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Data or Design First? Rethinking the roles and challenges of designers in the era of data-centric Artificial Intelligence

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ABSTRACT

The shift from model-centric to data-centric artificial intelligence (AI) represents a paradigm change that demands active engagement from designers. Using a high-level literature review and the Data-Information-Knowledge-Wisdom (DIKW) framework, this study identifies five key challenges designers face in AI development: aligning AI with user needs, leveraging small yet high-quality user data, uncovering nontrivial and meaningful patterns, refining AI models through iterative usability testing, and envisioning robust data pipelines. These challenges underscore the critical role of human input in mitigating blind spots in AI systems and fostering practical, human-centered solutions. The results emphasize the transformative potential of collaborative intelligence—an active learning process between human designers and AI systems. This approach bridges the gap between abstract computational processes and real-world applications, empowering designers to drive innovation while ensuring ethical accountability.

Keywords: Artificial Intelligence (AI), Data-centric AI, Data-Information-Knowledge-Wisdom (DIKW), Creative Intuition, Designer.

INTRODUCTION

How do microwaves work? What are the various components of a microwave? Many people might not know the answers to these questions, even though they use microwaves regularly. What's evident is that they trust the microwave to fulfill their needs. This trust doesn't stem from an understanding of its wiring diagram but from the device's ability to meet their expectations—namely, quick heating and the preparation of delicious meals. Dr. Cassie Kozyrkov, Google's chief decision scientist, uses this analogy to explain AI: "You can use a microwave without knowing how to build it or indeed how to build a new and better one" (Kozyrkov, 2018). However, unlike microwaves, building trust in artificial intelligence (AI) remains an ongoing and complex process.

Since its inception, both AI experts and everyday users have wrestled with the technology's opaque, "black-box" nature. Considerable effort has gone into making AI more transparent, reliable, and socially trustworthy (Mueller, 2019; Brundage et al., 2020). However, many HCI and design researchers argue that designers' limited understanding of AI often obstructs effective human-AI interaction. To address this, designers must urgently learn how to collaborate not only with data scientists but also with the algorithms themselves (Stembert & Harbers, 2019).

Returning to the microwave analogy, it is worth questioning whether the design research community is overly focused on the algorithmic and technical aspects of AI. Instead, should we not shift attention to the "ingredients" needed to create models and to the types of models (or "dishes") that truly meet human needs? This perspective resonates with the emerging concept of AI as a design material in the design research community (e.g., Yang et al., 2020; Yildirim et al., 2022), which seeks to explore new opportunities and applications of AI. For example, recent research on the intersection of AI and design (Verganti et al., 2020) shows that AI doesn't replace the principles of human-centered design. Instead, it extends the scale, scope, and learning potential of the design process, addressing previous limitations.

In this context, the study aims to explore the evolving roles and challenges designers face in working with today's AI. It also seeks to advance human-AI collaboration by encouraging designers to engage with these emerging challenges. To achieve this, the following three research questions were formulated:

1. How can the current design process be improved in this era of data-centric AI?
2. What are the opportunities that exist for designers that apply AI to address challenges?
3. What are the transformative roles for designers when working with AI?

To address these questions, a high-level literature review and holistic analysis were conducted, examining the transition from the model-centric to the data-centric AI era through a designer's lens. The well-known Data-Information-Knowledge-Wisdom (DIKW) framework was revisited to highlight the evolving role of data in AI systems. From this, five key challenges faced by designers were identified and linked to the AI development process and the DIKW model. Finally, the study discusses the transformative roles designers can assume to navigate this rapidly evolving landscape.

1. TOWARDS A DATA-CENTRIC AI ERA

Before we delve further into what AI is, it's important to note that most people, when asked to explain modern AI, tend to mention terms like "machine learning" or "deep learning." Those with more advanced knowledge might differentiate between machine learning, which offers higher interpretability due to its statistical foundation, and deep learning, which delivers unparalleled speed and accuracy for processing large-scale data (Dargan et al., 2019).

While these common statements are not incorrect, Larson (2021), in his book The Myth of Artificial Intelligence: Why Computers Cannot Think the Way We Do, emphasizes three key factors that critically shape our understanding of modern AI: empirical findings, data frequency, and model saturation. The first two factors highlight data concerns—training datasets represent empirical findings from the past, and their effectiveness often depends on the availability of larger data volumes. The third factor underscores model limitations, noting that accuracy often reaches a threshold. For example, despite years of advancements, top-performing models in the ImageNet Challenge have not surpassed 98% accuracy.

These limitations are more than theoretical. For instance, Roccetti et al. (2019) observed that a deep learning model trained on years of water consumption data with multiple attributes produced suboptimal results. However, domain experts achieved superior outcomes by applying their intuition to interpret the data and identify meaningful patterns. This case

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demonstrates how human expertise can compensate for low-quality data, leading to better predictive power. Why is this so?

Figure 1. Data-centric AI (Revised from the work of Ng et al. (2021)).

Figure 1 highlights the key concepts of AI as defined by Ng et al. (2021). Their research team introduced the concept of data-centric AI in early 2021, promoting the development of high-quality, small data-based AI as an alternative to traditional model-centric approaches. According to Ng et al. (2021), data-centric AI refers to computational algorithms designed to identify statistically significant patterns (statistical regularities) by analyzing accessible and collectible data. The focus is not on causality but on uncovering similarities and differences in phenomenological data patterns through associations or correlations across variables, attributes, or parameters.

AI algorithms represent intelligence (AI models) and are primarily composed of computer code. Data, particularly big data, serve as the foundational nourishment for AI models, enhancing their performance and capacity. While AI excels at solving well-structured problems, its application to ill-posed or wicked problems often yields less reliable results. Addressing such challenges requires converting real-world problems into structured formats and reprocessing or collecting new data. Moreover, AI's inability to fully comprehend societal contexts necessitates continuous human oversight, particularly for tasks like bias detection and ethical accountability. For instance, consumer-facing AI systems have faced criticism for amplifying societal inequities (Akter et al., 2021). This process, often termed defining the AI problem, relies heavily on human intervention.

Once the AI problem is defined, data collection becomes essential. Most datasets are gathered automatically using predefined protocols or pipelines. However, selecting and curating high-quality data often requires human input, which introduces the risk of unintended biases that can degrade AI performance. Recently, a shift towards using smaller, high-quality datasets has gained momentum. Unlike traditional approaches that emphasize large datasets, data-centric AI prioritizes smaller datasets with higher precision and relevance, such as customer behavior data from ethnographic studies (Lew et al., 2020). This approach minimizes bias and ensures reliable results even with limited data.

Despite these advancements, data remains one of the most significant bottlenecks in AI. As Larson (2021) points out, data is inherently retrospective, capturing past events but incapable of fully predicting future occurrences with certainty. For example, while historical data lacks records of hypothetical events—such as a new train route connecting Seoul to Paris via North Korea—such possibilities remain within the realm of future occurrences.

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2. NEW CHALLENGES FOR DESIGNERS IN THE DATA-CENTRIC AI ERA

In today's AI-driven world, data—whether big, small, high-quality, or noisy—has been heralded as the key resource for growth and innovation. Yet, data alone accomplishes nothing. It must be contextualized and structured to inform decisions and actions effectively.

The DIKW framework provides a clear hierarchy: data leads to information, information leads to knowledge, and knowledge culminates in wisdom. Each layer adds greater value than the previous one (Ackoff, 1989; Targowski, 2005) (see Figure 2a). Data, in its raw form, is objective and observational. It may exist in unstructured or unprocessed formats, such as income levels, geographic information, online behaviors, or survey results (VoCs). When contextualized and structured through pre-processing and exploratory data analysis (EDA), data becomes information. This information conveys meaning, though it may not always be immediately useful (Jifa & Lingling, 2014). Aggregated pieces of information can form knowledge, which allows decision-making for specific problems. At the pinnacle of the framework, wisdom—the rarest form of insight—is achieved through the deep internalization of knowledge patterns and relationships.

Progressing up the DIKW hierarchy has been the focus of data science and knowledge management communities, which have demonstrated strong capabilities in the first two layers: converting data into information and information into knowledge. Tools such as text mining, data warehousing, knowledge discovery in databases (KDD), and intelligent knowledge systems have proven effective (Leondes, 2010; Jifa & Lingling, 2014). However, significant gaps remain in the transition from information to knowledge.

The advent of AI has played a pivotal role in accelerating this progression. AI excels at uncovering context within information by recognizing unknown patterns, grouping elements, and performing classifications (Rao, 2018). This capability is particularly critical in design contexts, where labeled user behavior data is often scarce (Park, 2023).

Within the DIKW framework, we explore how AI processes translate into actionable outcomes by identifying five key challenges. These challenges emerge at various stages of AI development and reveal new opportunities for designers to collaborate effectively with AI systems during the development process (see Figure 2b).

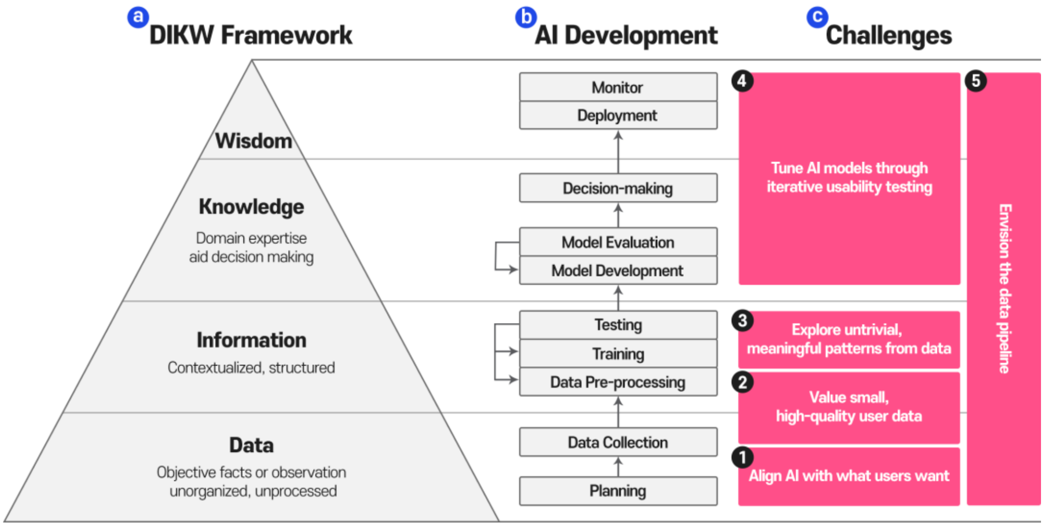

Figure 2. New challenges for designers working with AI within the data-information-knowledge-wisdom (DIKW) framework.

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2.1. Align AI with what users want

The section titles should be sub-numbered. The first letter of each word should be capitalized. In addition, you should apply the PARAGRAPH style to the body text.

When planning new AI products and services, it is crucial to ensure that the goals of AI align with user needs. Using the analogy of microwaves, trust in AI arises when users feel confident that the system will perform the desired task without unexpected outcomes. Trust, however, is fragile and can quickly dissipate if expectations are not met (Lew et al., 2020).

Prof. Stuart Russell, a pioneer in modern AI research, emphasizes that asking AI experts to ensure that AI creates only what is useful for humans is insufficient. Instead, he argues that AI must understand human values based on a provably beneficial concept (Russell & Norvig, 2022). This concept is guided by three principles:

- Principle 1. The purpose of the machine is to maximize the realization of human values.
- Principle 2. The machine is initially uncertain about what those human values are.
- Principle 3. Machines can learn about human values by observing the choices humans make.

These principles underscore the importance of prioritizing human values as a key objective in AI development and highlight the need for collaboration with designers to address the subjectivity and uncertainty of human behavior. Designers play a pivotal role, not only in facilitating data collection but also in maintaining consistent human-AI interaction to keep systems informed (Cordeiro et al., 2020).

The primary function of AI should not necessarily be to optimize outcomes but rather to efficiently and accurately determine human preferences. For instance, consider Amazon product reviews: AI decision-making based on the content of reviews is likely to better capture user preferences than a simple analysis of review numbers. Thus, AI goals should focus on identifying and reflecting actual human preferences rather than merely providing quick evaluations. Such systems can enhance decision-making processes for users by presenting relevant insights aligned with their needs.

2.2. Value small, high-quality user data

The second challenge highlights why active design research remains indispensable when working with AI. While aligning AI with human values is essential, identifying preferences for all stakeholders is inherently complex and uncertain. This uncertainty, which arises from the interplay of various objective functions, is often a key factor in the reduced reliability of AI systems.

To address this, the use of diverse user data—both physical and mental actions—becomes critical. Designers can collect such data through methods like observations, interviews, or surveys, enabling them to deeply understand problem domains and provide AI with small but high-quality datasets. This approach aligns with the ongoing debate about a data-first versus design-first approach. Stembert and Harbers (2022) argue that a data-first approach risks generating solutions misaligned with user needs or problem statements (Colborne, 2016).

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Russell's third principle, "Machines can learn about human values by observing the choices that humans make," reinforces the importance of an active learning approach. This method ensures the continuous collection of extensive decision-making data. For practical implementation, researchers like Dove et al. (2017) and Yang et al. (2018) emphasize the need for close collaboration among designers, data scientists, and domain experts. By valuing both small and large datasets—but ensuring quality—designers can ensure that human perspectives remain central to AI development.

2.3. Value small, high-quality user data

Before training and testing an AI model, designers must first evaluate whether the existing dataset contains errors or is suitable for analysis. Exploratory data analysis (EDA) is an essential tool for this process, offering a means to identify patterns and generate hypotheses. The primary objective of EDA is to uncover interesting, implicit, and potentially useful patterns or insights from large datasets that are often previously unknown (Behrens, 1997).

By recognizing such meaningful patterns, designers can bridge the gap between abstract data and practical, human-centered design needs. This approach enables the development of actionable insights that can directly inform the design process. To achieve this, designers frequently rely on statistical graphics and data visualization techniques, which are effective tools for exploring and presenting these findings in a comprehensible manner (Ma et al., 2017).

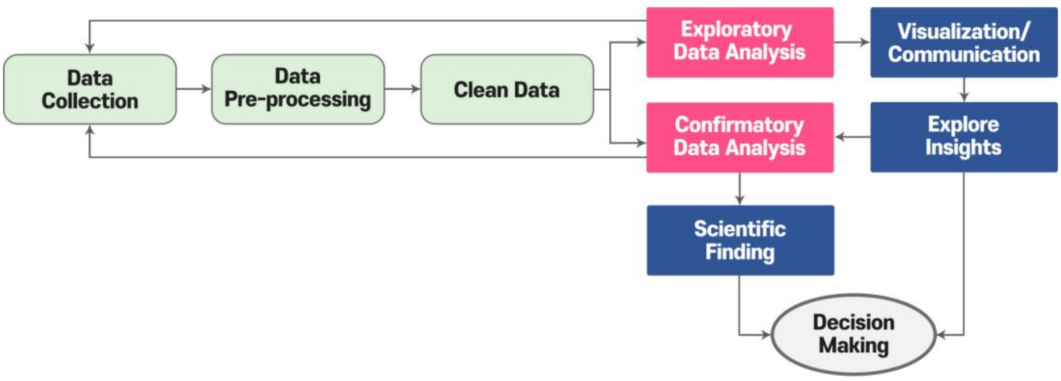

Figure 3. Key steps in a data analysis process (Revised from the work of O'Neil & Schutt, 2013).

As shown in Figure 3, compared to confirmatory data analysis (CDA), EDA offers a flexible and iterative cycle in the data analysis process. No hypothesis or models are needed in this stage; rather, EDA leads a data-driven adductive discovery using a plausible explanation for studied data. Earlier, Velleman & Hoaglin (1981) defined four basic components of EDA: data visualization, residual analysis, data transformation or representation, and resistance procedures. In particular, data visualization is primarily performed to communicate analysis results at the final and pre-decision-making stages of the study. Currently, many online tools are available to facilitate this stage, such as Excel, Tableau, and Microsoft BI.

2.4. Tune AI models through iterative usability testing

Once an AI model is trained, it is crucial to evaluate its outcomes. Usability testing aims to refine the model by observing how users interact with it and collecting implicit or explicit feedback. Depending on the project's goals and target audience, different usability methods must be employed (Amershi, 2019). In the early stages of development, when AI uncertainty

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is high, prioritizing human judgment and seeking in-depth expert feedback is beneficial (Xu et al., 2022). As the project matures, involving end-users or generalists can help conduct continuous usability testing while reducing time and costs (Hertzum, 2020).

Adopting up-to-date human-AI design guidelines, such as Microsoft's guidelines for human-AI interaction, the Google PAIR guidebook, or IBM's Design for AI, can bridge gaps in usability testing practices. Traditional design principles, like visibility, affordance, and consistency (Norman, 1988), often fall short when applied to AI products (Stembert & Harbers, 2019; Yang et al., 2020).

For instance, the interfaces of modern AI systems extend beyond graphical user interfaces (GUI) to include voice and face recognition, behavior-based interactions, and brain-computer interfaces. While GUI-based design principles, such as those using windows, icons, and menus, were effective for conventional systems, they are less suitable for AI products (Amershi et al., 2019). Furthermore, as AI systems evolve over time, traditional guidelines like "consistency," which minimize unexpected changes for users, often conflict with AI's dynamic nature. Therefore, it is vital to continuously revisit and adapt design principles to meet the unique demands of AI.

2.5. Envision the data pipeline

Envisioning the data pipeline for both existing and newly developed AI projects is arguably one of the most significant challenges designers face. Two primary scenarios often arise: (1) when data exists but its quality is questionable, and (2) when data is unavailable or difficult to access.

In the first scenario, despite the inherent challenges, systematic approaches can often address quality concerns effectively. For example, Sarfin (2021) outlines five key characteristics that ensure data quality: accuracy, completeness, reliability, relevance, and timeliness. Building on this, Lee (2022) provides an extended set of diagnostic questions that designers and developers should consider, including: "Does the dataset contain any non-factual values such as theories or interpretations? (factual data)"; "Is it collected from the (entire/randomly/evenly sampled) population of our interest? (unbiased data)"; and "Does it contain any duplicates or dummy records? (non-redundant data)." These guidelines are instrumental in enhancing the reliability and utility of datasets for AI applications.

It is also critical to recognize that human preferences evolve over time. Thus, continuous study of diverse user behaviors is essential. However, such studies often necessitate periodic data re-collection and retraining of AI models on varying time scales, depending on the specific application area.

The second scenario is more commonly encountered in the initial development phases of new AI systems (Yildirim et al., 2022). Early iterations of data-driven AI systems are typically incomplete, necessitating iterative development to refine the data pipeline. In such cases, designers must explore alternative solutions to overcome data limitations. One effective method is data prototyping, where designers create a preliminary data schema and flow tailored to the problem context and their interpretation of available data (Yildirim et al., 2022).

For instance, during the development of Amazon Echo, there were no pre-existing voice-command user datasets. To address this, Amazon conducted user tests, including the "Wizard

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of Oz" method, where simulated interactions were used to gather user behavior data. This data subsequently informed the training of their AI models (Strickland, 2019).

Finally, while ensuring the smooth functioning of data-driven decisions is crucial, equal attention must be given to investigating critical failure scenarios. These include instances where a model produces incorrect, incomplete, or no results at all (Fernandez et al., 2020). Addressing such scenarios is vital to developing resilient and reliable AI systems capable of performing consistently under various conditions.

3. TOWARDS A TRANSFORMATIVE ROLE OF DESIGNERS WORKING WITH AI

AI systems primarily rely on inductive inference to identify statistical similarities and differences across datasets and on propositional logic deduction based on factual reasoning. Modern AI predominantly uses supervised learning fueled by large datasets, employing inductive inference to solve problems or establish classification criteria. However, this reliance on inductive or deductive methods based on mathematical logic invariably leads to prediction errors.

Dr. François Chollet (2017), in his article "The Implausibility of Intelligence Explosion," contrasts this with human knowledge, which integrates situational, contextual, and temporal dimensions. Chollet emphasizes that causation—or causality—is the foundation of human trust, and AI's reliability will remain a challenge until it can establish causality (Pearl & Mackenzie, 2018). However, causality is developed through iterative cycles of hypothesis, experimentation, and verification over extended periods, making it practically impossible for AI to replicate causality in complex real-world applications.

Human intuition, while distinct from causality, provides a practical and realistic method for creating reliable data. Daniel Kahneman (2011), a Nobel laureate and renowned behavioral economist, highlights that heuristics, intuition, and guesswork, often associated with System 1 thinking, can outperform rational approaches in certain contexts. Supporting this, Roccetti (2019) demonstrates the efficacy of abductive inference, where data are presented to experts for iterative guesswork. Experts repeatedly determine why specific data are generated and subsequently enrich the data with meaningful attributes before applying machine learning or deep learning algorithms. This iterative and intuitive process is essential and must be consistently incorporated throughout the AI design process.

An active learning process emerges as an invaluable approach for integrating human intuition with AI development. Consider, for example, the classification of consumer reviews. While AI can classify textual reviews efficiently, achieving high accuracy without human intervention remains a challenge. Human oversight is necessary to train AI systems to focus on specific attributes or variables relevant to user needs, thereby improving the system's interpretability and performance over time. However, without such guidance, AI classification outcomes are prone to inaccuracy, particularly in initial iterations. This underscores why AI, despite augmenting human intelligence across various domains, has not yet surpassed human designers in their ability to intuitively solve complex problems.

The explanatory capabilities of AI can be further enhanced through active human intervention. By teaching AI systems to focus only on attributes that require human evaluation, designers can improve the system's transparency and trustworthiness. Bianchini and Maffei (2020)

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introduce the concept of experimental learning, emphasizing the emerging skillsets that designers must adopt to collaborate effectively with AI systems. These skills enable designers to leverage AI tools not as replacements but as complementary assets in the design process.

Figure 4 illustrates the active learning process between human designers and AI. In this process, human designers externalize their knowledge or intelligence to AI, preventing AI from setting the classification criteria, which is the modern AI design method or one of the greatest drawbacks of AI. Simultaneously, computer intelligence visualizes the process of inference to be able to communicate with designers and gains the opportunity to explain it, which is called an active learning process in the field of AI.

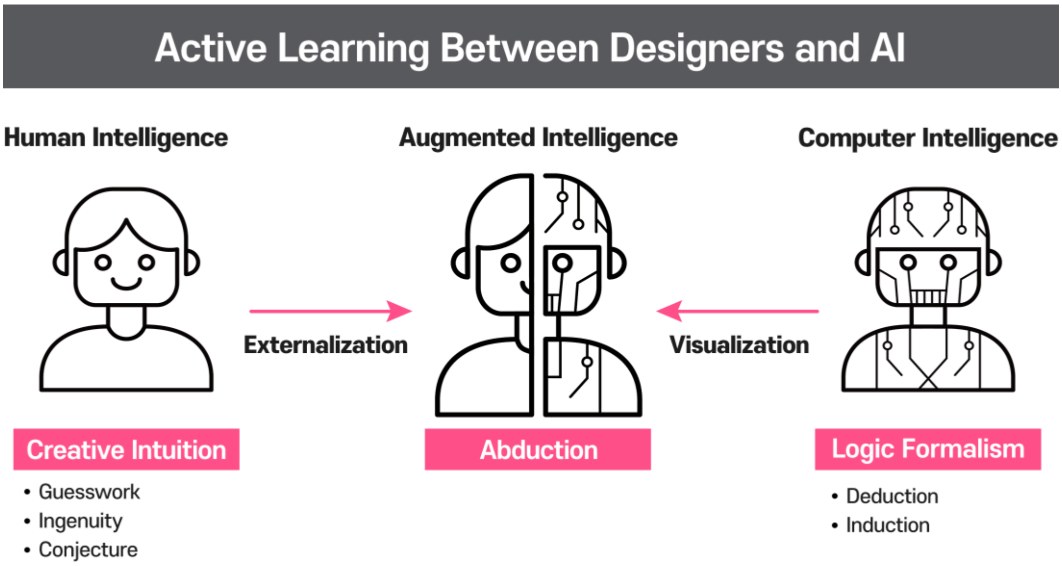

Figure 4. Active learning process between human designers and AI.

This active learning interface between a designer and AI plays the most important role in forming trust in AI, which informs humans of the predicted values, and humans have the authority to revise these values. Thus, AI models can be evolved through an appropriate level of designer involvement. However, possible bias in the data input by designers should be carefully dealt with through deliberation rather than by uncritically accepting them.

4. CONCLUSIONS

This study conducted a high-level literature review and holistic analysis of the ongoing transition from a model-centric to a data-centric AI era, focusing on a designer's perspective. Through this analysis, five critical challenges faced by designers in the AI development process were identified: (1) aligning AI with user needs; (2) valuing small, high-quality user data; (3) exploring nontrivial, meaningful patterns; (4) refining AI models through iterative usability testing; and (5) envisioning the data pipeline. These challenges highlight the indispensable role of human input in addressing blind spots during AI development and ensuring more robust outcomes.

Beyond its focus on design, this research extends its relevance to applied social sciences and emerging fields such as digital humanities, underscoring the potential of design principles to enhance data-driven AI systems. The findings reinforce the critical importance of a designer's creative intuition in the data-centric AI era, particularly in guiding AI systems toward achieving more meaningful and human-centered outcomes.

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By leveraging an active learning process, which facilitates collaborative intelligence between human designers and AI systems, better design decisions can be made. This approach not only fosters innovation in human-centered AI applications but also bridges the gap between abstract computational outputs and real-world user needs. Although the discussion on societal challenges and risks associated with the ubiquitous presence of AI in daily life remains measured, it lays the groundwork for addressing these pressing issues in future research.

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