made to these tools.

2. Objectives

This study examines the capabilities, needs, and knowledge of designers regarding the use of AI tools as support during the conceptual design phase. The aim is to identify opportunities for the development and integration of AI into professional practice. This research seeks to serve as a foundation for the development of strategies and tools that address the real needs of designers, fostering a synergy between human creativity and technology.

3. Methodology

To conduct the survey, a heterogeneous population of professional designers was selected, aiming to include the widest possible range in terms of both age and experience in the design field, as these are likely the two factors that most influence both the knowledge and the use of generative AI tools. In total, 30 professional designers from the Valencian Community and Teruel were selected and invited to complete the survey. Additionally, the survey was shared on the social media platform LinkedIn in order to increase both the sample size and its geographical scope.

The survey was structured into three sections, based on the type of information being collected:

The first section included demographic questions:

- Age
- Gender
- Years of experience as a designer

The second section focused on their knowledge of generative AI tools:

- Which text-based generative tools they are familiar with
- Which image-based generative tools they are familiar with
- Which of these tools they regularly use in their professional work

The third section addressed their usage of such tools:

- What they use them for
- What limitations they have identified
- What needs they perceive

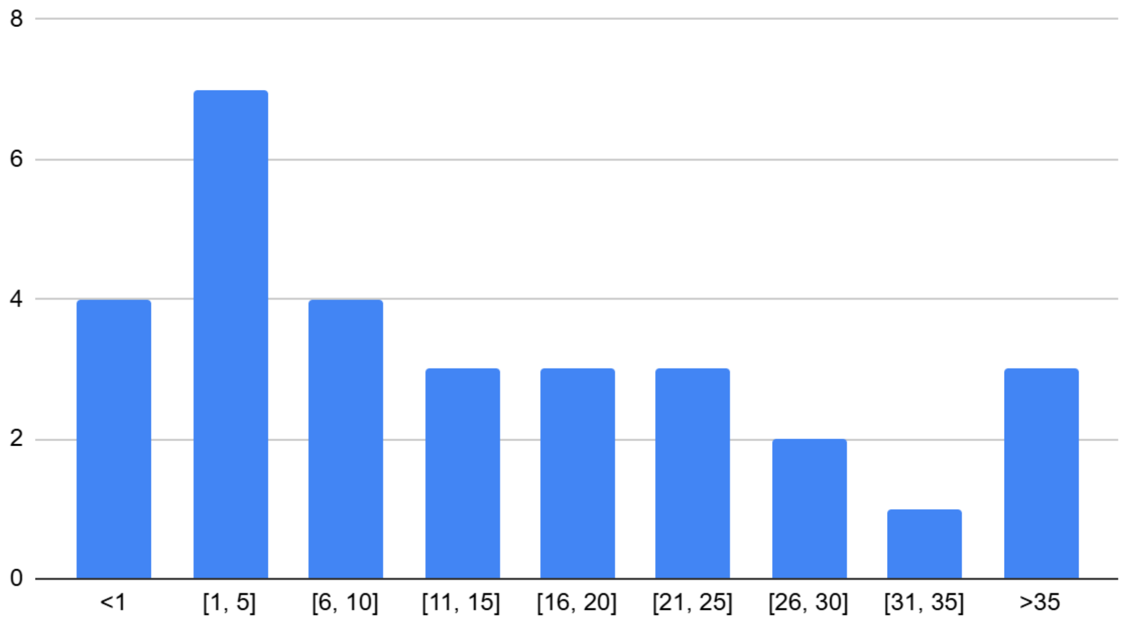
Finally, participants were asked about their willingness to collaborate in projects aimed at improving AI for use in the conceptual design phase.

These questions were answered on free-field forms so that designers were free to respond to as many tools as they knew without conditioning their answers. All this information will provide insight into the characteristics of the surveyed designers and their preferences when choosing or using AI tools.

4. Results

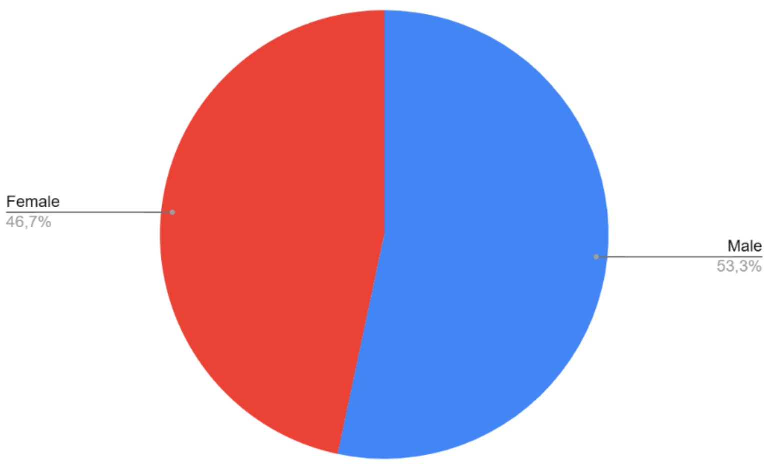
A total of 30 designers responded to the survey, with an average age of 37.2 years (standard deviation of 12.6), and an average professional experience of 15.4 years (standard deviation of 11.3). The standard deviation values indicate a highly heterogeneous group, covering a wide range of ages and levels of experience, which enhances the validity of the results. Figure 1 shows the number of designers surveyed for each age range indicated. There are 11 respondents with professional experience of 1 to 10 years and the same number between 10 and 20 years.

Figure 1: Number of designers surveyed by their professional experience (years).



In terms of gender, 16 respondents identified as male (53%) and 14 as female (47%), indicating balanced representation across genders (Figure 2).

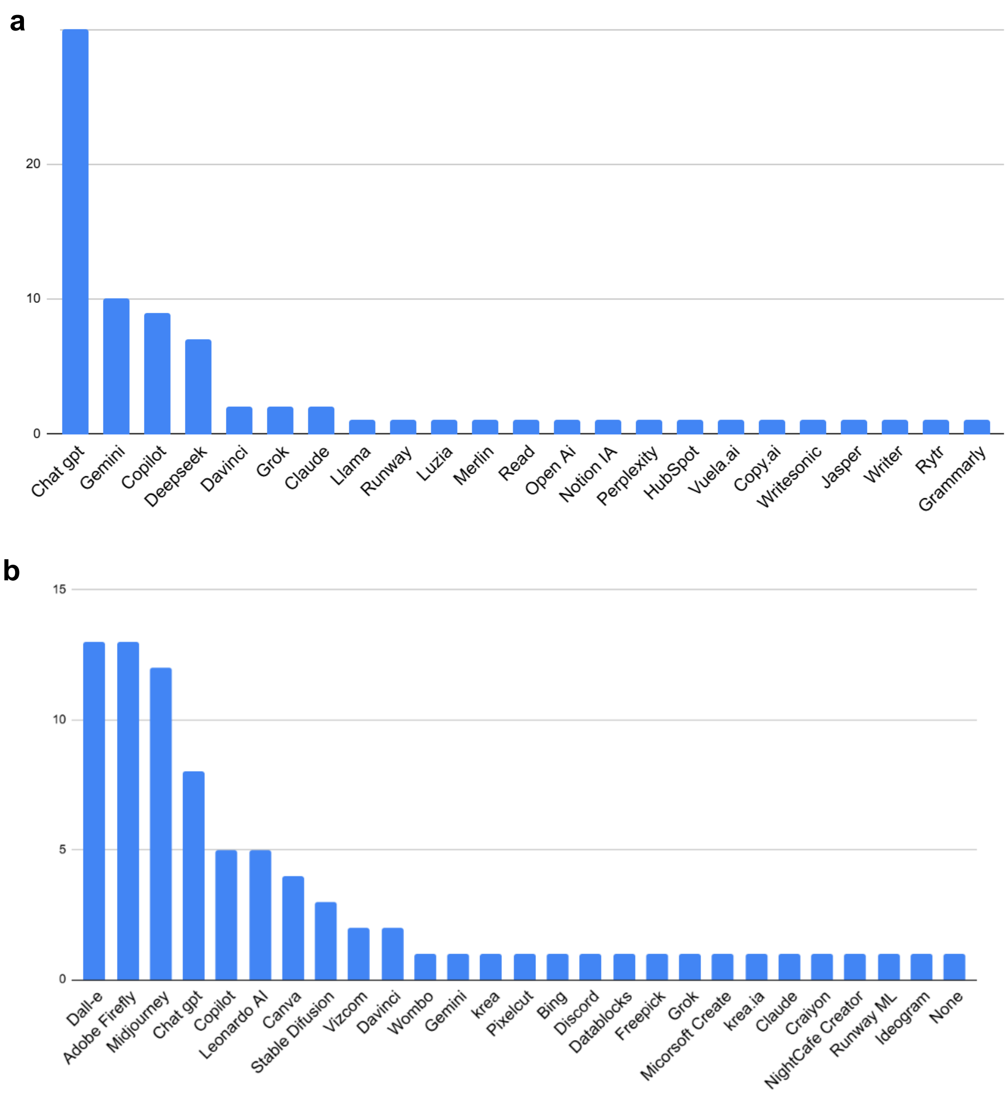
Figure 2: Gender of surveyed designers.



In the section related to their knowledge of generative AI tools (Figure 3a), results show that the most widely recognized text-based generative AI tool among professionals is ChatGPT, as all respondents reported being familiar with it. Other tools such as Gemini, Copilot, and Deepseek are also known by a significant proportion of designers (between 25% and 33%). Overall, respondents demonstrated familiarity with a broad range of text-based generative AI tools—23 in total. However, most of these tools were mentioned by only one or two individuals, such as Llama, Open AI or writer, among others, indicating a very limited awareness of their existence among the wider group.

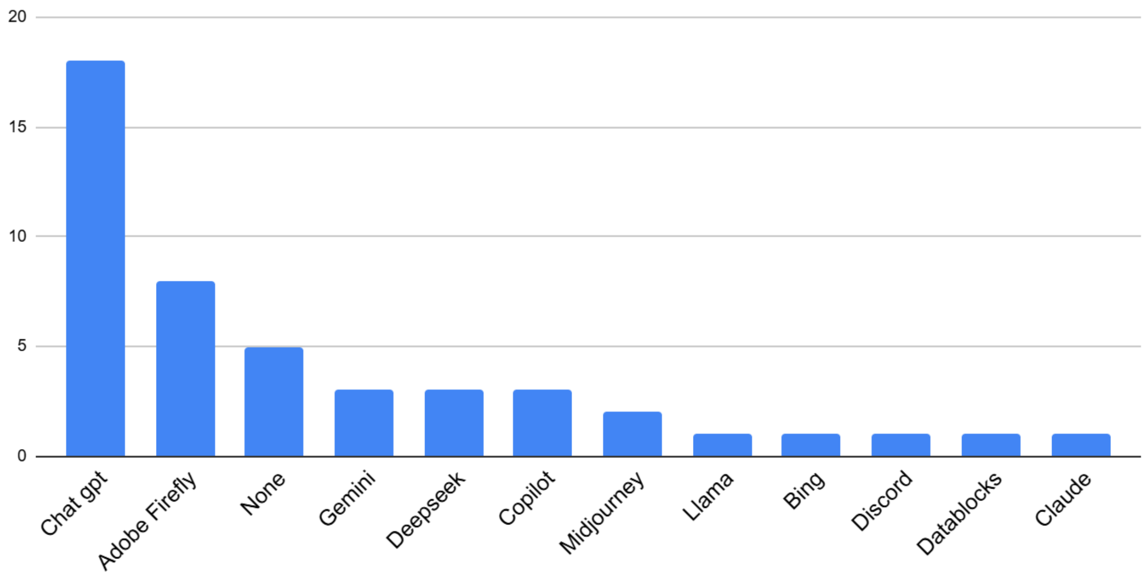
Regarding knowledge of image-based generative AIs (Figure 3b), among the 28 tools mentioned by respondents, none was known by all participants. However, a few tools stood out as being recognized by more than one-third of the respondents: DALL·E, Adobe Firefly, and Midjourney. Similar to the previous case, many tools were mentioned by only one or two designers (Claude, Ideogram, Open AI, Bing, among others), indicating limited awareness. In the mid-range, tools such as ChatGPT, Copilot, and Leonardo AI were reported as known by between 15% and 25% of participants.

Figure 3: a)Text-Based generative AI tools known by designers, b) Image-based generative AI tools known by designers.



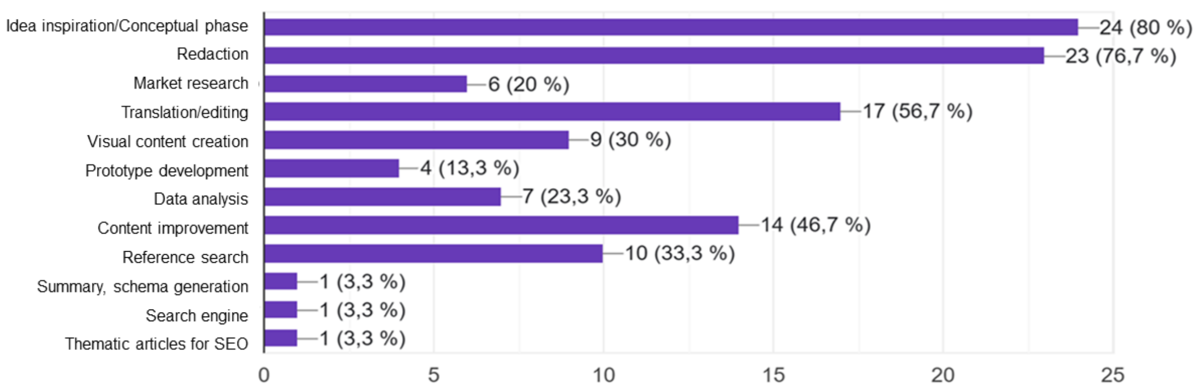
However, despite the wide range of generative AI tools known by the respondents, when asked about their regular use in their work, the total number of tools cited dropped to 11, most of which are used secondarily (Figure 4). The tool most frequently reported as being used by designers is ChatGPT, with 60%, followed by Adobe Firefly at 23.4%. In third place, 16.7% of respondents indicated that they do not use any generative AI tools in their professional work. Other tools that also stand out are Gemini, Deepseek and Copilot, which are ranked at a lower percentage.

Figure 4: Generative AI tools used in their work.



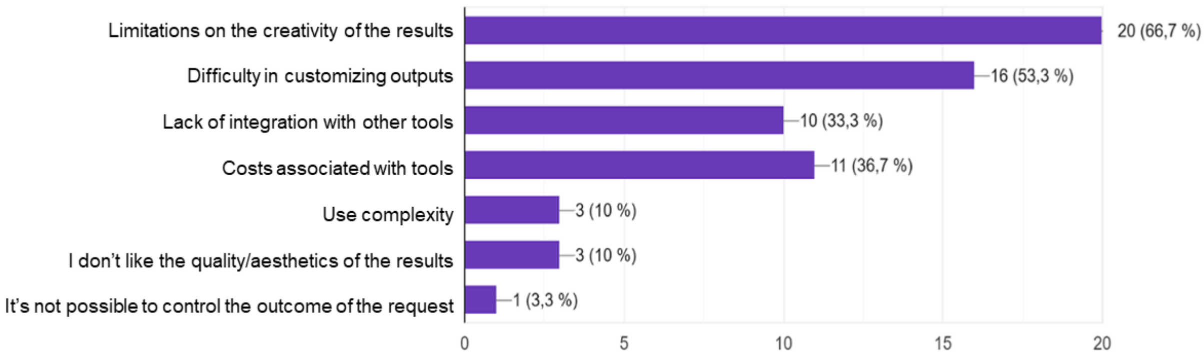
In the section of the survey related to the use of generative AI tools in their design work, we can see (Figure 5) that the most common uses are for inspiration searching in the conceptual phase (80%) and assistance in writing and redaction (76.7%). In addition to these uses, approximately half of the respondents also use them for translation or linguistic correction and for content enhancement. Other notable uses of AI tools by designers are also background research, visual content creation, reference searching for bibliography and finally, data analysis.

Figure 5: Use of tools employed.



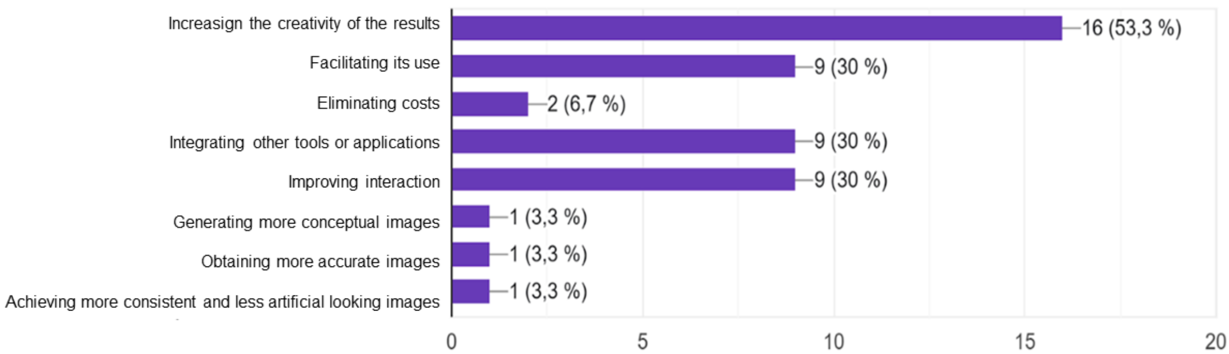
When asked about the shortcomings they perceive in these tools (Figure 6), the main issue identified was the limited creativity of the outputs generated by AI. The second most frequently mentioned concern was the difficulty in customizing the results. Additionally, approximately one-third of the respondents pointed to the associated costs of the tools and the lack of integration with other software as further limitations. Destacan respuestas como la complejidad de uso por parte de los diseñadores o bien la falta de calidad de los resultados.

Figure 6: Gaps in the tools used.



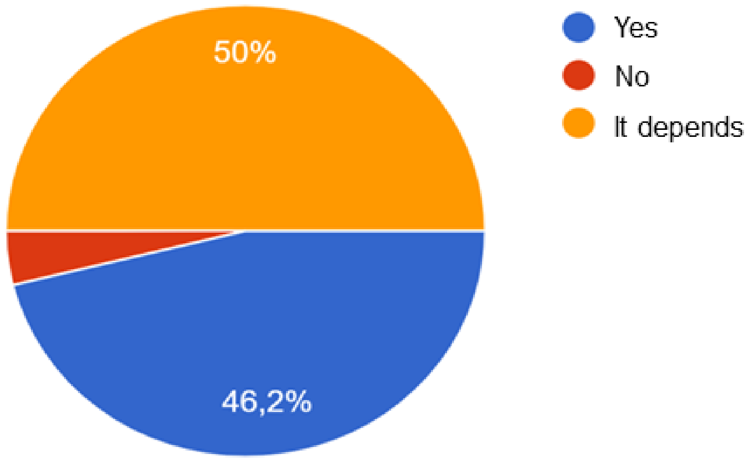
Regarding how they would like generative AI tools, to assist them in the design process (Figure 7), the most frequent response was to enhance the creativity of the outputs. Other common requests among respondents were improved interaction with different tools, ease of use, and better integration with other tools or applications.

Figure 7: How should the tools help in the design process?.



Finally, when asked about their willingness to collaborate on projects aimed at improving AI for use in the conceptual design phase, the majority of responses were positive (Figure 8), with only 3.8% of respondents expressing a negative stance. However, half of the respondents indicated that their participation would depend on the specific nature of the collaboration.

Figure 8: Willingness to collaborate in an AI improvement research project to optimize the conceptual creative design process.



5. Discussion and conclusions

From the first block of questions, related to demographic data, it is evident that the sample represents a heterogeneous group in terms of both age and professional experience. This is relevant, as diversity in participant profiles adds significant value to the validity and generalizability of the results. Furthermore, the nearly balanced gender distribution—53% male and 47% female—allows for the analysis of trends without gender bias that could otherwise affect data interpretation.

In the section related to knowledge of generative AI tools, although a large number of tools were mentioned (23 text-based and 28 image-based generative tools), most of them are known only marginally. This suggests that in-depth knowledge is concentrated around a few tools, likely due to their popularity or practical utility in the field. Regarding professional use, a significant gap is observed between awareness and actual application. Only two tools were mentioned as being used regularly and not just occasionally. This may indicate either a lack of understanding of the potential benefits offered by generative AI tools, or a perceived lack of practicality in their professional application.

This conclusion is further supported by the fact that 16.7% of professionals reported not using any generative AI tools in their work. This could be due to skepticism, a perceived lack of need, barriers such as the creative and customization limitations highlighted in the results, unawareness of potential benefits, or a preference for traditional methods. It is important to note that this is not attributable to an age-related bias, as the age range of professionals who reported not using any generative AI tools spans from 26 to 61 years.

In the section related to the professional use of generative AI tools, the main applications are centered on idea inspiration (80%) and writing assistance (76.7%). This suggests that professional designers primarily value these tools as support during the early stages of the creative process rather than as comprehensive design solutions, potentially indicating a lack of technical depth in the AI-generated design outcomes (Arkhipenko, 2016; Shuldeshova, 2016). It may also reflect a limited awareness of the full range of functionalities that these tools can offer in the design process (Chulvi, 2025), resulting in their use being restricted to these two basic functions.

Moreover, the perceived limitations—particularly in terms of creativity and result customization—suggest that generative AI tools still fall short of fully meeting the sector's expectations. In this regard, Jiang and Luo (2024) point out that, although tools capable of automating design methodologies are emerging, there remains considerable progress to be made in the integration of design and AI within professional practice.

These perceptions may explain why designers mainly use these tools for basic tasks such as text generation and idea inspiration, and why 16.7% of the respondents report not using them at all. Additionally, factors such as cost and lack of integration with other tools may be hindering broader adoption. When examining designers' expectations for these tools, the main demands align precisely with these areas, indicating a clear direction for the development of strategies and tools that address the real needs of designers—fostering a more effective synergy between human creativity and technological support.

After the analysis performed, and analyzing the results obtained, we suggest characteristics of use and application for future tools focused on the use by designers. First, to promote training in this type of tools in order to avoid barriers to their use. Secondly, an improvement in the development of the tools in technical and methodological knowledge of product engineering. Therefore, an integration of technical databases and an automation of methodological processes may be a good solution to consider for future developments.

In addition, and according to the results obtained from the last question of the questionnaire (Figure 8), 50% of the respondents would be willing to participate in improvement projects and tool analysis as long as they knew in advance the involvement of the collaboration. This willingness or interest also points to the need to generate this type of improvement.

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Use of Generative Artificial Intelligence

No generative artificial intelligence was used in preparing this communication.

Communication aligned with the Sustainable Development Goals

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

SUSTAINABLE DEVELOPMENT GOALS