World Journal of Advanced Engineering Technology and Sciences
eISSN: 2582-8266
Cross Ref DOI: 10.30574/wjaets
Journal homepage: https://wjaets.com/

(REVIEW ARTICLE)

INDUSTRIAL PRODUCT DESIGN IN THE AGE OF ARTIFICIAL INTELLIGENCE: FRAMING THE NEED, SHAPING THE USE

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World Journal of Advanced Engineering Technology and Sciences, 2026, 21(01), 136–146

Publication history: Received on 06 September 2026; revised on 12 October 2026; accepted on 14 October 2026

Article DOI: https://doi.org/10.30574/wjaets.2026.21.1.0476

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ABSTRACT

Artificial intelligence (AI) is increasingly embedded in physical products, from domestic appliances and vehicles to medical devices and wearables, yet the success of such products depends less on algorithmic performance than on whether people understand, trust and meaningfully integrate them into everyday life. This paper examines the contribution of industrial product design to the current need for, and use of, AI. Through a conceptual and integrative narrative review of literature in design research, human–computer interaction (HCI), computational design and AI ethics, it develops an analytical framework of five contributions: (1) framing human needs so that AI addresses problems worth solving; (2) making AI capabilities legible through form, interaction and feedback; (3) calibrating trust and control; (4) embedding AI in sustainable and ethical product lifecycles; and (5) integrating AI as a tool within the design process itself. The analysis indicates that industrial design acts as a mediating layer between technological capability and human practice, and that its contribution lies as much in deciding where AI should not be used as in enabling it. The paper closes with implications for practice, education and policy, and five propositions for empirical testing.

Keywords: Industrial Design; Product Design; Artificial Intelligence; Human-Centred AI; Generative Design; Trust; Sustainability

1 INTRODUCTION

Artificial intelligence (AI) has moved, within little more than a decade, from research laboratories and cloud services into the physical objects of everyday life. Robotic vacuum cleaners, learning thermostats, voice-controlled speakers, driver-assistance systems, hearing aids, fitness wearables and diagnostic devices now embed machine-learning components that perceive, predict and act on behalf of their users (Russell & Norvig, 2021). Advances in deep learning, and more recently in large-scale foundation models and diffusion-based image generators, have expanded both what such products can do and what designers can do with them (Bommasani et al., 2021; Ho et al., 2020; Rombach et al., 2022).

Yet technical capability alone does not explain whether an AI-enabled product is wanted, understood or used well. Research on automation has long shown that people may misuse, disuse or abuse automated systems when their capabilities are poorly communicated (Parasuraman & Riley, 1997), and studies of conversational agents and learning devices document a persistent gulf between what users expect and what the systems deliver (Luger & Sellen, 2016; Yang & Newman, 2013). Classic acceptance research reminds us that perceived usefulness and perceived ease of use, rather than technical sophistication, drive adoption (Davis, 1989). The question of how AI comes to be needed, and how it comes to be used, is therefore a question about design as much as about computation.

Industrial design, the discipline concerned with the form, function, interaction and meaning of manufactured products, occupies a distinctive position in this landscape. Industrial designers translate technological possibilities and human needs into tangible artefacts that people can perceive, handle and interpret (Norman, 2013; Ulrich & Eppinger, 2016). They shape what products communicate about themselves, their "product semantics" (Krippendorff, 2006), and they have long argued that innovation lies in new meanings as much as in new technologies (Verganti, 2009). Recent work suggests that this capacity for framing problems and giving meaning becomes more, not less, valuable as AI takes over parts of problem solving (Verganti et al., 2020).

Despite this, the contribution of industrial product design to AI remains scattered across separate literatures: human–AI interaction guidelines, computational and generative design tools, and AI ethics. Few contributions treat industrial design as an integrated mediating discipline that shapes both the need for AI in products and the manner in which AI is used. This paper addresses that gap through three research questions:

- RQ1. How does industrial product design contribute to defining where AI is genuinely needed?
- RQ2. How does industrial product design shape the way AI-enabled products are understood, trusted and used?
- RQ3. How is AI itself transforming industrial design practice, and with what consequences?

The paper makes three contributions. First, it synthesises literature from four streams that are rarely read together. Second, it proposes a five-part analytical framework that specifies the mechanisms through which industrial design influences the need for and use of AI. Third, it derives propositions and implications for practitioners, educators and policymakers. Section 2 reviews the theoretical background; Section 3 describes the methodology; Section 4 presents the results of the analysis; Section 5 discusses implications and limitations; and Section 6 concludes.

In conclusion, we stress the importance of all digital technologies along with AI in the field of design education. These technologies are highly effective and productive, facilitating and improving assessment, intervention, and educational procedures through mobile devices that bring educational activities anywhere [54], various ICTs applications that are the main supporters of education [55-58], and AI, STEM, and ROBOTICS that raise educational procedures to new performance levels [34-37]. Furthermore, the development and integration of ICTs with theories and models of metacognition, mindfulness, and the development of emotional intelligence [63-64] accelerate and improve educational practices and results even more.

2 THEORETICAL BACKGROUND AND LITERATURE REVIEW

2.1 Industrial design as problem framing

Design has been characterised as the activity of devising courses of action aimed at changing existing situations into preferred ones (Simon, 1969). Unlike well-defined engineering problems, the situations in which products are used are typically "wicked": they lack definitive formulations, and every formulation of the problem is already a proposal for its solution (Rittel & Webber, 1973). Buchanan (1992) extended this view by describing design as operating across four orders, namely symbols, things, actions and environments, with the highest orders concerned with the systems and ideas within which products acquire significance. Empirical and theoretical accounts of designers at work stress reflection-in-action (Schön, 1983), the co-evolution of problem and solution (Cross, 2011; Lawson, 2006), and a human-centred, prototype-driven approach that has been popularised as design thinking (Brown, 2008).

Industrial design also attends to the experiential and emotional dimensions of products. Consumers respond to products aesthetically, semantically and symbolically (Crilly et al., 2004), and emotional responses influence whether products are cherished, trusted or rejected (Norman, 2004). Participatory methods, in which future users act as co-creators rather than passive informants, have further broadened the designer's role from shaping objects to facilitating the definition of needs (Sanders & Stappers, 2008). These traditions provide the conceptual basis for the argument, developed below, that the need for AI in a product is itself a design outcome rather than a given.

2.2 AI as a design material

Machine learning differs from earlier technologies that designers have worked with. Its behaviour is probabilistic, dependent on data, capable of changing over time, and impossible to fully specify in advance. Dove et al. (2017) showed that designers find it difficult to work with machine learning as a "design material" because they struggle to understand its capabilities, to sketch and prototype its behaviour and to anticipate its failures. Yang et al. (2020) identified two root causes of the difficulty of designing human–AI interaction: uncertainty about what the AI can do and the complexity of its outputs. Suchman's (2007) analysis of situated action adds a caution: machines act on limited models of the situations in which they operate, so that mismatches between the machine's model and the user's context are inevitable and must be designed for rather than assumed away.

2.3 Interaction, trust and explanation

A substantial body of work translates these insights into design guidance. Amershi et al. (2019) synthesised eighteen guidelines for human–AI interaction organised around four moments: initially, during interaction, when the system is wrong, and over time. Central to many of them is the aim of helping users form accurate expectations of what the system can do and how well it will do it. The trust literature complements this view by emphasising *appropriate reliance*. Lee and See (2004) argued that the design goal is calibrated trust, in which reliance matches the actual capability of the automation, while Parasuraman and Riley (1997) documented the costs of both over-reliance (misuse) and under-reliance (disuse).

Explanation is a related design concern. Miller (2019) demonstrated that useful explanations are contrastive, selective and social, which suggests that dumping technical detail on users is rarely helpful. Shneiderman (2020, 2022) has argued for a two-dimensional view of human-centred AI in which high levels of automation and high levels of human control are simultaneously attainable, a proposition that has direct consequences for how control is physically and digitally embodied in a product. Finally, studies of social responses to technology show that people readily apply social rules to computers (Nass & Moon, 2000) and that near-human appearance can provoke discomfort (Mori, 2012), so decisions about anthropomorphism are consequential design decisions.

2.4 AI in the design process

AI is also changing how products are designed. Generative design methods, in which computational systems explore large spaces of form according to specified goals and constraints, have a history reaching back to shape grammars and evolutionary approaches (Shea et al., 2005; Krish, 2011), and are closely related to topology optimisation, which distributes material to maximise performance under given loads (Bendsøe & Sigmund, 2003). Deep generative models now extend this tradition by combining optimisation with learned representations of form (Oh et al., 2019). Diffusion-based image generators can produce large numbers of visual concepts from textual prompts (Rombach et al., 2022), and early work on generative AI in innovation suggests that it can accelerate digital prototyping and concept exploration (Bilgram & Laarmann, 2023). The notion of hybrid intelligence, in which human and machine capabilities are combined so that each compensates for the limitations of the other, offers a useful frame for such collaboration (Dellermann et al., 2019).

2.5 Ethics, regulation and sustainability

Alongside these technical and interactional strands, a normative literature asks what responsible AI-enabled products should look like. A review of AI ethics guidelines found convergence on principles such as transparency, fairness, non-maleficence, responsibility and privacy (Jobin et al., 2019), and similar principles underpin European guidance on trustworthy AI (European Commission, 2019; Floridi et al., 2018). Mittelstadt (2019) cautioned, however, that high-level principles are hard to translate into practice. This is where design methods such as value sensitive design, which proactively embeds human values into technical artefacts (Friedman et al., 2008), become relevant. The design tradition of social responsibility (Papanek, 1971) and of circular, "cradle to cradle" product thinking (McDonough & Braungart, 2002) adds an environmental dimension, and studies of the energy and carbon costs of training large models (Strubell et al., 2019; Patterson et al., 2021) show that AI is not environmentally neutral. Regulation is now reinforcing these concerns: the EU Artificial Intelligence Act introduces risk-based obligations that include transparency and human oversight (Regulation (EU) 2024/1689), and the Ecodesign for Sustainable Products Regulation establishes a framework for durability, reparability and related product requirements (Regulation (EU) 2024/1781).

3 METHODOLOGY

The study adopts a conceptual and integrative narrative review design, appropriate for a topic that spans disciplinary boundaries and for which the aim is theory building rather than the estimation of effects. No primary data were collected. Accordingly, the findings reported in Section 4 are analytical propositions grounded in the literature, not empirical measurements, and they should be read as hypotheses for future testing.

The analysis proceeded in three steps. First, literature was purposively selected from four streams: (i) design theory and product development; (ii) HCI and human–AI interaction; (iii) AI ethics, governance and sustainability; and (iv) computational and generative design. Sources were chosen for conceptual relevance, influence within their field and their explicit bearing on either the need for AI in products or the use of AI by people or by designers. Second, the selected sources were thematically analysed by asking, for each, what mechanism it identified through which design decisions affect the need for or use of AI. Recurrent mechanisms were grouped iteratively into categories until a stable set of five emerged. Third, the resulting framework was examined against well-documented cases from the literature, notably domestic service robots (Forlizzi & DiSalvo, 2006), learning thermostats (Yang & Newman, 2013), conversational agents (Luger & Sellen, 2016) and generative structural design (Oh et al., 2019), to test whether it could account for the reported patterns.

Quality was pursued through transparency of reasoning, triangulation across the four streams, and conceptual coherence. The principal limitations are the absence of a systematic, protocol-driven search, which makes the review illustrative rather than exhaustive, and the reliance on cases reported by other researchers, which restricts the empirical grounding of the framework. These limitations are revisited in Section 5.

4 RESULTS AND ANALYSIS: FIVE CONTRIBUTIONS OF INDUSTRIAL DESIGN

The analysis yields a framework in which industrial product design acts as a mediating layer between human needs, contexts and practices on the one hand, and AI capabilities and limits on the other (Figure 1). Through five contributions, design determines whether an AI-enabled product addresses an appropriate need and whether it is used appropriately. Use in turn generates feedback that reshapes needs and expectations. Table 1 summarises the contributions, and each is analysed in the sections that follow.

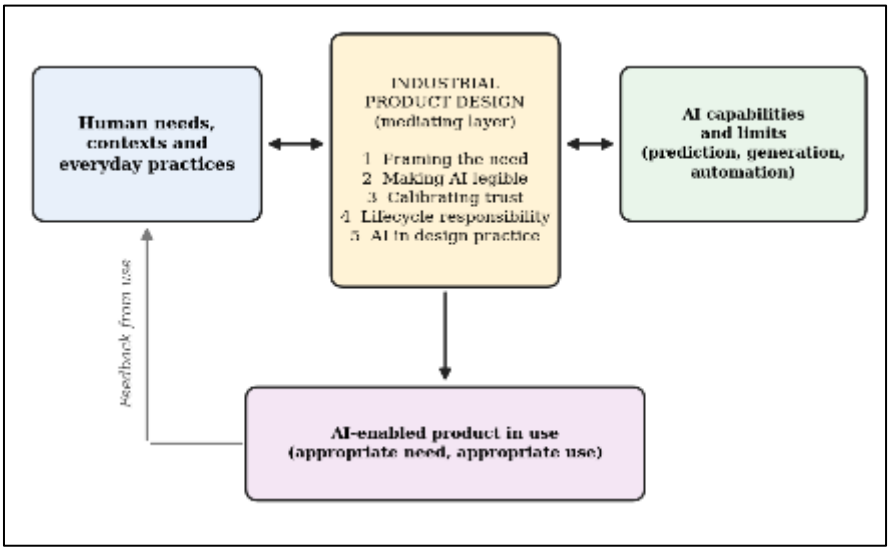


Figure 1: Conceptual framework: industrial product design as a mediating layer between human needs and AI capabilities

Table 1: Summary of the five contributions of industrial design to the need for and use of AI

Contribution	Mechanism in product design	Effect on the need for and use of AI	Key sources
1. Framing the need	Field research, co-creation and problem reframing; deciding where prediction, personalisation or automation adds value, and where it does not	Directs AI to problems worth solving; reduces technology-push products	Buchanan (1992); Sanders & Stappers (2008); Verganti et al. (2020)
2. Making AI legible	Product semantics, signifiers, feedback, physical form and controls; management of expectations and anthropomorphism	Improves understanding of capabilities and limits; supports discoverability and habitual use	Norman (2013); Krippendorff (2006); Luger & Sellen (2016)

3. Calibrating trust and control	Confidence cues, explanations, graceful failure, override and undo, progressive autonomy	Supports appropriate reliance rather than over- or under-trust	Lee & See (2004); Miller (2019); Shneiderman (2020)
4. Embedding lifecycle responsibility	Privacy by design, on-device processing, repairability, modularity, material and energy choices, inclusive design	Makes AI use sustainable, fair and compliant over the product's life	Friedman et al. (2008); Mittelstadt (2019); Strubell et al. (2019)
5. Integrating AI into design practice	Generative design, diffusion-based ideation, AI-assisted research synthesis, hybrid human–AI workflows	Accelerates exploration; shifts the designer's role towards framing and curation	Krish (2011); Oh et al. (2019); Dellermann et al. (2019)

4.1 Contribution 1: Framing the need for AI

The first and most fundamental contribution concerns the question of need. Because product problems are wicked (Rittel & Webber, 1973), the decision to introduce AI into a product is never a purely technical one. It rests on a framing of the situation: who is the user, what are they trying to achieve, and which part of that activity would benefit from prediction, personalisation, perception or automation? Industrial designers, trained in observation, co-creation and reframing (Brown, 2008; Sanders & Stappers, 2008), are well placed to answer these questions before technology is committed. Verganti et al. (2020) argue that AI intensifies the importance of this activity: as AI becomes increasingly capable of solving well-specified problems, competitive advantage shifts towards the ability to frame which problems are worth solving and what they mean to people.

The analysis suggests that four criteria can guide the design judgement of whether a function is "AI-worthy": (i) the task exhibits variability that fixed rules cannot handle; (ii) the outcome depends on personal or situational context that the system can sense; (iii) the task is burdensome or repetitive enough for delegation to be welcome; and (iv) errors are tolerable or recoverable at acceptable cost. Where these criteria are not met, the design contribution is to advise against AI, or to confine it to a supporting role. This gatekeeping function, deciding where AI should not be used, is easily overlooked yet is arguably as valuable as any enabling contribution, and it responds to the design tradition that questions the social value of what is produced (Papanek, 1971).

The domestic robot vacuum cleaner illustrates the point. Forlizzi and DiSalvo (2006) reported that households adapted both their spaces and routines around the device and that its physical form influenced how it was perceived and how it fitted into domestic life. The success of such a product thus depends on framing cleaning as a chore that people are willing to delegate, and on a form and interaction that make delegation feel safe and simple, rather than on the sophistication of the navigation algorithm alone. This leads to the first proposition.

Proposition 1. AI-enabled products whose AI functions are selected through need-finding research and explicit AI-worthiness criteria will achieve more durable adoption than products driven mainly by technology push.

4.2 Contribution 2: Making AI legible through form and interaction

Once AI is judged appropriate, the second contribution is to make it understandable. Norman (2013) argues that good design makes the possible actions discoverable and the system state visible through signifiers and feedback. For AI-enabled products, this requirement is heightened, because the underlying behaviour is hidden, adaptive and probabilistic (Dove et al., 2017; Yang et al., 2020). If the product does not communicate what it senses, what it has learned and how confident it is, users are left to build mental models from a small number of unexplained events. Yang and Newman (2013) reported that users of a learning thermostat had difficulty forming accurate models of what the device had learned, which undermined their ability to correct it. Such findings support the view that legibility is a design achievement rather than an inherent property of the technology.

Industrial design has several instruments for this task. The first is product semantics: the form, materials and behaviour of an artefact can signal its category, capability and limits (Krippendorff, 2006). A product that looks like a simple appliance invites simple expectations, whereas one that presents itself as an all-knowing companion invites expectations that current systems cannot meet, as the experience of conversational agents suggests (Luger & Sellen, 2016). The second is the physical expression of sensing and privacy: visible indicators of when a microphone or camera is active, or a physical switch that disables sensing, make otherwise invisible processes tangible. The third is the deliberate management of anthropomorphism. Since people respond socially to machines (Nass & Moon, 2000), humanlike cues can accelerate acceptance, but they can also inflate expectations or provoke discomfort when the

resemblance is imperfect (Mori, 2012). Designers therefore have to decide how much social presence a given product warrants.

The guidance of Amershi et al. (2019) is consistent with this analysis: making clear what the system can do, showing how well it can do it, and supporting efficient correction all depend on interface and product decisions that sit within the designer's remit. The second proposition follows.

Proposition 2. The legibility of an AI-enabled product's capabilities and limits, expressed through form, feedback and controls, will be positively associated with the accuracy of users' mental models and with sustained, appropriate use.

4.3 Contribution 3: Calibrating trust and control

The third contribution concerns the relationship between the user and the system over time. The design objective is not to maximise trust but to calibrate it (Lee & See, 2004). Excessive trust leads to complacency and misuse, particularly in safety-critical products such as vehicles and medical devices, while insufficient trust leads to abandonment of capable systems (Parasuraman & Riley, 1997). Industrial design contributes to calibration through a set of recurring mechanisms.

First, products can express uncertainty, for example by signalling low confidence, so that users know when to double-check. Second, they can fail gracefully, defaulting to safe and predictable behaviour and making the handover to the user explicit. Third, they can provide explanations that are proportionate to the situation: following Miller (2019), a brief, contrastive account of why the system acted ("because the room was empty for an hour") is likely to be more useful than a technical description. Fourth, they can preserve human control by means of accessible override, pause, and undo functions. Shneiderman's (2020) two-dimensional framework indicates that such control is compatible with high automation, so long as the interface is designed accordingly. Fifth, products can support progressive autonomy, in which the system begins with suggestions and grants itself greater independence only as the user's confidence and consent grow, an approach consistent with the guideline that systems should adapt cautiously over time (Amershi et al., 2019).

These mechanisms are physical as well as digital. A tactile control that can be reached instantly, a light that reveals the system's state at a glance, or a mechanical stop that ends an action are all forms of trust calibration that cannot be reduced to screen-based settings. This is a distinctive advantage of industrial design relative to purely software-oriented approaches.

Proposition 3. Design features that support graded autonomy, uncertainty communication and easy override will be positively associated with calibrated trust, that is, with reliance that matches the system's actual performance.

4.4 Contribution 4: Embedding lifecycle responsibility

The fourth contribution extends the design lens from the moment of use to the whole product lifecycle. AI-enabled products are physical objects that contain sensors, batteries, processors and connectivity; they consume energy in operation and generate data throughout their lives. Decisions taken in industrial design, such as where computation is placed, how components are joined and which materials are used, therefore determine much of the product's privacy, fairness and environmental profile.

Privacy is a clear case. Performing inference on the device rather than in the cloud, limiting sensing to what is necessary and making data flows visible are architectural and industrial design decisions that embody the value of privacy in the artefact itself, in the spirit of value sensitive design (Friedman et al., 2008). Mittelstadt (2019) noted that principles alone cannot guarantee ethical AI; design provides a route from principle to practice by turning abstract commitments into concrete features, defaults and constraints. The same logic applies to fairness and inclusion. Products sense and interpret people, and a product that performs well for some bodies, voices or households and poorly for others reproduces bias physically. Inclusive design, testing with diverse users and providing alternative modes of interaction are means of reducing this risk.

Sustainability introduces further considerations. Training and operating large models entails non-trivial energy and carbon costs (Strubell et al., 2019; Patterson et al., 2021), and connected products risk premature obsolescence when software support or cloud services are withdrawn. Design principles associated with circular product thinking (McDonough & Braungart, 2002), such as modularity, repairability, upgradeable components and material recovery, extend the useful life of AI-enabled products and reduce their footprint. These principles are increasingly backed by regulation: the Ecodesign for Sustainable Products Regulation (Regulation (EU) 2024/1781) addresses durability and reparability, and the AI Act (Regulation (EU) 2024/1689) establishes transparency and oversight obligations that must be realised in the product's interface and behaviour. In practice, compliance with both frameworks will be delivered through design.

Proposition 4. AI-enabled products designed for repairability, on-device processing and long-term software support will show longer useful lives and higher user-perceived privacy than functionally equivalent cloud-dependent products with limited support.

4.5 Contribution 5: Integrating AI into design practice

The fifth contribution reverses the perspective: AI is not only an object of design but also a tool of design. Table 2 maps the principal stages of the industrial design process to the kinds of AI support currently available, the residual contribution of the designer and the principal risks.

Table 2: AI support, designer contribution and risks across the industrial design process

Design stage	Typical AI support	Designer's contribution	Principal risk
Discovery and research	Transcription, clustering and summarisation of qualitative data; trend analysis	Choosing whom to observe, interpreting meaning, questioning findings	Loss of nuance; bias inherited from training data
Ideation	Text-to-image generation of concept variations (diffusion models)	Setting the brief; curating, combining and critiquing outputs	Aesthetic homogenisation; unclear provenance of training images
Concept development	Rapid rendering; exploration of form, material and colour variants	Judging semantics, brand and meaning; ensuring coherence	Plausible-looking but unmanufacturable concepts
Engineering and optimisation	Topology optimisation, generative design, surrogate simulation	Defining goals, constraints and manufacturing context	Optimising the wrong objective; opaque trade-offs
Prototyping and testing	Prototyping of adaptive behaviour; analysis of user-test data	Designing test situations; interpreting behaviour in context	Over-reliance on synthetic users or simulated data
Communication and production	Automated documentation, visualisation and variant configuration	Ensuring a consistent narrative and quality	Over-automation; erosion of tacit craft skills

Two observations follow from the table. The first is that AI expands the range of options that can be explored. Generative design and topology optimisation can produce forms that human designers would be unlikely to draw by hand while meeting stated performance goals (Bendsøe & Sigmund, 2003; Krish, 2011; Oh et al., 2019), and image-generating models permit rapid visual exploration early in the process (Bilgram & Laarmann, 2023; Rombach et al., 2022). The second observation is that every entry in the "designer's contribution" column involves framing, judging, or interpreting, that is, tasks concerned with meaning and value rather than with generating alternatives. This is consistent with the argument that as AI takes over problem solving, the scarce human contribution is problem framing (Verganti et al., 2020), and with the hybrid intelligence view that human and machine capabilities should be arranged so that each complements the other (Dellermann et al., 2019).

The risks are equally clear. Generative tools trained on existing imagery may pull outputs towards familiar styles, questions of authorship and data provenance remain unsettled, and computationally generated forms may satisfy formal criteria while ignoring manufacturing, ergonomic or cultural realities. There is also a risk to skill: if early-stage exploration is delegated to machines, designers may lose the tacit knowledge developed through hands-on making and sketching, which underpins reflection-in-action (Schön, 1983). These risks call for structured workflows in which designers retain responsibility for framing the brief and selecting among outputs.

Proposition 5. Design teams that use AI tools within structured, human-led workflows will explore wider concept spaces without loss of concept quality, provided designers retain responsibility for problem framing and selection.

5 DISCUSSION

5.1 Synthesis: design as a mediating layer

Taken together, the five contributions portray industrial design as a mediating layer that translates between three domains: what people need, what AI can do, and what happens when the two meet in daily practice. The first contribution operates on the demand side by shaping the need for AI. The second and third operate at the point of use by shaping understanding and trust. The fourth extends responsibility across the lifecycle, and the fifth transforms the means by which products are conceived. Figure 1 shows that these are not independent: the way a product is used generates feedback that alters needs and expectations, which in turn changes what designers should frame, communicate and build (Poli, 2021).

In response to RQ1, the analysis indicates that industrial design contributes to the need for AI primarily by framing problems and by exercising the judgement not to use AI where it adds little. In response to RQ2, it shapes use through legibility, calibrated trust and lifecycle responsibility, converting abstract principles into perceivable and controllable features. In response to RQ3, AI enlarges the space of design exploration while reinforcing the importance of human judgement regarding meaning, context and consequence.

5.2 Implications for practice, education and policy

For practice, the analysis suggests that AI-enabled product development should bring industrial designers into the team before the technical architecture is fixed, since decisions about need, sensing, control and lifecycle are hard to reverse later. Dove et al. (2017) suggest that designers need ways to experience machine learning behaviour early; techniques that let teams simulate or prototype adaptive behaviour before models are complete can help, as can testing with real data and in real contexts of use. For education, curricula in industrial design increasingly need to cover data literacy, the properties of machine learning as a design material, human–AI interaction guidelines and ethics, without displacing foundational skills in form, materials and making (Papakostas et. al. 2023).

For policy, the results suggest that regulation of AI operates in practice through design. Requirements for transparency, human oversight, durability and reparability (Regulation (EU) 2024/1689; Regulation (EU) 2024/1781) are met or missed in decisions about interfaces, controls, components and materials. Policymakers and standards bodies would therefore benefit from engaging with product designers, and organisations may wish to treat design review as part of compliance processes.

5.3 Limitations and directions for future research

The paper has several limitations. It is conceptual, its propositions are untested, and its review is purposive rather than systematic. The cases used to examine the framework were drawn from published studies, which cover a limited range of product categories and mostly consumer contexts. Future research could test the propositions in several ways: comparative studies of AI-enabled products that differ in legibility and control features; longitudinal in-home studies of how mental models and trust evolve; measures of calibrated trust in place of simple satisfaction; life-cycle assessments comparing on-device and cloud-dependent architectures; and controlled studies of design teams working with and without generative tools. Extending the framework to medical, industrial and public-space products, where the consequences of error are greater, is a further priority.

6 CONCLUSIONS

This paper has argued that the current need for, and use of, artificial intelligence in products cannot be understood through technology alone. Through a conceptual review of design, HCI, ethics and computational design literature, it identified five contributions by which industrial product design shapes AI: framing the need, making AI legible, calibrating trust and control, embedding lifecycle responsibility and integrating AI into design practice. Together they position industrial design as a mediating discipline that turns technical capability into products that people can understand, rely on and live with.

Two conclusions stand out. First, the contribution of design to AI is as much about restraint as about enablement: deciding where AI is not needed, and limiting its autonomy where trust has not been earned, are integral to good practice. Second, the growing use of AI within design does not diminish the designer's role but relocates it towards framing, judging and taking responsibility for meaning and consequence. The five propositions offered here provide a basis for empirical work that can test, refine and extend these claims. As AI becomes an ordinary component of manufactured products, the quality of its integration will depend increasingly on the quality of the design decisions that surround it.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Acknowledgments

The Authors would like to thank the SPECIALIZATION IN ICTs AND SPECIAL EDUCATION: PSYCHOPEDAGOGY OF INCLUSION Postgraduate studies Team, for their support.

Disclosure of conflict of interest

The Authors proclaim no conflict of interest.

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