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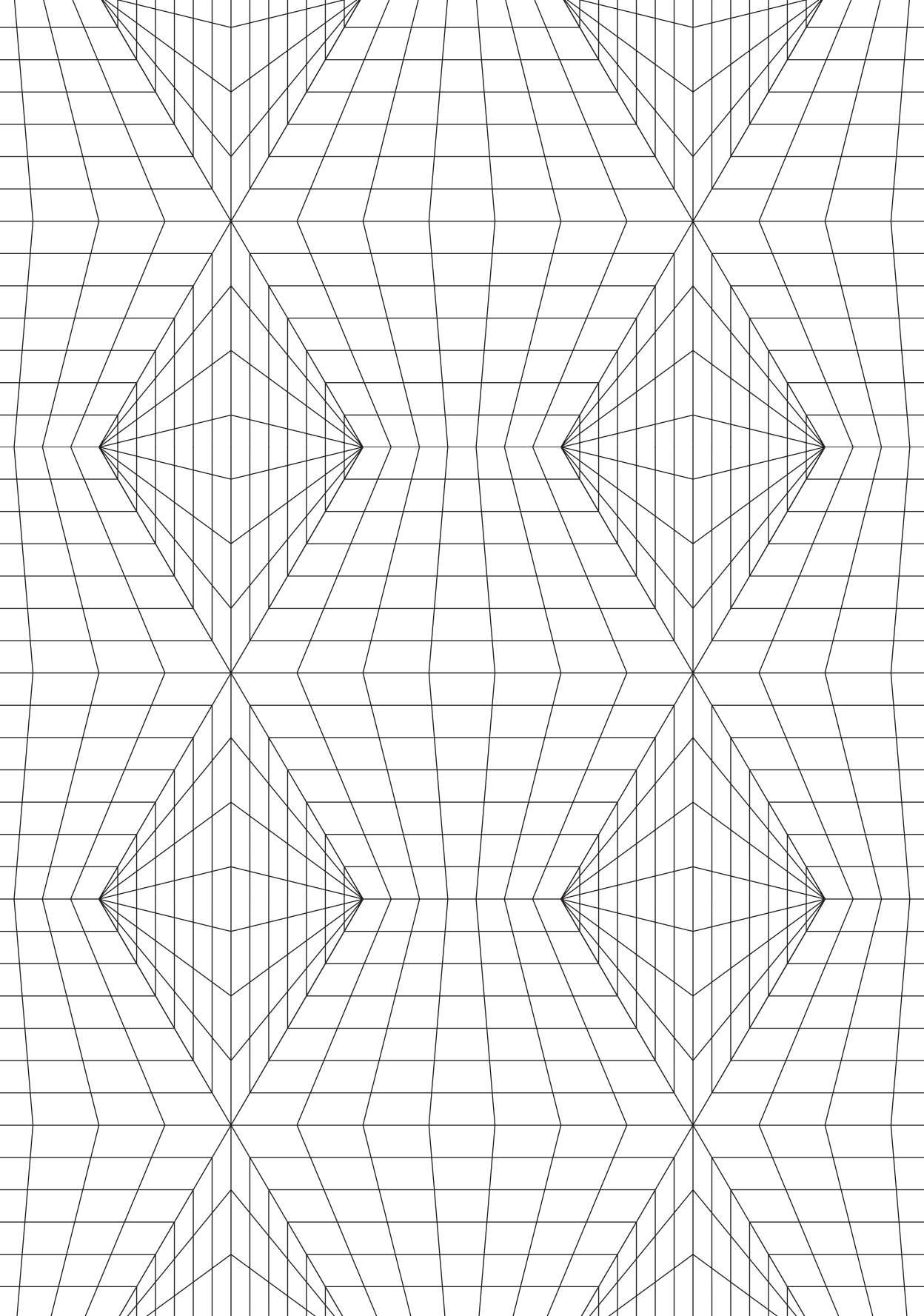

Disegno

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Aims and Scope

Disegno publishes original research papers, essays, and reviews on all aspects of design cultures. We understand the notion of design culture as resolutely broad: our aim is to freely discuss the designed environment as mutually intertwined strands of sociocultural products, practices, and discourses. This attitude traverses the disciplinary boundaries between art, design, and visual culture and is therefore open to all themes related to sociocultural creativity and innovation. Our post-disciplinary endeavour welcomes intellectual contributions from all members of different design cultures. Besides providing a lively platform for debating issues of design culture, our specific aim is to consolidate and enhance the emerging field of design culture studies in the Central European academia by providing criticism of fundamental biases and misleading cultural imprinting with respect to the field of design.

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Contents

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FROM PARTICIPATION TO EXTRACTION: THE RISE OF PREDICTIVE DESIGN

Dávid Csűrös and Ákos Schneider

ABSTRACT

This paper introduces the concept of predictive design (PD) to critically examine how data-driven design methods are reshaping human-centred design (HCD). While HCD traditionally emphasises participation, empathy, and qualitative insight, the rise of predictive practices—such as anticipatory design and predictive UX—signals a shift toward a different mode of futuring in digital environments: one rooted in data science rather than open-ended dialogue with users. At the same time, the rhetoric of user-centredness is often used to justify large-scale data extraction, blurring the line between service and surveillance. This shift creates a tension with HCD's commitment to designing by, for, and with people. Drawing on historical, epistemological, and cultural perspectives, we trace how predictive practices have gained momentum in design, particularly within the platforms of Google and Facebook. The paper outlines the epistemic logic of PD, distinguishes it from adjacent concepts, and explores its implications for user agency, participation, and the role of design in surveillance capitalism.

#Predictive Design, #Human-Centred Design, #Data-Driven Design, #Design Culture, #Algorithmic Culture

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1. INTRODUCTION

All user-centred design is predictive to some degree: when a handle is shaped, the designer anticipates how it will be grasped; when a sign is created, it presumes a trajectory of visual attention; when a button is placed on a webpage, assumptions are made about where users are likely to click; when an app sends a notification, it forecasts the most opportune moment to prompt engagement. Designing for users has always involved anticipating behaviours, needs, and expectations, making prediction and abductive reasoning[1] integral aspects of design practice. However, in recent decades, both the methods of operationalising prediction and the epistemological assumptions behind it have shifted significantly.

Traditional design frameworks—such as user-centred and human-centred design—rely on several key approaches, including user research methods like interviews and surveys to gain insight into user behaviours and needs; the development of personas to embody typical users and inform design choices; prototyping to build preliminary models of potential solutions; user testing to assess these prototypes; and iterative design, which emphasises ongoing refinement based on feedback and evaluation (Norman [1988] 2016; Brown 2009). These practices emphasise active user participation and focus on producing solutions that are practical and intuitive.

While such methods are grounded in qualitative engagement, contemporary design practices adopt different epistemic approaches—yet remain essentially user-centred. Data-driven design practices now rely on the analysis of large-scale behavioural data, statistical modelling, and algorithmic inference. This transformation has been fuelled by the widespread availability of digital traces generated through everyday user interactions.

The growing integration of data science into UX design[2] marks a profound shift in how knowledge about

[1] *Design practices typically involve projections and assumptions, the testing and revision of which drive the iterative process forward. According to Wolfgang Jonas, abductive reasoning is central to design, where conclusions gravitate toward the "best available" or the "most likely" explanation—thus always involving a degree of uncertainty. Jonas aligns this mode of reasoning with projection, stating that "projection represents the abductive step" as the "central designerly phase" (2014, 4)—a form of inference that operates alongside, but distinct from, deduction and induction.*

[2] *User Experience (UX) design refers to the process of creating products or systems that offer meaningful, intuitive, and engaging interactions by focusing on users' needs, behaviours, and the contexts of use. The concept emerged from the convergence of human-computer interaction (HCI), cognitive psychology, and design, with roots tracing back to ergonomics and usability studies in the mid-twentieth century. Hassenzahl defines UX as "experience that comes about through the use of (interactive) products," ([2010] 2022, 4) emphasizing that it focuses on shaping how people feel, think, and act through interaction with technology rather than just what they accomplish with it. He further argues, "User Experience is not much different from experience per se. It simply focuses our interest on interactive products… as creators, facilitators and mediators of experience" ([2010] 2022, 13). The term "user experience" was popularised by Donald Norman in the 1990s while working at Apple. Norman ([1988] 2016, xiii–xiv, 233) emphasises the importance of designing not just for functionality and efficiency but for holistic, emotionally resonant user experiences. This shift echoes the historical transition from engineering-driven to human-centred technology.*

users is generated, how design choices are legitimised, and how possible futures are enacted. Instead of relying on interpretative engagement or participatory methods, design is increasingly steered by predictive analytics that extrapolate future behaviour from past data. This evolution not only challenges the epistemological underpinnings of human-centred design (HCD) but also raises ethical concerns about user autonomy and agency, while reframing design practice as a mode of behavioural forecasting.

This paper introduces predictive design (PD) with the aim of offering a conceptual and critical framework for understanding how data-driven, anticipatory design practices accelerate this transformation. By treating behavioural traces as its primary design material, PD contributes to the reconfiguration of users as dynamic, probabilistic data profiles, and in doing so participates in a wider reshaping of design culture. Our inquiry is guided by two questions:

(1) In what ways does the emergence of PD redefine the core principles of HCD, particularly its commitment to participation?

(2) What are the broader epistemological and ethical implications of PD practices that frame human behaviour as a resource to be modelled and optimised?

We propose PD as a conceptual tool for Design Culture studies (Julier [2000] 2014; Julier and Munch 2019), which understands design not merely as a set of professional practices but as a cultural, economic, and political force embedded in everyday life. Julier (2017) argues that design culture encompasses the work of designers, the production of design (including its mediation and circulation), as well as the consumption of designed artifacts and systems—all of which shape and are shaped by social and economic imaginaries. From this perspective, PD can be seen as part of a wider cultural transformation, where design no longer simply mediates human experiences, but actively anticipates, modulates, and monetises them through algorithmic systems.

In this light, PD is not only a set of emerging practices within predictive UX design but also a symptom of deeper shifts in how design functions under platform capitalism[3] (Srnicek 2016). It reflects what Julier calls the "instrumentalisation of design" (2000 [2014], 12): its alignment with the business logics of commodification and corporatisation, optimisation imperatives, and data-driven governance. As such, PD marks a moment where design culture itself is reconfigured—moving from participatory engagement toward predictive control. In drawing on design culture as a critical lens, we aim to foreground PD as more than a methodological trend: it is a manifestation of a changing cultural paradigm in which the role of design is increasingly tied to behavioural extraction, anticipatory systems, and the production of predictive value.

While focusing on the user is by no means new in the history of modern design[4], the rise of personal computing and the emergence of

[3] *According to Nick Srnicek (2016), platform capitalism refers to a new economic model in which digital platforms and tech companies—like Google, Amazon, and Facebook—operate as intermediaries that extract, analyse, and monetise user data, becoming central infrastructures of contemporary capitalism.*

[4] *See Lupton (2014) for a historical overview of user-centred approaches in twentieth-century design.*

human-computer interaction (HCI) introduced a new level of complexity. Making digital technologies usable for non-experts required more structured and refined approaches. As a response, user-centred and human-centred design methodologies were developed—laying the groundwork for what would later become the field of user experience design. In the context of this paper, references to "design" generally pertain to UX design in digital environments—specifically, the design and engineering of digital interfaces and services that enable social communication, content sharing, and information organisation, such as Facebook, Instagram, YouTube, and Google—as the concept of PD is primarily traceable and applicable within this domain. Unless otherwise specified, "data" refers to quantitative user data, including both pre-existing datasets (e.g., user profiles, browsing history, content preferences) and real-time data streams (e.g., location tracking, scrolling behaviour, click patterns, and watch time).

The study is structured as follows: section 2 outlines the conceptual and methodological foundations of HCD, introducing a spectrum of user involvement that ranges from designing *for* to designing *by* users. Section 3 traces a brief history of data use in design, situating current practices within a longer lineage of scientific management, ergonomics, and participatory approaches. Section 4 examines the shift "from participation to extraction," focusing on how large-scale data capture and analytics have reoriented design practice in the platform economy, with particular attention to Google and Facebook. Section 5 identifies the rise of a new epistemological paradigm rooted in algorithmic culture, drawing on Kitchin, Galloway, and Striphas to frame the cultural and epistemic conditions under which prediction becomes a dominant design logic. Section 6 introduces PD as a critical concept for Design Culture studies, detailing its conceptual position, thematic priorities, and methodological foundations. Section 7 discusses the implications of PD for participation, agency, and the political economy of design, before the paper concludes by situating PD as both a methodological evolution and a cultural formation that reflects—and reinforces—broader transformations in contemporary design culture.

2. HUMAN-CENTRED DESIGN

Over the past century the scope of design has undergone a radical transformation from form-giving to the design of interactions, systems, organisations and human experience itself. HCD stands at the forefront of this shift. It is an umbrella term for methodologies that place the user at the centre of the design process—opposed to technology-driven or designer-centred approaches that emphasise technological innovation or the designer's intuition. The aim of HCD is to develop products, services, and interfaces that are not just intuitive and usable but responsive to

a broad spectrum of human needs; ranging from ergonomic and cognitive dimensions to emotional, social, and even metaphysical concerns (Giacomin 2014). Understanding people's psychological and socio-cultural dispositions is therefore central to HCD, and this endeavour has been supported by empirical knowledge developed throughout the twentieth century in fields such as ergonomics, medical science, experimental psychology, cognitive science, and the social sciences. These insights proved foundational in shaping early forms of HCD, including user-centred design, participatory design (and its later evolutions in co-design), social design, and inclusive design.

The degree to which these approaches involve users—and the methods they do so—varies and can be mapped along a spectrum (fig.1): at one end lies design *by* users, emphasizing user autonomy and co-creation; at the other , design *for* users, where designers act on behalf of users; while design *with* users represents a collaborative middle ground. For example, as an end-user development framework meta-design[5] exemplifies designing *by* people; co-design and participatory design align more closely with designing *with* people; whereas inclusive design and user-centred design typically represent approaches to designing for people.

As we move along this spectrum from "design *by*" to "design *for*", we also observe a corresponding shift in methodological orientation: the prevalence of qualitative, interpretive methods diminishes, while quantitative, data-driven approaches gain dominance. Methods emphasising co-creation or user-led development often rely on ethnographic research, contextual inquiry, and participatory workshops to grasp users' situated knowledge and tacit practices. In contrast, methods positioned toward the "design *for*" end of the spectrum—particularly within the context of large-scale UX design—tend to employ behavioural tracking, A/B testing[6], and statistical modelling to infer preferences and optimise user flows. This methodological drift reflects not only different forms of user involvement but also diverging epistemologies: one rooted in understanding human meaning-making, the other in modelling and predicting behaviour through measurable patterns.

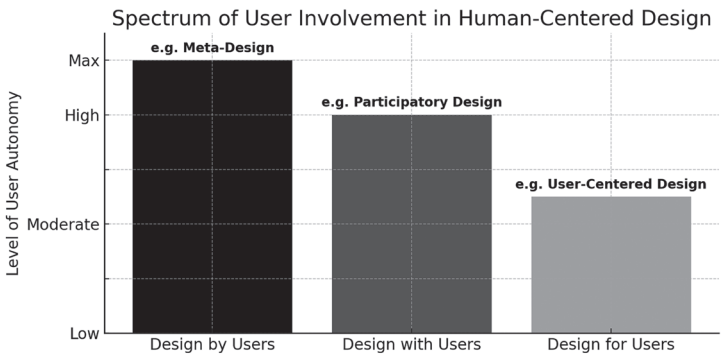

FIGURE 1. *A spectrum of user involvement in HCD processes.*

[5] *Meta-design refers to "design for designers" (Fisher and Scharff 2000), that is, the creation of tools, platforms, and frameworks that enable end users—as "owners of problems"—to act as co-designers by adapting, extending, and evolving a system to fit their needs over time (Fischer et al. 2004, 35). It emphasises open-endedness, user empowerment, and collaborative creativity, and is often associated with open-source software, participatory platforms, and maker cultures. In the HCD spectrum, meta-design aligns with "design by users," as it maximises user autonomy in shaping outcomes.*

[6] *A/B testing is a controlled experimental method in which two or more variants of a design are presented to different user segments under the same conditions, and their performance is compared using statistical analysis to determine the most effective version. In contemporary UX practice, A/B testing is often integrated into continuous optimisation workflows, allowing design decisions to be guided by behavioural metrics rather than solely by designer intuition (Kohavi et al. 2009).*

3. BRIEF HISTORY OF DATA IN DESIGN

The use of quantitative and qualitative data in the design process has evolved significantly since the beginning of the twentieth century, due to a complex interplay of technological advancements, shifting epistemological paradigms, changing concepts of the user, and the increasing entanglement of design with other disciplines.

Some of the earliest systematic attempts to rationalise and optimise human activity through data include Taylor's time-and-motion studies, the Gilbreths' principles of motion economy, Neufert's standardised measurements, and Le Corbusier's Modulor. These methods exemplify a broader modernist ambition to render bodily movement measurable, standardised, and ultimately governable, laying the groundwork for what would later become a central concern in human-machine interaction: the systematic observation and modelling of the user.

After World War II, industrial design was increasingly reoriented towards consumer goods, and the founding of the Ergonomics Research Society in 1949 points to the institutionalisation of design practices that optimise products for human use. This was part of a broader movement from purely aesthetic or engineering-driven design toward systematic study of human capabilities, limitations, and comfort in human-machine interactions. Although the direct use of ergonomics in design was sporadic, it had a long-lasting effect: it shifted the focus of design from things to their relationships with humans, representing the "human-machine ensemble" as fundamentally knowable by statistical analysis. As Theodora Vardouli (2016, 68) observes, the basic techniques of ergonomics were developed through experimental data collection and analysis, effectively "producing design norms for the statistical normal." Henry Dreyfuss' *The Measure of Man* (1960) exemplifies this logic with its reliance on anthropometric data, aiming to standardise design around the average Joe and Josephine.

In the 50s and 60s—affected by wartime system-thinking and a newly found techno-optimism—figures like Christopher Alexander, Bruce Archer, and Horst Rittel sought to improve the design process by making it more "scientific" (Langrish 2016, 4). Design methods in the UK and the Design Methods Movement in the US were initially shaped by positivist ideals, drawing from ergonomics and systems engineering to formalise design as a rational, data-driven process. Early approaches prioritised optimisation, predictability, and statistical norms—often modelling the user as a generalisable, measurable component of a system. By the late 1960s, this view faced growing internal critique; Rittel, Alexander, and Jones themselves began questioning whether such scientific formalism could address the ill-defined and contextual nature of real-world design problems (Vardouli 2016, 66).

This marked a second-generation shift in design methods—reflected in initiatives like DRS's Design Participation conference in 1971

and the founding of the Environmental Design Research Association (EDRA)—which emphasised qualitative research, user participation, and human-centred values. It recognised that good design required not only empirical data, but also situated knowledge, ethical judgment, and collaboration among diverse stakeholders (Sanoff and Cohn, 2021).

In parallel, a participatory perspective emerged in the form of Scandinavian Participatory Design during the 1970s, where users, especially workers, became co-designers. Here, qualitative input, like stories, feedback, and lived experiences became central, evolving design from a top-down activity toward a horizontal, collaborative project. The result of this design process is seen as the culmination of agreements and interactions. The principle of participation has provided many successful examples, spanning from communities redesigning urban spaces and individuals customising personal devices to user-centred transformation of services. A core principle of participative methods, such as Meta-Design or Co-Design asserts that users are recognised as "experts on their own experiences" (Visser et al. 2005).

Meanwhile, in the United States, a different but related trajectory was unfolding in the emerging field of Human–Computer Interaction. A landmark moment came in 1968 with Douglas Engelbart's "Mother of All Demos," presented while he was director of the Augmentation Research Center at Stanford Research Institute. The demonstration showcased innovations such as the computer mouse, hypertext, real-time collaborative editing, and video conferencing. Beyond its technological breakthroughs, the demonstration embodied a vision of interactive computing as a partnership between humans and machines, foreshadowing many of the usability and interaction paradigms that would later become central to HCI and, eventually, to user-centred design (UCD).

By the late 1980s, these threads coalesced into UCD, first linked to developments at IBM. At the Thomas J. Watson Research Center, Gould and Boies (1983) introduced a methodological framework that foregrounded four key components: focusing on the user group, integrating users into the design process, relying on empirical data, and iterative development. Later, Gould and Lewis (1985) revised this approach by excluding direct user participation, consolidating the remaining elements into the "three principles of system design." Donald Norman, Stephen Draper and Liam Bannon (1986) reframed these principles as a design philosophy and introduced user-centred system design—the predecessor of UCD and HCD. Norman and his colleagues aimed to broaden the scope of design beyond empirical approaches and simple usability, while simultaneously emphasising the importance of understanding users' cognitive profiles through behavioural data. In a guiding essay from *User Centered System Design*, Bannon argues that to design usable systems, we need not only "detailed psychological models of how people think and communicate" but also "a more enlightened view of people" (Norman and Draper 1986, 25-26). Over

time, the user-centred framework evolved into human-centred UX design, which attempts to balance quantitative metrics with qualitative methods.

The historical trajectory of data use in modern design reveals a gradual expansion from early twentieth-century efforts to standardise and optimise human activity—rooted in industrial efficiency and modernist ideals—towards more participatory, qualitative, and human-centred approaches. While ergonomics, systems thinking, and design methods brought scientific rigor to the field, they also risked reducing users to statistical norms. The emergence of participatory design in Scandinavia, the visionary technological paradigms introduced in the field of Human-Computer Interaction, and the formalisation of user-centred design in the 1980s collectively reframed the role of the user from a passive subject of measurement to an active participant—or even co-creator—in the design process. This evolution laid the conceptual and methodological groundwork for contemporary human-centred design, where empirical data and human experience are intertwined in shaping products, systems, and services.

4. FROM PARTICIPATION TO EXTRACTION

This shift toward user participation laid the foundation for data-driven design, where user input became data to be captured and analysed. The term data-driven design was coined by Domazet et al. (1995) and the discussion about the role of modern data science in design started a few years later with the work by Kusiak and Tseng (2000), who described the first prototyped application of a data mining algorithm to generate, select, and validate solutions (Bertoni 2020). Subsequent research (e.g. Agard and Kusiak 2004; Menon et al. 2004) has proposed data mining methods for product development, showing how algorithms could be applied efficiently in the process. After the early interest in data-driven design, the real expansion of the field started with the emergence of big data and advanced machine learning algorithms.

User-centred system design's early ambition to model users' cognition and behaviour became technically feasible with the rise of the internet. Server logs and cookies in the mid-1990s enabled tracking of navigation and persistent user identification, while client-side scripting like JavaScript allowed fine-grained interaction monitoring. The rise of web analytics and A/B testing made it possible to collect and use behavioural data at scale, gradually pushing UI/UX design from participatory methods towards data-driven approaches. While contemporary design teams often embrace the principle that quantitative and qualitative insights must co-exist to "truly know the user" (Chilana et al. 2012; Lu et al. 2021), the rise of big data and predictive analytics has disrupted this balance—especially in large-scale UX environments such as social media platforms and search engines.

4.1 The Case of Google and Facebook

Google has played a key role in the shift from traditional user-centred methods to large-scale data collection and predictive practices. One of the early inflection points that positioned Google at the forefront of the data-mining business was the invention of the PageRank algorithm by Larry Page in 1998. In the early days of the web, searching for information was like finding a needle in a haystack. By emphasising relevance and speed, Google revolutionised web searches and also laid the foundation for a new model of targeted advertising. PageRank initially assessed the relevance of a webpage through the structure of inbound links, but this approach quickly became vulnerable to manipulation via link spam. In response, Google engineers began to integrate behavioural data—such as where users clicked and how long they remained on a page—into their ranking systems. The incorporation of such implicit feedback proved to be a decisive innovation, setting Google apart. However, the price users paid for this enhanced user experience was the commodification of their behaviour: every click, pause, and scroll became a data point in an ever-expanding apparatus of surveillance-based optimisation and advertising. As Shoshanna Zuboff (2019) notes, Google realised in the early 2000s that the behavioural data it collected—initially seen as a byproduct of user interaction—possessed immense economic potential. This "behavioural surplus" became the raw material for new predictive products and the foundation of a powerful surveillance-based business model.[7]

Later, Google became famous for constantly improving the design of their system based on insights gained by analytics and experiments. The company's chief economist, Hal Varian (2010) classifies "computer mediated transactions" into four categories: facilitate new forms of contract; facilitate data extraction and analysis; facilitate controlled experimentation; facilitate personalisation and customisation. This suggests that, from early on, Google recognised itself not merely as a service provider, but as an infrastructure for large-scale data extraction. As Varian's framework makes clear, the company's objective was to convert every digital interaction into predictive capital—a resource for targeted advertising and UX optimisation. Following this approach, by the late 2000s, Google had fully embraced a culture of continuous experimentation, embedding large-scale A/B testing into its everyday operations. In 2008 for instance, engineers and designers conducted more than 6,000 trials leading to hundreds of system modifications, many of which targeted either interface design or core algorithmic behaviour (Varian 2010, 9). Google's approach to predictive practices is reflected in a comment by co-founder Larry Page in the early 2010s, where he made clear that the company's aim is to anticipate users' preferences and find things they do not know but want to know (Levy 2011, 58). As stated on the company's official philosophy page: "We try to anticipate needs

[7] *Zuboff highlights this discovery as a pivotal moment in the emergence of surveillance capitalism, pointing to a key insight that transformed how user data was understood and utilised: "Amit Patel, a young Stanford graduate student with a special interest in 'data mining,' is frequently credited with the groundbreaking insight into the significance of Google's accidental data caches. His work with these data logs persuaded him that detailed stories about each user—thoughts, feelings, interests—could be constructed from the wake of unstructured signals that trailed every online action. These data, he concluded, actually provided a 'broad sensor of human behaviour' and could be put to immediate use in realising cofounder Larry Page's dream of Search as a comprehensive artificial intelligence." (Zuboff 2019, 69)*

not yet articulated by our global audience" (Google n.d.). What remains unacknowledged is that this predictive capacity rests on large-scale data collection and behavioural analysis.

Google's approach was adopted by Facebook, when one of the top executives of Google became Mark Zuckerberg's number two (Zuboff 2019, 92). By that time, Facebook had already introduced the algorithmically curated "News Feed" and its success marked the company's first step toward predictive content delivery. Facebook soon launched the "Facebook Platform" for third-party apps and the "Beacon" program which was an early data-mining initiative: it tracked Facebook users' actions on partner websites (like purchases) and broadcast them to friends' feeds without clear consent. The idea was to leverage user data from across the web for social advertising. While Beacon was shut down early, Facebook Platform continued to allow third-party apps to harvest data, and this expansive data sharing (nominally for richer user experiences) would later lead to the Cambridge Analytica scandal.[8]

The introduction of the "like" button in 2009 was also a step towards measuring users' preferences in nuanced details. Whenever a logged-in user visited a site with an integrated Facebook plug-in, data about that visit was sent back to Facebook, even if no click occurred. The like plug-in essentially functioned as a web tracker, allowing Facebook to gather information on which users were visiting what websites. Another significant step in the development of the predictive design paradigm was the establishment of Facebook's Growth Team led by Chamath Palihapitiya, who strongly believed that metrics should be preferred over designer intuition. This led to the famous "7–10 rule"—a pattern that emerged from user data—, which states that if people make at least 7 new friends on Facebook in 10 days, they will be far more likely to remain active on the site. According to Palihapitiya (2013), the 7–10 rule "was the single, sole focus" that governed every design decision at the time. A former employee at the Growth Team notes that "new product ideas at Facebook come from looking at correlations in data and seeing what aligns with the company's north star metric: retention." (Heintzman 2022)

A controversial example of Facebook's approach to design occurred in 2012: the "emotional contagion" experiment. Without informing users, Facebook's data science team manipulated the content of the news feed for about 689,000 people to be slightly more positive for some and more negative for others. Researchers wanted to know if seeing happier or sadder posts would influence users' own posting behaviour, essentially testing a hypothesis about emotional contagion through social networks. The results, published in 2014 (Kramer et al.), showed that users who saw fewer positive posts tended to post slightly more negative content themselves (and vice versa). From a design perspective, this experiment illustrates a new frontier: Facebook wasn't just reacting to user needs, it was attempting to predict and influence user emotions

[8] *The Cambridge Analytica scandal was the 2018 revelation that the political consulting firm improperly harvested personal data from more than 50 million Facebook users via a third-party quiz app, using it to build psychographic profiles for targeted political advertising—raising global concerns about data privacy, consent, and the political manipulation of social media platforms (Cadwalladr and Graham-Harrison, 2018).*

via algorithmic content curation. The study was widely condemned for breaching informed consent standards. Indeed, unlike a traditional HCD user test (where participants are informed and volunteer), users in the experiment had no idea that their experience was being altered for research purposes—it wasn't just testing UI layouts; it was testing psychological responses. Facebook subsequently added a clause to its terms of service allowing user data to be used for research, essentially formalising this quantitative, experiment-first design method as part of its operation. By 2014, Facebook could predict, with a high degree of accuracy, which posts users would comment on or which ads they would click, and designed the product to surface those items. This maximised certain engagement metrics but also meant each user's experience was being implicitly designed by machine predictions.

Taken together, Google may have invented the core strategy of leveraging user data exhaust for design/monetisation, but Facebook expanded it into the realm of intimate social interaction and scaled it globally. Key milestones like the news feed algorithm, the like button ecosystem, the Growth Team's metrics focus, and the various data controversies all illustrate a common theme: design decisions increasingly made by data and for data. This trajectory shows a departure from designing *with* users—the heart of HCD—to designing *through* users.

5. THE RISE OF A NEW EPISTEMOLOGICAL PARADIGM

As clearly reflected in this evolution of design methods, data has become one of the most critical assets of our time. Its influence is so pervasive that we are witnessing the emergence of a new epistemological paradigm, one that challenges foundational assumptions about how knowledge is created.

In contrast to traditional scientific methods—which rely on the formulation of hypotheses and their subsequent testing through experimentation—the algorithmic age privileges an *exploratory* mode of discovery where methods often search for patterns in large datasets without starting from a clear question or theory. Rob Kitchin (2014) articulates this transformation as a paradigm shift in epistemology in which data-intensive science gives rise to a data-driven (rather than knowledge-driven) mode of knowing. In this view, meaning is not imposed upon the data by the researcher but is instead revealed through algorithmic processes.[9] Kitchin emphasises that this shift is not merely technical but epistemological: it reconfigures the nature of knowledge, placing emphasis on immediacy, correlation, and predictive capacity over explanation and causality. This epistemological transformation is not confined to the sciences or knowledge production alone; it has profound implications for how societies imagine and govern their futures through anticipatory regimes.[10]

[9] *Cf. "Data-driven design (DDD) begins by considering the data in the absence of knowledge regarding its specific uses in order to foreground relationships within the data that may not have been previously considered." (Diamond et al. 2017, 515)*

[10] *Anticipatory regimes, as anthropologist Vincanne et al. (2009) call them, are contemporary ways of thinking, feeling, and governing through the future. In anticipatory regimes, the future is treated as a calculable terrain that should be optimised via prediction, risk management, and preparedness.*

If, as Kitchin suggests, the algorithmic turn reorders how knowledge is produced, Alexander R. Galloway reminds us that this reordering is felt first at the level of the digital interface: not as a neutral membrane, but as a threshold of mediation and control where actions are formatted, routed, and made legible. In Galloway's account, an interface is less a thing than an effect—"it is always a process or a translation" (2012, 33)—a site where bodies, symbols, and protocols meet and where power is exercised by shaping what can be seen and done. Designers, as the architects of these mediating layers, play a crucial role in defining how such processes are structured, what actions they enable or constrain, and how they translate broader systems into user experience. As Galloway states, "the interface is the place where information moves from one entity to another, from one node to another within the system" (2012, 31). Reading the contemporary screen this way links epistemology to governance: the same infrastructures that surface patterns from data also pre-format culture and conduct by delimiting the field of possible inputs, outputs, and relations. In the context of Kitchin's account of data-driven epistemology, this means that interfaces do not merely display the results of algorithmic processes; they co-produce them, shaping what patterns are surfaced, how they are acted upon, and ultimately how cultural and political agency is distributed. This sets the stage for *algorithmic culture* (Galloway 2006), where curation, decision-making, and organisation of cultural experience migrate from human gatekeepers to computational procedures. Here, automation not only curates culture but subtly governs the terms of participation itself.

Following Galloway's concept of algorithmic culture, Ted Striphas (2015) argues that in today's cultural environment—which has emerged from big data, predictive analytics, and cloud computing—the production and consumption of culture are increasingly affected by algorithmic manipulation[11]. Traditionally, cultural production was a domain governed by individuals and institutions; artists, designers, curators, critics, and other cultural gatekeepers played essential roles in determining what was considered valuable or noteworthy. However, the advent of sophisticated algorithms has gradually shifted these responsibilities from human hands to automated systems. Algorithms now curate our news feeds, recommend music and movies, and even influence the development of new cultural artifacts through data-driven insights.[12]

These developments point to the fact that algorithmic rationality has become a central organising logic across diverse domains, including design and culture. In the following section, we examine how this shift challenges the foundational commitments of user- and human-centred design and we introduce the concept of predictive design.

[11] *Lev Manovich (2018) refers to this stage of technological media as media analytics while also emphasizing that automation extends beyond cultural production to encompass the presentation and retrieval of all online content.*

[12] *A clear example of this cultural shift is Netflix's attempt to utilise big data analytics to identify user preferences and develop shows based on these predictions, contributing to the rise of "algorithmic television" (Shapiro 2020).*

6. PREDICTIVE DESIGN

Before addressing the challenges that algorithmic culture poses for design, it is important to note that data-driven design and predictive analytics have been recognised in academic research for their positive contributions across many domains. In healthcare, these methods enhance proactive risk identification and intervention (Rajkomar et al. 2019; Wiens et al. 2019; Wang et al. 2024); environmental applications benefit from predictive models that support sustainability by optimising energy use and reducing emissions (Ukoba et al. 2024; Rajaram 2025); urban planning leverages big data analytics to improve resilience, resource efficiency, and community engagement in smart cities (Al Nuaimi et al. 2015; Hashem et al. 2016; Soomro et al. 2019); and educational technologies utilise data-driven personalisation and accessibility features to support inclusive learning environments (Wang et al. 2014; Ayeni et al. 2024). Yet, while these applications demonstrate the clear utility of predictive analytics, their increasing integration into design practices raises critical theoretical and ethical concerns, as discussed in the literature (e.g. Friess 2010; van Bodegraven 2017; Gillespie 2013; Manovich 2018). The very mechanisms that enable predictive systems to anticipate needs and optimise outcomes also introduce new forms of power, opacity, and normativity into the design process.

To highlight these issues and to capture the deeper temporal and epistemic logic of anticipatory, data-driven design practices in contemporary algorithmic design culture, we introduce the concept of predictive design (PD). We propose PD as a comprehensive framework for understanding a diverse set of contemporary design phenomena that share a common feature: the use of predictive analytics as the primary basis for anticipating and shaping both design processes and user experiences. In a broad sense, PD refers to the underlying design logic of services that leverage behavioural data, machine learning, and profiling to anticipate and modulate user behaviour, while accumulating predictive capital—insights that are turned into commercial value and reused to refine user experience.

By foregrounding prediction as the dominant mode of reasoning in digital environments, PD aligns with the cultural and epistemic paradigm shift we discussed in the previous section. PD—viewed as an anticipatory regime—treats the future not as an open-ended space of speculation and negotiation, but as something knowable and operationalizable through extrapolation from past behaviour (cf. Schneider 2025). In doing so, it reshapes the aims, ethics, and politics of design. As Bratton (2015, 257) notes, "the evasive distance between the predicted path and the one taken directs the portraiture of future Users, one by one or in populations, as the repetition of irregular interactions is normalised into new models [...] second by second and measurement by measurement." (Bratton 2015, 257)

In reorienting design around the continuous anticipation of behaviour, PD also unsettles the very figure of the "user" on which human-centred design has traditionally relied. PD makes explicit what Bratton (2015, 271–289) describes as the "death of the user": a shift from a user imagined as a coherent subject at the conceptual centre of design strategy, to a multiplicity of statistically derived user-agents whose positions are continuously recomputed. From this perspective, platforms do not simply serve pre-given users, but actively construct and dissolve user positions.

The four main, interlinked themes in PD are *prediction, personalisation, automation, and optimisation. Prediction* involves anticipating user behaviour from historical and real-time data, as when Netflix's recommendation system forecasts what a viewer is likely to watch next based on past viewing patterns. *Personalisation* tailors interfaces and content to individual users, exemplified by Spotify's "Discover Weekly" playlists, which create a sense of bespoke curation while feeding back into the platform's predictive models. *Automation* delegates decision-making to algorithms, for example when Google Maps automatically reroutes drivers based on live traffic data without explicit user prompts. *Optimisation* continuously refines these processes through data-driven feedback loops, as seen in Amazon's constant A/B testing to maximise click-through rates and conversion.

In PD, these themes do not function in isolation: prediction informs personalisation, automation enacts those predictions in real time, and optimisation ensures the entire cycle becomes progressively more accurate and efficient. Together, they form the operational backbone of services that—under the banner of user-centred design—sustain continuous data capture while subtly reshaping user behaviour.

Within the framework of design culture studies, PD can be understood not only as a methodological development in UX practice, but as a cultural formation in its own right. design culture studies, as outlined by Julier ([2000] 2014; 2017; Julier and Munch, 2019), examines design as a complex interplay of interconnected practices and meanings that link the work of designers, the institutions and media that shape it, and the ways designed artifacts and systems are produced, circulated, and used. From this perspective, PD is more than a set of tools for anticipating user behaviour—it is a manifestation of the ways in which predictive logics permeate everyday life, shaping how we imagine the future, how we interact with technology, and how our behaviours are rendered as economic resources.

The conceptual position of PD within this field rests on three, connected observations:

Epistemic shift—PD embodies the algorithmic, data-driven mode of knowing discussed in earlier sections, translating it into design practice. It reframes the act of design from proposing possibilities to operationalising probabilities, embedding statistical reasoning at the core of creative decision-making.

Reconfiguration of participation—PD modifies the participatory ethos central to HCD by repositioning the user as a data subject rather than a dialogic partner. In doing so, it transforms the cultural politics of design, shifting agency from collaborative negotiation to algorithmic inference.

Alignment with platform capitalism—PD operates within, and reinforces, the extractive logics of platform economies (Srnicek 2016; Zuboff 2019). Prediction becomes a commodity, predictive accuracy a form of capital, and the design process itself a mechanism for the continual monetisation of human behaviour.

For Design Culture studies, this positions PD as both a symptom and a driver of broader cultural transformations in the algorithmic age.

6.1 Predictive Design in Practice

Understanding PD as a cultural formation also requires unpacking its technical and methodological foundations. PD may foreground the epistemic and cultural implications of designing through prediction, but it is built on a set of established practices that make such prediction operational. Chief among these is data-driven design (6.1.1.), which provides the infrastructures, workflows, and feedback loops for collecting and interpreting behavioural data at scale. Yet PD also incorporates the statistical modelling and machine learning techniques of predictive analytics (6.1.2.), the behaviour-shaping strategies of predictive user experience (6.1.3.), and the proactive, decision-making logics of anticipatory design (6.1.4.). Together, these interconnected approaches furnish the analytic capacity, operational mechanisms, and interface paradigms that allow PD to function. By clarifying these conceptual and methodological relationships, the seemingly neutral processes of data collection, analysis, and optimisation become the enabling conditions for the anticipatory, behavioural-shaping ambitions of PD.

6.1.1 *Data-driven design*

Data-driven design (DDD) is an umbrella term for design practices where data scientific techniques heavily inform decisions. The growing recognition of data science's potential in design and development is evident among both practitioners and researchers (Kim et al. 2016). Trauer et al. (2020) define DDD as "a framework for product development in which the goal-oriented collection and use of sufficiently connected product lifecycle data guides and drives decisions and applications in the product development process."

Data may come in many forms, such as natural language processing of reviews and social media, surveys, market research activities, historical transaction data, analytics of use phase data, and real-time data streams (such as location tracking and viewing time). Cantamessa et al. (2020) argue that data-driven technologies are triggering a paradig-

matic shift in product design which is characterised by the continuous integration of real-time data from both users and production systems, fundamentally altering the roles of designers and how artefacts are conceived and developed.[13]

How can PD be conceptualised in relation to DDD? We argue that data-driven design is the technical and operational substrate of predictive design. While DDD maps the transformation of design through data, PD examines the ontological, ethical, and epistemological consequences of this shift—particularly the transformation of human subjects into anticipatable, optimisable profiles within total design environments.[14] The notion of PD therefore goes beyond the practical use of anticipatory design methods, aiming to critically expose and question the underlying assumptions of these practices from both the designer's and the user's perspective.

6.1.2 *Predictive analytics*

Another, related field is predictive analytics, a discipline in data science focusing on the use of statistical algorithms and machine learning methods to identify patterns in large datasets and predict future events or behaviours (Kumar et al. 2018; Panda and Agrawal 2024). In the context of design, predictive analytics might be used to infer a user's personality traits from their digital footprints (such as IBM's Watson Personality Insights), or to predict what content a user will find engaging.

In the PD paradigm, designers leverage these analytics to shape user experiences and to decide what should be designed and how. This move from prediction to suggestion is a characteristic of prescriptive analytics—a technique enabled by AI—which not only forecasts likely outcomes but also proposes actions to achieve them (Trauer et al. 2020).

6.1.3 *Predictive user experience*

Predictive User Experience (predictive UX) is a relatively recent concept (Nwasra et al. 2025) that refers to methods aimed at anticipating and responding to users' needs before they are explicitly articulated. By integrating data-driven insights and predictive analytics into the design process, predictive UX enables the proactive delivery of relevant content, services, or interactions—often in real time—while minimising friction in the user journey. Personalisation, optimisation and (churn) prediction are the key benefits of predictive UX methods (Lau 2024).

6.1.4 *Anticipatory design*

Anticipatory design (AD) is an emerging approach in the field of predictive UX. The term refers to interfaces and systems that leverage AI and machine learning to proactively make choices to "reduce the cognitive load of users by making decisions on their behalf" (van Bodegraven 2017). Aron Shapiro—founder of the design agency Huge—has introduced

[13] *Designers today work within complex socio-technical systems alongside engineers and data analysts, requiring new competencies and organisational structures. Artefacts themselves become dynamic, adaptive systems, blurring boundaries between design, use, and iteration. As a result, design agency is redistributed, and traditional linear design models give way to fluid, data-centric processes.*

[14] *Total design environments refer to socio-technical systems in which user activity, interface interactions, and service delivery are integrated into a single, continuous feedback loop of observation, prediction, and optimisation. Such environments collapse the boundaries between interaction, data collection, and behavioural modulation, making design inseparable from surveillance and control. Examples include platform ecosystems like Google (search, Gmail, Maps, YouTube), Facebook/Meta (News Feed, Instagram, WhatsApp), and Amazon (retail platform, Alexa, Prime Video), where every user action is both a service interaction and a source of predictive data feeding back into the system's design.*

the concept as a user-centred approach to reducing decision-fatigue in digital environments. As he explains, "The goal is not to help the user make a decision, but to create an ecosystem where a decision is never made—it happens automatically and without user input. The design goal becomes one where we eliminate as many steps as possible and find ways to use data, prior behaviours and business logic to have things happen automatically, or as close to automatic as we can get." (2015). AD thus exemplifies a practical application of predictive technologies within user experience, aiming to streamline decision-making through automation.

However, while AD reflects *what* is being designed—namely, interfaces that act on behalf of the user—PD shifts the analytical lens to a broader level. The key distinction between PD and predictive UX methods such as AD lies not only in scope—methodological versus theoretical—but also in their orientation. While AD focuses on what is designed, PD interrogates how and why design itself is being reshaped under the logic of prediction. PD thus serves as a broader design cultural framework that encompasses not only the design of anticipatory systems, but also the design of the epistemic, infrastructural, and cultural conditions under which anticipation becomes possible.

7. IMPLICATIONS

In what follows, we outline two central lines of critique that expose how PD departs from the foundational values of HCD and reconfigures the role of design in algorithmic culture: first, the erosion of participatory design values; and second, the emergence of user-centredness as a guise for data-driven surveillance.

7.1 Erosion of Participation

We argue that the participatory ethos of HCD is being undermined, since predictive design methods—aligning with the exploratory mode of knowledge production—privilege statistical correlations over causal understanding. While HCD emphasises qualitative engagement, co-creation, and user agency, contemporary UX practices increasingly rely on behavioural analytics—as we pointed out in Google's and Facebook's cases. This shift risks narrowing the imaginative scope of design, steering it away from speculative, critical inquiry toward the optimisation of existing behaviours (Schneider 2025). In this data-centric paradigm, even granular decisions—such as a button colour or the size of a border—often require validation through metrics (Hern 2014; Hurst 2021). This reliance on data risks marginalising a "more enlightened view of people" (Norman and Draper 1986, 25–26) and may gradually hollow out the democratic, participatory ethos at the core of HCD[15].

Earlier in this paper, we outlined a spectrum of user involvement in HCD, ranging from *design by users* (maximizing user autonomy) through

[15] *It is important to recognise that what people want and what they do often diverge—a phenomenon known as the "intention–behaviour gap" (Sheeran and Webb 2016). Relying solely on behavioural analytics risks privileging observable actions over users' articulated intentions and higher-order goals, potentially obscuring the deeper needs and values that should inform design.*

design with users (collaborative co-creation) to *design for users* (designers acting on behalf of users). PD reinterprets this spectrum in a way that challenges and complicates its original participatory intentions.

While PD inherits the *for users* orientation of late-stage HCD—where design decisions are often justified by claims of user benefit—it replaces much of the interpretive, qualitative grounding of that position with inference from behavioural data. In effect, the "user" becomes less a dialogic partner or co-creator and more a data profile whose likely actions can be modelled, anticipated, and optimised for.

At the same time, PD borrows selectively from the *with users* end of the spectrum, but here "participation" often takes the form of involuntary data contribution rather than active collaboration. Every click, scroll, or dwell time becomes input into predictive systems, generating design-relevant knowledge without the explicit consent, awareness, or agency typically associated with co-design.

Finally, the *by users* pole—the domain of Meta-design and end-user development—finds an ambiguous place in PD. While predictive systems can, in theory, adapt to user-led configurations or emergent practices, the underlying predictive infrastructure often constrains these possibilities, prioritising behavioural pathways that serve platform-level optimisation goals.

Viewed through this reframed spectrum, PD signals a structural shift: it maintains the rhetorical language of human-centredness but redistributes agency toward algorithmic systems and corporate interests. The result is a mode of design where "for users" is subsumed into "through users," and where the primary medium of user involvement is their ongoing transformation into predictive data subjects. This marks a shift toward a paradoxical form of (predictive) participation—where users shape systems through their data traces, but without the awareness, consent, or influence traditionally associated with participatory design.

7.2 Service as Surveillance

Second, we argue that the rhetoric of user-centredness often obscures the underlying logic of large-scale behavioural surveillance. While "seamless interaction" and "intuitive interfaces" are framed as empowering design choices, they frequently serve to normalise data extraction and algorithmic profiling. Concepts such as efficiency, usability, and accessibility are used to frame systems participatory and human-centred (e.g. Meta), even though these systems often rely on the large-scale capture of behavioural data—not merely to enhance user experience, but to predict, influence, and monetise user behaviour. As Shoshanna Zuboff (2019) argues, this data is treated as a surplus resource, feeding predictive models that are sold into "behavioural futures markets"[16]—a logic that exceeds UX optimisation and enters the realm of behavioural

[16] *Zuboff's "behavioural futures markets" are places where companies sell predictions about what people will do in the future. They collect huge amounts of data about user behaviour (what we click, where we go, what we say), turn it into predictions (e.g., "this person is likely to buy X tomorrow"), and then sell those predictions to advertisers, insurers, political campaigns, and others who want to influence or profit from our future actions. It is like a stock market, but instead of trading shares of companies, they trade bets on people's future behaviour. (Zuboff 2019, 96)*

modification for profit. In this context, design does not foster agency or critical engagement, but rather renders behaviour more computable, and monetisable. Thus, in the PD paradigm, services are motivated to improve data collection, essentially creating a feedback loop between design and data. Better data allows for more accurate predictions, which can improve design decisions, and at the same time, the design of a system affects the kind of data it can collect and how reliable that data is. Products and services within the predictive framework are thus designed to encourage user engagement and continuous data generation. Seamless interaction—as a core principle of UCD—plays a major role in this process. Miriam Rasch (2020) argues that seamless interaction is "an important dogma of dataism" because it reinforces the notion that design should recede into the background, enabling continuous, passive data flows unimpeded by user resistance or reflection. The optimisation of design for data-capture is clearly reflected in the shift from prioritising standalone, offline products to developing online services, subscriptions, and product ecosystems (Bürdek 2015, 9). By transitioning to cloud-based services, companies are able to exert long-term control over user engagement and data.

However, under the banner of understanding and serving the user, tech companies often overreach in harvesting personal data. For instance, as shown in multiple investigations, Google collects location data even when users have explicitly disabled "Location History" in their settings. According to the company's spokesperson, "There are a number of different ways that Google may use location to improve people's experience, including: Location History, Web and App Activity, and through device-level Location Services." (Nakashima 2018). Yet the use of this data extends far beyond enhancing user experience—it feeds into Google's advertising ecosystem, allowing hyper-targeted marketing based on physical movements, routines, and behaviours.

At the same time, there are limits to how fully this extractive logic can appropriate human life, for prediction is bound to what can be computed—an assumption that, as Dunne and Raby (2013, 39) remind us, leaves much of the complexity of human experience outside the frame of design: "Dark, complex emotions are usually ignored in design; nearly every other area of culture accepts that people are complicated, contradictory, and even neurotic, but not design. We view people as obedient and predictable users and consumers." PD amplifies this reduction by treating human action as fully legible through platform-specific datasets. But no database can account for the contradictions, discontinuities, or off-platform practices that constitute real human life, which means that prediction necessarily operates on partial, biased, and often misleading portraits of users. Acknowledging this epistemic shortfall is essential: the very incompleteness of data is not an accidental flaw but a structural condition that constrains predictive design methods.

In the era of *surveillance capitalism*, as described by Zuboff, corporations claim human experience as "raw material" without users' full awareness or consent. This business model, pioneered by internet giants, turns HCD on its head: instead of empathetically serving the user, it treats the user's behaviour as a product to be sold. The rhetoric, however, often claims it's all to enhance user experience. This underscores a modern tension: the same user data that can improve a service's usability can also erode privacy and autonomy if misused.

Zuboff's critique is not merely economic but ontological: surveillance capitalism enacts a transformation in how the human is conceptualised and operationalised within digital systems—PD, in this context, is not simply a set of design tools and ideas, but a critical concept that names and interrogates this transformation.

8. CONCLUSIONS

Throughout this paper we have traced how PD emerges from the technical and methodological infrastructures of data-driven design, predictive analytics, predictive UX, and anticipatory design. We have situated PD historically, showing its roots in the rationalisation and optimisation logics of modern design, its methodological debt to HCD, and its current embedding in platform capitalism. We have also located it conceptually within design culture studies, emphasising that PD is more than a toolkit—it is a cultural formation that reconfigures the relationship between designers, users, and systems.

By reframing the "design by/with/for users" spectrum in predictive terms, we have shown that PD complicates the participatory ideals of HCD. "For users" becomes "through users," as their interactions are continuously harvested and fed back into systems that anticipate and steer behaviour. Participation is often reduced to passive data contribution; agency is redistributed toward algorithmic decision-making; and design itself becomes a mechanism for maintaining the conditions of further data capture and optimisation.

This analysis also underscores the dual nature of PD. On the one hand, predictive techniques can enhance efficiency, personalisation, and responsiveness across domains from healthcare to education. On the other, they embed new asymmetries of knowledge and power, normalising surveillance, constraining user agency, and narrowing the imaginative scope of design to what is already probable. In doing so, PD not only changes the mechanics of design practice but also contributes to the shaping of a broader algorithmic culture—one in which the governance of futures is increasingly delegated to computational systems.

What is at stake in the rise of PD is not simply how design is done, but what design is for—and for whom. PD marks a shift in the cultural, epistemic, and political economy of design: from processes grounded in

dialogue, speculation, and participatory engagement toward systems oriented around behavioural forecasting, optimisation, and extraction. While drawing on the rhetoric of human-centredness, PD redefines the role of the user—from an active participant in shaping outcomes to a predictive data subject whose past behaviours are leveraged to model, anticipate, and monetise future actions.

Like all conceptual work, this study has its limitations. Our analysis is primarily theoretical and interpretive, drawing on a curated set of historical, theoretical, and cultural sources rather than on systematic empirical data. While this allows for a broad, critical framing, it also means that the nuances of PD's operation in specific industries, geographic contexts, or cultural settings remain underexplored. Additionally, our focus has been on large-scale, corporate platforms—often the most visible and influential examples—but this emphasis risks overlooking alternative or counter-examples in smaller-scale, activist, or public-interest design contexts.

These gaps point toward several avenues for further research. Empirical studies could investigate how predictive design logics are implemented, adapted, or resisted in different sectors, from civic technology to education, healthcare, or cultural institutions. Comparative research could explore variations across regulatory environments or cultural contexts, highlighting how legal frameworks, societal values, and local practices mediate the adoption of predictive techniques. Finally, speculative and critical design methodologies could be employed to prototype alternatives—systems that use predictive capacity to enhance rather than diminish participation, agency, and plurality.

By locating PD within the interdisciplinary framework of design culture studies, we have aimed to contribute to a critical vocabulary for examining how contemporary design mediates power, participation, and knowledge in the digital age. PD is not merely a methodological evolution; it is both a symptom and a driver of a changing cultural paradigm. As such, it is also a site of contestation—raising urgent questions about how design might reclaim spaces for openness, critical engagement, and the co-creation of alternative futures beyond the imperatives of prediction and optimisation.

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