Prototyping with Uncertainties: Data, Algorithms, and Research through Design

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Seen both as a resource and an obstacle to clarity, uncertainty is a concept that permeates many areas of design. As the concept gains prominence in HCI, this special issue specifically explores the interplay between uncertainty and prototyping in Research through Design (RTD). We first outline three histories of uncertainty in design, in relation to its philosophical significance, its role in statistical and algorithmic processes, and its importance in prototyping. The convergence of these aspects is crucial as design evolves towards more agentive and entangled systems, introducing challenges such as Design As A Probabilistic Outcome. We then investigate the design spaces for engaging with 'being uncertain' that emerge from the papers: from nuancing the relationship between designers and quantitative data to blurring the line between humans, fungi, and algorithms. Finally, we illuminate some preliminary threads for how RtD can navigate and engage with these shifting technological and design landscapes thoughtfully.

CCS Concepts: • **Human-centered computing → HCI theory, concepts and models**.

Additional Key Words and Phrases: Algorithms, Data, Prototyping, Research through Design, Uncertaintities

1 INTRODUCTION

Data brings changes to design that reach far beyond a shift in materiality and means of industrial production. It implies working with unstable objects that are defined not just by their initial form and intended use, but by the sustained feedback loops between design and use that data technologies make possible. These new digital objects may even possess the capability to create new 'things' themselves [28, 64]. For example, Spotify can transform historical listening data into personalized playlists, while wearable trackers can use personal data and physical activity to generate tailored insurance plans. As design transitions from prototyping self-contained objects with well-defined form factors to exploring the possibilities and risks associated with connected and massively decentralized digital things, new challenges arise.

This shift necessitates a rethinking of design practices to address the dynamic and autonomous nature of these interconnected systems. Consequently, the design practices that are foundational to Research through Design (RtD) are also profoundly challenged. Emerging algorithmic practices imply deep shifts in design, particularly concerning the agentive and infrastructural roles that nonhumans such as algorithms may take in decentralized design processes [29, 30].

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To better understand the shifts taking place and what this means for how we can respond to and make use of the inherent uncertainties of design, there is a need for knowledge regarding how forms of RtD that experiment with data and algorithms differ from RtD traditions of making and prototyping informed by practices of skillful crafting and industrial design manufacturing. The emerging challenges are not just technical [22, 87], nor is aligning design and research intentions just a matter of interdisciplinary collaboration [4]. Working with diverse streams of data brings new aspects of connectivity and context to design and to the entangled assemblages it now engages in making [36]. These aspects require new ways of engaging with model-based technologies in design processes [49, 53, 68, 71, 79] and new ways of thinking into what the technologies might mean [30, 46, 54].

Established RtD practices often emphasize the importance of using data as a design material for the purpose of exploring and co-creating with users new design directions [8, 33, 89]. Emphasis is also placed on the need to gain deeper insights into user experience by integrating quantitative and qualitative methods for long periods of time and engaging with users continuously and remotely [32, 81]. However, algorithms also make judgments and perform actions that create new connections and shape new relations with people and machines: "[u]nstable, probabilistic and agentive, the artifact becomes part of a decentralized making process through which future practices are endlessly experimented and reconfigured" [29] (p. 146). Combined with data, algorithms can automate tasks in the design process. The more complex these tasks are, the greater the uncertainty about how the algorithms perform them, fundamentally changing their use for design. It is clear that the design that they enable and promote is no longer a "stabilizing process" [21].

This new interplay of human and (uncertain) nonhuman resources profoundly challenges the stabilizing character of the artifact and brings new aspects of uncertainty to design. Reconceptualizing the things we make as capable of making things in their own right destabilizes the locus of doing design. The practice moves towards fundamentally recursive and probabilistic relations, both between design and use and between producer and produced. These new relationships need to integrate and balance capabilities and doings uniquely human and uniquely artificial [29, 42].

This fundamental shift opens new roles for designerly processes of knowledge production as well as new perspectives on data in design. For example, while A/B testing and continuous monitoring of user behavior have become essential aspects of design practice in the data-driven domain, it has also become increasingly clear that automating design decisions risks reducing design to construction and optimization of already defined trajectories [31]. Given what is at stake as data-driven artifacts and AI systems permeate and govern our everyday lives, *algorithmic RtD practices offer an important experimentation space for imaginative and critical perspectives on the relations between design and data, and how these can be put into practice*.

In this introduction to the special issue, we build four lines of discussion. Firstly, we unpack and connect three parallel conceptualisations of uncertainty: (1) its philosophical and practical role within design as a discipline, (2) the treatment of uncertainty as a measure within statistical and algorithmic processes, and (3) the role of uncertainty in prototyping, specifically within RtD practices.

Secondly, on these foundations, we sketch ways in which these convergences are important, particularly in the light of designing more agential, fluid and entwined artifacts and systems—"design as a probabilistic outcome" [29]—and we draw out some of the productive tensions about working in this space.

Thirdly, we describe and position the papers in this special issue, mapping these diverse ways of seeing uncertainty across the space that we have built with respect to working with data-driven artifacts, machine learning algorithms, and computational models.

Finally, we build upon these correspondences to develop some embryonic threads for shaping future practices that engage with, navigate, and embrace uncertainty.

2 CONCEPTUALIZING UNCERTAINTY

In this section, we interconnect three parallel conceptualizations of uncertainty, each playing a crucial role in the field of design and its related practices. First, we explore the philosophical and practical significance of uncertainty within design as a discipline aimed at creating intentional change in an ever-evolving world. Next, we address the treatment of uncertainty as a measurable element within statistical and algorithmic processes, considering how data and algorithms handle and quantify uncertainty in design contexts. Finally, we examine the role of uncertainty in prototyping, with a particular focus on RtD practices. Here, uncertainty is not merely a challenge to be overcome but a dynamic force that shapes the iterative and experimental nature of prototyping, fostering a deeper understanding of the relationship between design and use.

2.1 Histories of Uncertainty in Design

Uncertainty is inherent to designing for several different reasons, quite a few of them directly related to the ambition to create intentional change in a complex and constantly changing world. In a system complex enough, the distinction between what is yet undetermined and what will remain indeterminate blurs as a result of how the many different factors come to interact over time. As such, the inherent uncertainties of designing lies as much in the framing of intentional action, as they lie in deciding and then enacting how to then achieve it. But there are also other reasons why design tends to embrace uncertainty, and why it seems more obvious to associate design with the term 'research' rather than 'science'. To illustrate why, consider the following remark by Bruno Latour [43]:

"In the last century and a half, scientific development has been breathtaking, but the understanding of this progress has dramatically changed. It is characterized by the transition from the culture of "science" to the culture of "research." Science is certainty; research is uncertainty. Science is supposed to be cold, straight, and detached; research is warm, involving, and risky. Science puts an end to the vagaries of human disputes; research creates controversies. Science produces objectivity by escaping as much as possible from the shackles of ideology, passions, and emotions; research feeds on all of those to render objects of inquiry familiar." [43] (pp. 208-209)

While many times seemingly at odds with certain traditions of knowledge creation within the academic realm, RtD is in a way also a typical example of a change that has been taking across many disciplines (and perhaps especially in what is called Mode-2, inter-, intra-, trans- and post-, etc. disciplinary research). [1] In other words, we find uncertainty to be central to design not only with respect to where it happens and for what reasons, but equally at the center of how it is done and what it results in [63].

Even among the early proponents of a rational and more scientific approach to designing that emerged in the late 1950's, uncertainty was identified as a key challenge not only with respect to what is being designed but also to the framing of designing as such. Discussing aspects of rationality, Herbert Simon (1996) once remarked: "At each step toward realism, the problem gradually changes from choosing the right course of action (substantive rationality) to finding a way of calculating, very approximately, where a good course of action lies (procedural rationality). With this shift, the theory of the firm becomes a theory of estimation under uncertainty and a theory of computation – decidedly non-trivial theories as the obscurities and complexities of information and computation increase." [73] (p. 26).

Over time, there was a realization that designing is characterized by judgment as much as reasoning as a way of addressing uncertainty. In a text about design education preceding the more famous account of "wicked-problems" in the early 1970's, Horst Rittel, once a professor in design methods at HfG Ulm during a time (and in a place) when much of what is still practiced in the context of technology design was beginning to take form, very accurately captured a central concern: "Design problems have another feature which makes them difficult to deal with: they are ill-behaved". Rittel further argued that: "All these difficulties are different expressions of a basic dilemma of human existence: if one tries to be rational (i.e., tries to anticipate the consequences of one's

[1] See also Nowotny et al. [58]

"doings") there is no beginning and no end to reasoning [...] On the other side, nonrational spontaneous action on a large scale is likely to get the actor and others into trouble: it is irresponsible. Thus both extremes have little survival value." [66] (p. 19).

The uncertainty and unpredictability of the world that design's intentional change is meant to affect brings related uncertainties into designing as such, with little hope of eliminating them. Consequently, the focus has come to be on how to find a balance between on one hand embracing the inherent, and therefore unavoidable, uncertainties of design while on the other finding systematic ways of dealing with, and in many cases, eventually reducing it. *Naturally, there is no consensus as to where that balance lies, perhaps with the exception that there might be agreement that such a balance is context dependent.* In taking a stance against the very field he was part of creating, John Chris Jones (1991) argued that: "As you take more and more of life to be part of the problem you don't get a more stable problem you get a less stable problem", and therefore: "If you wish for certainty you might as well leave this subject alone. Because design is to do with uncertainty." [40] (p. 20)

This brief historical illustration hopefully provides some background as to why notions of uncertainty play such a central role in much design development. As designing enters new contexts, engages with new technologies, or aims to respond to emerging challenges, yet new kinds of uncertainties come into view – and with this a need to develop new means for addressing them.

Indeed, this history is key for grasping current design process models, like the double-diamond model popularized by the British Design Council, [2] with its sequence of first embracing uncertainty (divergence), destabilizing the design problem to explore it beyond initial assumptions and interpretations, followed by acts to reduce it and to respond by means of a reasonably stable solution (convergence). [3]

2.2 Uncertainty in Data Technology and Machine Learning

In the previous section, we saw that uncertainty has been formalized in design development and research. But design, with emerging technologies based on data, predictive, and generative technologies, is bringing new forms of uncertainty. In this section, we provide a background to these forms of uncertainty arising from data-driven technologies, such as machine learning.

Uncertainty has a long history within mathematical and computational disciplines, appearing wherever probabilistic models are needed to understand the world. Shannon's theory of communication [72] was built on a foundational question of how transmitted symbols relate to uncertainty, either in the sense of possible communicative choices at any given moment, or in how much uncertainty is removed when a receiver gets a message [15]. In disciplines such as machine learning or signal processing, information (or *signal*) indicates the desirable part of the data – "what we are looking for" – and everything else is referred to as *noise*. The signal is the least uncertain part, the underlying structure we wish to draw out, and the noise is the uncertainty added by a deviation from an ideal, pure transmission. At an extreme, white noise is a random signal, which has the most uncertainty, and also requires the most information to represent, as there is no underlying structure to capture. As Weaver puts it: "Uncertainty which arises by virtue of freedom of choice on the part of the sender is desirable uncertainty. Uncertainty which arises because of errors or because of the influence of noise is undesirable uncertainty" [84] (p. 8). As such, it touches many domains: behavioral research [86], information retrieval [86], systems engineering [50], waste management [35], and so on. When looking at probabilistic phenomena, two types of uncertainty are usually considered: *aleatoric* and *epistemic* [37, 44]. Aleatoric uncertainty is the element of chance inherent in the phenomena captured by the data. A classic example is a coin toss. By convention, there is a 50% chance that the coin will come up heads and a 50% chance that it will come up tails. Epistemic uncertainty, however, is the amount of uncertainty due to a lack of knowledge in what we observe – if we could include another process

[2] https://www.designcouncil.org.uk/our-resources/the-double-diamond/

[3] Cf. also John Chris Jones' Design Methods regarding divergence, transformation and convergence [39].

or procure additional data, the prediction might become more certain. Differentiating between these types of uncertainty is useful in order to differentiate between the part of the uncertainty that we can try to reduce by increasing our knowledge of what we are observing, and the irreducible part that we will have to use as it is.

In this context, *we look in particular at the uncertainties involved in the kinds of machine learning models that might be brought into design processes: models that might categorize, generate, interact, decide and otherwise be deployed as part of a thing, system, or other assemblage to be created.* In general, the objective of machine learning is to produce models from data. These models can then be used to perform tasks such as prediction, which means providing an output based on unseen data, i.e., data that has not been used in the construction of the model. Models may learn from text data how to translate text from one language to another, or how to classify images into categories. In general, *the interesting uses of machine learning involve situations that the model has not encountered before*, which implies "generalising beyond the data" [37], and hence an inherent element of uncertainty. Here, we look at two broad types of uncertainty that are relevant to design practices: data and generalization uncertainties.

2.2.1 Data Uncertainties. On one hand, uncertainty lies in the data. *Data is an ambiguous representation of observed phenomena and entities, a particular set of information that has been chosen to be captured and interpreted from the world* [20, 41]. It is, first, a *simplification.* A digital image of a landscape is a representation of that landscape but simplified. The photograph of the landscape does not convey the tangible sensation of terrain or of being part of the scenery. If we capture data from a living system, this data can give a confusing account of the behavior of this living system and of interactions with other living systems. Similarly, data representing human behavior may capture real information, such as movement in space, arm movement, and posture, but the data will not easily capture the intentions behind that behavior, leaving uncertainty about them. Hence, the things not captured by the data remain uncertain. When connected to humans, *these elisions can become intensely problematic.* Muller and Strohmayer talk about "data silences" [52]—spaces in otherwise saturated spaces, the assumption that "what you see is all there is", the use of traces instead of experiences, and so on.

Data is also uncertain due to the technicalities of its collection. Typically, physical measurements come with a reported measurement error that reflects the uncertainty of the measurement's accuracy in relation to the actual physical variable. Additionally, the choice of spatial units for data collection can alter the outcomes derived from the data [60]. Moreover, classification systems can become contentious "sites of political and social struggles" [12] (p.195), with different systems yielding varying results. Datasets can have several sources mixed, leaving uncertainty about what is actually observed. As data is repurposed, the connection between the computational representation and its origins is attenuated, and it may be brought into situations where it is not suitable. A key example of this is Crawford and Paglen's "Excavating AI" [16], which looks at the process of labeling pictures that gave rise to many image-based models, as well as Lyons's rebuttal [47] about the purposes of the original datasets. Going back to the distinction between signal and noise above, particularly in a design process, separating information from noise means making a decision about what we consider to be useful, what we want to highlight, or what we consider to be part of what we are trying to design.

2.2.2 Generalization Uncertainties. The most common purpose of producing a model is to generalize over unseen data - to classify a *new* image, to translate a *novel* sentence, to *generate* a new image in response to a prompt. Technically, this process of generalizing from observations (data) is called induction, and this inductive process necessarily induces a form of uncertainty as it is working with data that were not used to train the model. A model cannot be certain about data that it has never seen, or that it does not directly contain. If this data is very similar to already seen data, the model could infer a prediction with high confidence. However, if a data point is further away from the type of data used for training, uncertainty is higher. The practice of validation within machine learning holds back some of the training data in order to see how well a model generalizes to new data, and avoid 'overfitting' where existing data is well explained, but generalization is poor. However, *these kinds of* *practices can only account for data that is already captured.* As models are brought into new contexts, or when the limitations of their data are reached, the quality of their generalization is fundamentally uncertain. These kinds of generalization problems can manifest as unintended behaviors, nonlinearities, impossible outputs, and so on. The challenge for designing with such systems is how to understand the limits of generalization, and determine which situations allow confidence and which do not.

2.3 Uncertainty and the Making of Prototypes in Research through Design

The relationship between how we understand designed artifacts and why we make them is important as it reveals how theoretical groundings and methodological concerns have evolved over time [34, 62]. In RtD , designed artifacts are often referred to simply as prototypes. No matter whether we use artifacts to demonstrate possibilities or provoke and speculate on alternative futures, as a vehicle for critique or for developing theories, and independent of whether they are props or fully functional devices, artifacts play an essential role in RtD [76]. They are the primary means to ask particular research questions. Made for research purposes and referred to as research artifacts [88], they are not to be confused with products intended for the consumer market. Their role "as vehicles for research about, for and through design" is manifold [85] (p. 262).

However, developing a useful conceptual framing for RtD practices with data and algorithms may require moving past ideas of the artifact as prototype. *It requires reimagining how prototyping may look like and what processes of knowledge production it may serve in light of technologies and within design conditions that have fundamentally changed.* This means that before offering an overview of the tensions and productive frictions through which uncertainties are navigated and embraced in practices of RtD with data and algorithms, we first need to briefly outline how ideas of making and prototyping are further complicated by data technologies and how data-driven artifacts come to exist in a connected world. To follow, we will build upon the distinction between conceptualizations in RtD based on ideas of *"design as stabilizing process"* and *"design as probabilistic outcome"*, as proposed by Giaccardi [29].

Much RtD making (including that of digital artifacts) has been significantly influenced by the long-established practices of skillful crafting and industrial design manufacturing, implicitly reflecting an understanding of the artifact as a single object. This is an artifact that although not final is equally conceived as a material embodiment [78] or manifestation [45] of the ideas, skills and knowledge of the designer and which can be experienced by others. Referred to as prototype [77], it is a sketch, a mock-up, or polished material outcome confronting the world of ideas and skills of the designer with the world-out-there before a final artifact exists [13].

Although not all RtD converges on a single product stance, and we know there are other historical threads mixed into the heterogeneous RtD community that present ideas about design beyond the product, including 'thinging' and infrastructuring [7, 24], *one way to theoretically and methodologically frame how ideas of making and prototyping have come about in RtD is in relation to concerns of 'stabilization'* [29]. As argued by Donovan and Gunn [21], the role of the prototype in established design practices is to support people to imagine, discuss, and shape future states at project time. In this sense, doing design is a kind of stabilizing process through which future practices are imagined and experimented at project time, then realized. In RtD approaches informed by participatory processes of co-reflection and co-design, this stabilizing character of the artifact is expressed in the way in which the prototype helps achieve a sort of consensus among designers and non-designers [69]. The same orientation is also reflected by the way that ethnographic methods have been traditionally adopted and domesticated in RtD practice. Motivated by the need for the artifact to be deployable in the field for an extended duration and to be lived-with and experienced over time in the context of everyday life, Odom et al. [59] propose that the artifact of RtD should be considered as a research product. This proposition emphasizes the actuality of the designed artifact and suggests that the engagement that people have with it should be "predicated on what it is as opposed to what it might become" (p. 2550).

This understanding of what a prototype is and does has its historical roots in the early days of industrial design and the transformation of making from the production of complete and finished things to the new forms of making needed for industrial manufacturing to follow [63]. This brought about a need to navigate conflicting requirements, desires, and constraints, *making the prototype both the venue and the tool for addressing increasingly complex design challenges*. It facilitated iterative and extensive experimentation, becoming integral to the process of refining design solutions. Specifically, it helped address the uncertainties inherent in mass production, allowing for the identification and resolution of problems, errors, and other unintended consequences before moving to serial production. Such use of prototypes became central to the approach and pedagogy of design schools such as the Bauhaus: "The Bauhaus attempts to produce the elements of the house with this economy in mind – therefore to find the single solution that is best for our times. It applies itself to this task in experimental workshops, it designs prototypes for the whole house as well as the teapot, and it works to improve our entire way of life by means of economic production which is only possible with the aid of the prototype." [51].

There is a certain tension at the core of most prototyping practices between on one hand envisioning and proposing, and realizing and negotiating on the other. Indeed, the orientation towards design as a stabilizing process can be seen as a matter of finding a stable resolution to such tensions, in many ways being a material expression of what such a (re)solution could be like. Discussing the training of the future industrial designer, Thomás Maldonado once remarked that as design evolves, the role of the designer becomes one of coordination across both disciplines and conflicting concerns, arguing that the designer's "responsibility will be to coordinate, in close collaboration with a large number of specialists, the most varied requirements of product fabrication and usage; his will be the final responsibility of maximum productivity in fabrication, and for maximum material and cultural consumer-satisfaction." [48] (p. 34).

This history does not deny the inherently transformative nature of the design process; rather, emphasizes the original orientation of crafting and manufacturing practices toward resolution: "Although provisional, unfinished and not for sale, the prototyping of artifacts that is grounded in long-established RtD practices of skillful crafting and industrial design manufacturing is an object around which behaviors and values are meant to precipitate and converge, if then to diverge again at use time" [29] (p. 141). As we will explore next, recent advancements in RtD, driven by the use of data and algorithms, have moved beyond traditional practices and the concept of the artifact as a stable, standalone object. These developments encourage creative exploration of probabilistic spaces, including the complex entanglements between nonhuman actions and human intentions [1, 5, 6, 18, 56, 68, 71] as well as the recursive, resourceful, and experimental relationships between design and use in designerly processes of knowledge production [28, 57, 67, 80, 83].

3 SYNTHESIZING UNCERTAINTY IN RESEARCH THROUGH DESIGN

In this space between design and computational practices there are several threads to bring together in support of looking across the various ways of working. Drawing on trends and developments in HCI, the sense of the agency of data has gradually increased, from early calls to think into designing 'from, with and by' data [75] to the modern profusion of smart connected devices. At the same time, uncertainty has begun to join ambiguity [27] as an important concept within HCI.

In their analysis of how uncertainties have been approached in HCI, Soden et al. [74] argue that there are at least four modes of addressing uncertainty. First, it can be *disciplined*, treated as a problem to be solved through scoping, pinning down, measuring. and predicting. Second, it can be approached *politically*, shaping our encounters with data, by asking "what counts" questions, revealing hidden structures and exposing the priorities implicit in the answers. Third, uncertainty can be *generative*, embraced as a means to foster imagination and creative thinking. Finally, an *affective* approach troubles bodily experiences of certainty and helps engage with the plurality of lived experiences. Scoones and Stirling [70] provide an in-depth discussion of the political conceptualization of uncertainty. They explore how uncertainties permeate knowledge, materiality, experience, embodiment, and practice, arguing that embracing uncertainty can challenge the idea of progress as a hard-wired race to the future along a singular path. *Uncertainties produce concrete, material futures, experienced differently by different people, and give rise to distinct practices and actions.* The silences produced by models are as important as the answers they provide, and the complex architectures become devices for telling particular stories (ibid, p.6; cf. also [55]).

We identify the following two key conceptual directions to further our reflection and chart an area of interest for future RtD endeavors: firstly, the things, artifacts, and systems we are making today are inherently probabilistic and uncertain due to their gradual becomings and multiple entanglements; secondly, practices we use to prototype, make, and investigate are increasingly connected to data and its tensions between certainty and uncertainties. Both of these help to think into how uncertainty plays into HCI and design to productively create critical futures and actions.

3.1 Design As A Probabilistic Outcome

Let us go back to the conceptual distinction in RtD between "design as stabilizing process" and "design as probabilistic outcome," as proposed by Giaccardi [29]. Something is changing fundamentally with data-driven artifacts that hold both perception and possible agency. These are artifacts that can detect, record and react to data streams and that can autonomously make judgements (or be perceived as doing so) and make connections with other products and services. *Data represents the world, machine learning models create these connections.* Machine learning methods (the basis of AI) are designed to find tacit correlations in data sets so that predictions can be made on the basis of new data. These predictions (or judgements) are, by design, statistical: a prediction is associated with a degree of confidence in the prediction and therefore with uncertainty. Predicting the behavior and inherent uncertainties of these 'things' poses a significant challenge, and changes the way they are conceived. To some extent, these 'things' participate in both their design and use, in a way that earlier handmade or industrially produced objects could not. The involvement and behavior of these objects within potentially unpredictable arrangements and collaborations of human and nonhuman resources profoundly challenges the stabilizing nature traditionally associated with prototypes from past practices of skilled craft and industrial manufacturing practices. Furthermore, this stabilizing effect is increasingly under scrutiny with artifacts whose behaviors remain beyond full control. In other words, *designing with these data and technologies involves not only giving form to a prototype but also delegating a portion of the designer's agency to the artifact and shaping its behavior.* Examples of these new design practices in RtD include materializing industrial infrastructures for design participation [17], repurposing automation in agriculture [19], exploring (machine) learning mechanisms in artistic practice [14], and addressing the socio-political aspects of lived environments through data [10].

To further challenge notions of prototypes and their historical role in stabilizing designs, Redström and Wiltse [64], argue that digital objects, or 'things,' are fundamentally different from single products. A thing such as a smartphone can be used in a vast number of ways. It also becomes something different in terms of what it is, what it does and why, depending on how the user intentionally frames it as an object. My smartphone is not the same as yours. It uses different apps, different data, for different purposes, it means something different and it does it differently. In other words, with digital objects, the relations and assemblages that 'make things' in everyday life become unstable. Furthermore, in the realm of computational technology, devices often function by 'simulating' other machines, as seen when software updates allow significant changes without corresponding hardware alterations. In agile development methodologies, for instance, the idea of prototypes is almost completely absent, having been replaced by notions such as 'minimum viable product' instead. This approach diverges from the conventional industrial process that requires settling on a single solution for mass production. Instead, software iterations can be rapidly deployed and tested in a networked environment, allowing for the deployment of various design versions followed by A/B testing to determine the most effective design. In this way, a company like Spotify might have hundreds of teams conducting "tens of thousands of experiments annually" [2]. Furthermore, in design research, the pace of iterations has accelerated significantly. This is evident when rapidly testing a concept using a pre-trained Large Language Model (LLM) or making minor adjustments to existing code to explore new interactions with a device. In essence, *digital technologies challenge not only the prototype as a necessary step on the way towards a product, but also the relations between, and figurations of, design and use.*

Things are complicated even further with advanced data technologies and AI. Autonomous vehicles, conversational assistants such as ChatGPT , Claude, and Gemini, generative AI tools like DALL-E, Midjourney and Jasper, drones that deliver purchases within minutes of placing an order, and smart contracts wrote on Ethereum tokens are things that increasingly 'do business' with humans and with each other [38]. As things become enabled through the exchange of data to make judgments and perform actions that create new connections and shape new relations to both people and other things, we must acknowledge that things not only change, 'things make things too' [28, 29]. *Unstable, probabilistic, and agentive, the prototype becomes part of a decentralized making process through which future relations and social practices are endlessly experimented and reconfigured. Such a decentralized process is further blurring distinctions between design and use, subject and object, producer and produced, collapsing the traditional division in design processes between participation (before design), interaction (in use) and the creation and distribution of products and services (after design). It is not just about making, evaluating, and using prototypes; it is about finding new designerly ways to engage with and bump against different uncertainties. In this perspective, prototyping becomes a way to prototype relations, balance and integrate capabilities and doings uniquely human and uniquely artificial, locate the right kind of agency, and engage shared processes of reflexivity, value creation, and creativity* [29].

With respect to such issues, the 'prototype' in RtD should no longer to be understood as an expression of a development stage, as it was traditionally viewed. Instead, it retains its relevance as it denotes *a site for exploration and negotiation*, and as it points to a genealogy of design expressions that address how conflicting matters of envisioning and actualizing can be addressed, and perhaps only (re)solved through making.

3.2 Productive Tensions in Doing Research through Design with Data and Algorithms

As we've discussed, RtD inherently involves dealing with uncertainty. With the advent of data technologies and machine learning, the nature of this uncertainty has expanded, presenting both challenges and opportunities. This special issue aims at understanding and engaging with these uncertainties through a nuanced approach, recognizing their sources and implications. Firstly, we have situated conceptions of uncertainty within the histories and technological developments that inform these conceptions. Secondly, we surface the implications of these conceptions through practices developed in response to how we may engage with these uncertainties, as described in the contributions to the special issue.

Historically, we have seen that uncertainty in design has been acknowledged as a fundamental aspect, from early rational approaches to the recognition of 'wicked problems' that are ill-defined and complex. Design has always grappled with uncertainty, but data technologies introduce new dimensions, adding layers of uncertainty due to the nature of data as simplified and ambiguous representations and the probabilistic nature of machine learning models, which rely on inductive generalizations. As a result, *designing has evolved from a process aimed to stabilization to one concerned with engaging and negotiating probabilistic outcomes.*

This shift necessitates a deep understanding of the sources of uncertainty and its effects on the design process. Aleatoric uncertainty highlights the randomness inherent in data, such as the unpredictable outcomes of a coin toss. This type of uncertainty is intrinsic and unavoidable, reflecting the natural variability and chance occurrences in the data. Epistemic uncertainty, however, underscores the gaps in our knowledge, which can potentially be mitigated by gathering more data, refining models, and improving the methodologies used to analyze and interpret data.

The practical implications of these uncertainties manifest in various gradients and tensions within the design practices engaged in the articles of this special issue. *One significant tension is between viewing uncertainty as a problem to solve versus a creative impetus or a source of reflexivity.* In approaches developed in contexts where predictable results are important, uncertainty is an issue to be mitigated or resolved when aiming for clarity and stability in design outcomes. In contrast, considering uncertainties as opportunities for addressing the intrinsically wicked problems of the real world offers a chance to explore new design methodologies, challenge existing assumptions, and incorporate broader perspectives, including acknowledging human biases and colonial histories.

Another important distinction lies in whether data is perceived as either objective or as intrinsically entangled with the design ecosystem. Some view data as a reliable tool for informing design decisions, emphasizing its accuracy and dependability. This perspective treats data as a largely objective resource (or at least one where any biases can be effectively managed), providing a solid basis for making well-informed choices. Designers who adopt this view often rely on quantitative methods, statistical analyses, and empirical evidence to guide their processes. They believe that by gathering precise and extensive data, they can minimize uncertainty and make more reliable predictions about the outcomes of their designs. This approach aligns with a more scientific view of data, where the goal is to uncover consistent and reliable insights and apply them effectively to improve design outcomes.

Others, however, recognize data as part of a complex, interactive system, where data is not merely a passive input but actively shapes and is shaped by the design process. This perspective acknowledges that data is inherently situated and context-dependent. It highlights that data collection, interpretation, and application are influenced by human decisions, cultural contexts, and social dynamics. This view understands that data is imbued with the biases and assumptions of those who collect and analyze it, and that these influences must be critically examined. Recognizing data as part of an interactive system means acknowledging that data can both inform and be influenced by design decisions. For example, the way data is collected can shape what is deemed important or relevant, while design interventions can alter the context in which new data is generated. This dynamic interplay suggests that data is not a static entity but evolves in response to the ongoing design process. It also implies that data should be interpreted reflexively, considering the impact of the designers' perspectives and the broader societal implications.

An entangled perspective encourages designers to be more reflective and critical about the role of data in their work. It pushes them to question the sources of their data, the methods used to collect it, and the potential biases that may be embedded within it.

Lastly, *another point of tension lies in the dual role of uncertainty, which can be seen either as an informative input in the design process or as a source of ambiguity that shapes how design outcomes are perceived and interacted with by users.* When uncertainty is viewed as an input, it acts as a critical component that guides the creative exploration phase, allowing designers to question assumptions, explore various possibilities, and innovate. This perspective encourages embracing the unknown to generate novel ideas and solutions.

On the other hand, perceiving uncertainty as ambiguity acknowledges that uncertainty persists even after the design is implemented. This focus is on the user's experience and interpretation of the design, recognizing that the final outcome may be understood and interacted with in unforeseen ways. This element of uncertainty can influence user interactions and perceptions, leading to diverse and sometimes unexpected responses.

As the authors grapple with these tensions, however, *it becomes clear that uncertainty in the world and the design process differs from the mathematical quality of uncertainty in data and models.* The former focuses on the inherent unpredictability of real-world contexts and processes, reflecting the dynamic and often chaotic nature of the environments in which design operates. The latter treats uncertainty as a quantifiable attribute, emphasizing statistical and probabilistic methods to manage and measure uncertainty.

In conclusion, *staying with the trouble of uncertainty in algorithmic RtD practices involves a dynamic interplay between embracing and managing uncertainties*. By understanding the different sources and types of uncertainty and adopting flexible, context-sensitive approaches, designers can navigate the complexities of data-driven design. This process not only mitigates the challenges associated with uncertainty but also leverages it as a catalyst for ingenuity and creative explorations.

4 CONTRIBUTIONS TO THIS SPECIAL ISSUE

4.1 A Modeling-Oriented Take on Uncertainty

In "Addressing Uncertainty in Biodesign through Digital Twins: A Case of Biofabrication with Mycelium", Vu, Funk, and Barati (this issue, [82]) draw on the traditional split between *aleatoric* and *epistemic* uncertainty to question what the limits of models are when applied to living systems. This is nuanced by relating the uncertainty about modeled features to questions of designerly interest: agency, interdependencies, and entanglements, as well as the particulars of individuals as distinct from the averages of groups. From the perspectives of a modeling process, these all cause difficulties: they add complexity, additional feedback and variables that must be accounted for, and place limits on the level of fidelity that may be achieved. However, for those attending to the world as a source of inspiration and engagement, these are the fabric from which meaning may come.

Vu et al. identify several nuanced forms of uncertainty two of which we would term *interdisciplinary* and *worldly* uncertainty. Interdisciplinary uncertainties arise when knowledge crosses disciplinary boundaries, leading to potential misunderstandings and reinterpretations. Worldly uncertainties pertain to biological processes, such as the unpredictability of how specific actions or circumstances might impact outcomes or how organisms relate to general ideas. Models, while useful for integrating knowledge, highlight the cracks between the digital twin and the living world, inviting exploration. The divergence between the digital system and the living matter encourages respect and empathy for the latter, with the authors suggesting that "designers can leverage uncertainty as a form of creative material that invites critical reflection," aligning with Soden et al. [74]'s taxonomy of uncertainty as a *generative* quality.

The work also proposes a new approach to managing uncertainty. The introduction of a digital twin clarifies specific uncertainties related to model structure, variable measurements, and the interaction between simulation and organisms. Although this introduces more uncertainties, it provides a detailed and accurate picture of an otherwise opaque system. These productive uncertainties draw attention to discrepancies between models and reality, implicitly raising questions that might remain unnoticed without such differences. Finally, in relation to the political sense of uncertainty, Vu et al. argue that digital twins offer a public space for shared storytelling and engagement, adding a voice to the material unfoldings.

4.2 Generative Potentials of Uncertainty

In "Dynamics for Movement in a Design Space: Uncertainties as Generative Resources for Research through Design", Epp, Poikolainen Rosén, and Sanchez (this issue, [25]) continue this exploration of the *generative* potentials of uncertainty. They situate their work largely relative to Soden et. al [74], in particular providing a counterpoint to the view that uncertainties may be 'disciplined out' of situations. The uncertainty discussed is situated less with the way that models represent the world, but more in the sense that designers carry out their practice with uncertainty about the current and future states of the world. The work focuses on two key moves. Firstly, there is the construction of a particular typology of uncertainties. This is a specific typology, which nuances the uncertainties encountered within design processes into being: *epistemic*, *ontological*, *teleological*, *stochastic*, *collaborative*, *ethical*, *contextual*, and *temporal*. These various types of uncertainty become operationalised through case studies, where for example knowing that there are ethical uncertainties is a prompt to ask "What are the implications of implementing the design?", in contrast to a stochastic uncertainty of "How imprecise is the sensor data?" or a teleological question of "Would the technology help community members?". Hence, the typology points at a bridge between uncertainty as a concept and the traditional concerns of situating and enacting design processes. Secondly, the paper develops the idea of journeys that use uncertainties as landmarks, which can be used as meta-heuristics over design processes: circling back to an uncertainty in a way that generates new insights is contrasted with 'unproductive dwelling' within the uncertainty that is indicative of lack of progress. Oscillating between uncertainties can be a productive route for uncovering more – previously unperceived – uncertainties in the surrounding space. Through offering these as ways to understand the deliberative design process, the paper gives tools for designers to advance their pragmatics around uncertainty.

4.3 Data and Ambiguity

In "Designing with Data: An Annotated Portfolio", Gaver and Boucher (this issue, [26]) take a specific approach to uncertainty. The devices in the annotated portfolio are designed in terms of data, and in ways that question the relations between the data, its embodiment, and surrounding humans. In general here, data provides a frame for systems, but the uncertainty is not so much about the veridicality of the data as it is about their interpretation and import. This of course connects back to questions of ambiguity [27] as being a form of uncertainty about the reception and interpretation of a system. This often means purposefully introducing uncertainty: the Home Health Horoscope introduces a sense of uncertainty about whether it is meaningful to sensorize our activities in service of better health outcomes. The Local Barometer undermines the widespread use of proxy data to determine neighborhood characteristics by highlighting the uncertainty that lies in the translation. The Datacatcher confronts people's certainties in their beliefs with their willingness to question the certainty of data they are presented with. There are questions raised of temporal uncertainty: does the identity of the Drift Table change as the landscapes that it shows are changed? Should the Prayer Companion use a static set of news items, or update itself to project into an uncertain future? The uncertainty written through these pieces is in how they are felt, the (multiple) intentionalities that arise around them, and the way that they are situated within the flows of time, politics, and data.

4.4 Pragmatic Approaches to Data Uncertainty in Design

In "How Design Researchers Make Sense of Data Visualizations in Data-Driven Design: An Uncertainty-aware Sensemaking Model", Dritsa and Houben (this issue, [23]) step momentarily back from the poetics of ambiguous data-driven devices and look into a pragmatic question of how to use data within a design process, and in particular, how to represent and relate to the uncertainties of models of human activity. In contrast to previous papers that frame uncertainty as a generative tool, here the authors are interested in how these uncertainties can undermine the quality and significance of design insights generated from data, working towards a more *affective* stance. Here the uncertainties are multiple, but strongly grounded. The authors situate their work in relation to existing typologies of uncertainty, particularly Boukhelifa et al. 's division [11] into data uncertainty, model uncertainty, interface, and cognitive uncertainty. They are particularly interested in the uncertainty introduced in the data collection process and in the ways that people will interpret it based on their personal background, their domains of study, or their previous experiences with data. The visual representation of uncertainty is the heart of this paper, looking at what happens when uncertainty and sensemaking are brought together: how do uncertainties around data quality, visualization techniques, and viewer characteristics affect the generation of knowledge? However, uncertainty is not entirely 'disciplined out' here - when the behaviors observed by their participants lacked uncertainty, they were seen as too normal, and too boring to inspire creativity.

4.5 Data Collection and Indeterminacy

In "Shifting Ambiguity, Collapsing Indeterminacy: Designing with Data as Baradian Apparatus", Reed, Benito, Caspe, et. al (this issue, [65]) dives into the ways that data is collected and understood, this time through the lens of creating digital musical instruments. The core is an interrogation of the ways that formalization and data collection create jagged edges in otherwise fluid fields, such as musical ideas of 'notes' segmenting the production of sound into pitches, with specific onsets. Indeterminacy stands in for uncertainty here, as a Baradian view of the world looks at apparatuses as collapsing the indeterminacy of the world through data collection. Two mechanisms support this view: firstly, the idea that making certain features explicit captures the attention, so the shape of data representation focuses the eyes of designers and users alike; secondly, that data never exists in a pure, isolated form, it is always co-produced by an entangled apparatus, and as such remains connected and shaped by the context in which it was produced. This is a diffractive account (after Sanches et. al. [67] and Scurto et al. [71]), pointing to possibilities of slow exploration with attention to mess and difference. Fundamental uncertainties, such as the trade-off between frequency resolution and time resolution, abound when bringing digital systems to bear on musical production, and here they account for explorations of these kinds of losses. This leads to some provocative maxims focused on a *generative* sense of uncertainty, such as attempts to "make everything explicit" and note the places we "fail to be messy". The call to "don't observe what you don't need" highlights indeterminacy as a one way street, that once collapsed can never be regained. In the context of AI systems, the move towards explicitness of concepts is important: loss functions and the ways that distances are measured within their internal spaces bring concepts in 'through the back door', and attending to these is part of making sense of what the system is doing.

4.6 Reflexive Data Practices

In "Reflexive Data Curation: Opportunities and Challenges for Embracing Uncertainty in Human-AI Collaboration", Arzberger, Lupetti, and Giaccardi (this issue, [3]) continue the investigation into the ways that critiquing data collection can give insight into sensitive phenomena - in this case playing in the space before gender is forcibly collapsed into categories. RtD, in concert with reflective practices and queerness forms the basis of an exploration in how controlling the data used in training models shapes the outcomes into spaces of indeterminacy that question assumptions, biases, and default categorisation. There is a push along the *generative* direction that rather than seeing "algorithmic uncertainty and unexpected results as problems to be solved", reflexively creating uncertainties forms part of a move towards creating AI systems that are more broadly reflective of society, and give a standpoint for imagining alternative worldviews. In support of this generation of critical possibilities through uncertainty, three particular tactics are developed: 'autoconfrontation' uses the process of training classification systems to examine exemplars of personal preference; 'change of perspective' uses algorithmic viewpoints and latent spaces to prompt alternative conceptions; and 'clash of expectations' uses the gap between hopes and model outputs as a lever to pry into areas of discomfort and uncover unexpected directions. These approaches relate to the idea that the systems being designed are probabilistic - they draw on the possibilities of exploring probabilistic spaces, and potential for surprise inherent in the uncertain outcomes. However, they also connect with the productive tensions that can be worked through when RtD approaches entangle not just with the mathematical qualities of data but its worldly production and cultural embeddings.

4.7 Uncertainty As Entanglement and Algorithmic Creativity

Finally, in "The Choreographer-Performer Continuum: A Diffraction Tool to Illuminate Authorship in More Than Human Co-Performances", Bomba, Menéndez-Blanco, Grigis, et. al (this issue, [9]) draw from agential realism and entanglement thinking and explicitly focus on the agency of nonhuman things and the probabilistic outcomes of designing with complex technologies. They use engagements with LLM to explore a kind of cultural uncertainty, looking at how experimental artists can act as problem makers while drawing on the hidden or unplanned possibilities of malleable technological artifacts. There is a particular focus on creating uncertainty around agency, in blurring the lines between choreography and performance - or control and response. Through the lens of an artistic project that re-synthesises psychedelic trip reports into vibrantly nonsensical forms, they co-perform the idea of an agential algorithm that participates in the co-creation of films and music, enlisting humans to bring the ideas to fruition. The uncertainty dealt with here is of a different kind. Beyond the uncertainly modified relations to the world provoked by psilocybin,[4] there is a generative uncertainty about the *authorship* of the outcomes. Through a material unfolding that includes the mushrooms and the machines, the uncertain agencies prompt a reframing of the algorithmic contributions on a spectrum between performance and choreography. As the actors become codependent on each other, the outcomes become less predictable along with the authorship. The human partners are required to re-interpret their roles, to discover productive levels of detachment or engagement with the operations of the model. While this kind of openness to uncertain outcomes is not new in the world of art, or technological art - Pask's experimentation with agential chemical systems being a key instance [61] - the agencies that are enacted by language models have a range that sits clearly with political and cultural experimentation. We can see this very much as *generative* uncertainty: it is harnessed purposefully to create a new kind of configuration for art-making, but also as a *political* take on the uncertain and obscured relations between models and the world, and a critical reification of 'hallucination' as a means of challenging the discourse around what the models are performing.

A glossary of the types of uncertainty defined or referred to by the contributors in this special issue is provided in Table 1.

5 EMERGING DESIGN SPACES: THREADS OF INTEREST

New design spaces emerge around these uncertainties, offering dimensions and tensions ripe for exploration. The intersection of uncertainties in design and unstable, algorithmic RtD practices opens new avenues for understanding the future of design. *These spaces encourage us to question the boundaries between knowing and not knowing, to explore the creative potential of uncertainty, and to develop more adaptive and resilient design practices.* We have seen multiple treatments in the contributions to this special issue: a connection between uncertainty and ambiguity [26], the idea that uncertainties serve as landmarks [25] or are where excitement lies in data [23], moves to preserve uncertainties against formalization [65], and so on. Here we pull out some of the resonant threads that start with these papers but go beyond to map out directions for working with uncertainty in RtD.

5.1 Navigating Uncertainties

In the evolving landscape of RtD with data and algorithms, uncertainties present a rich field of exploration. *The space between aleatoric and epistemic uncertainties offers a fascinating arena where these concepts, viewed through Barad's lens, can be seen as different facets of the same phenomenon.* Aleatoric uncertainty, rooted in randomness, and epistemic uncertainty, arising from gaps in knowledge, converge to create a situated property of uncertainty. For instance, a coin flip, appearing random due to our limited understanding of its intricate physics, illustrates this point. Navigating this space is a common theme in the papers: Epp, Poikolainen Rosén, and Sanchez [25] are perhaps most on the nose here, as they look at uncertainties as landmarks within a design process, and how to best wayfare around them, so that journeys through the space are productive. Vu, Funk, and Barati [82] look at the ways that we change, multiply, and co-shape uncertainties through digital practices, and Reed, Benito, Caspe, et al. [65] highlight what happens when we navigate differently around some *fundamental uncertainties*. This sense of navigation connects to the productive tensions of uncertainty highlighted earlier, as the multiple uncertainties constitute a landscape, and signpost areas of interest as well as dangerous terrain to traverse.

[4]Psilocybin is a naturally occurring psychedelic drug compound produced by more than 200 species of fungi.

Table 1. Glossary of types of uncertainty defined or referred to in this special issue.

Scheme and Reference	Type	Definition
Modelling uncertainty in probabilistic representations (e.g. Hüllermeier et al. 2021. See also Li et al. 2013)	Aleatoric	The element of chance inherent in the phenomena captured by the data (e.g. a coin toss)
	Epistemic	Uncertainty due to a lack of knowledge in what we observe
Modes of engagement for HCI with uncertainty (Sodden et al. 2022)	Disciplining	Treating it as a problem, characterized by scoping, pinning down, measuring and predicting.
	Political	Shaping our encounters, characterized by asking “what counts” questions, looking at the hidden structures beneath the questions that get asked.
	Generative	Embracing uncertainty as a means to produce doubt to serve imagination and creative thinking.
	Affective	Considering lived experiences, characterized by centering on the bodily experience of certainty.
Causes for uncertainty (Epp et al. 2024, this issue)	Epistemic	Incomplete or erroneous information or its understanding
	Ontological	Known unknown and unknown unknown factors in design
	Teleological	Unawareness or lack of clarity of the intended design outcome
	Stochastic	Random variation of events and processes (c.f. Aleatoric above)
	Collaborative	Difficulties in having shared understanding within a design team
	Ethical	Effects that the artefact will have when taken into use (cf. Arzberger et al. 2024, this issue)
	Contextual	Complexity and unpredictable nature of the design context
	Temporal	Multitude of possible futures for which to design
Digital twin uncertainties (Vu et al. 2024, this issue)	Interdisciplinary	Due to ontological issues with knowledge crossing disciplinary boundaries (c.f., collaborative above)
	Worldly	The unpredictability of biological processes relative to digital twins
Sources of uncertainty in data work (Boukhelifa et al. 2017)	Data	“Errors; imprecise or inaccurate data; inconsistency; missing or unknown data; and vagueness, ambiguity, and fuzziness” (p. 3648)
	Model	“Inaccuracy and error, wherein the model may be an approximation of processes described by the data” (ibid.)
	Interface	“Algorithmic errors and inconsistency between the system and interface” (ibid.)
	Cognitive	“Pertains to the human reasoning process, such as sense-making or interpersonal dynamics” (ibid.)
Fundamental uncertainties - a general concept, mentioned by Reed et al. (2024, this issue)		Situations where there is a fundamental tradeoff, so that e.g. phenomena can be precisely specified in time, or frequency, but not both simultaneously
Authorial uncertainty (Bomba et al. 2024, this issue)		Related to interdisciplinary uncertainty, when existing concepts such as ‘author’ are troubled by new technology, there is uncertainty about how things should be encoded in the existing system.

5.2 Caring for Uncertainty

Purposefully introducing uncertainties is a common practice in design. The double diamond model explicitly injects uncertainty at the beginning of the process to rethink and redefine the problem space. This method acknowledges that the journey from not knowing to knowing is integral to design, although it often concludes with a sense of certainty in the solutions proposed. Yet, design is seldom about achieving complete certainty; it is more about understanding and navigating partial knowledge.

Designers act as stewards of uncertainty, balancing the need to explore unknowns with the practicalities of producing workable solutions. This stewardship includes making deliberate choices about when to introduce uncertainties and when to seek resolution, understanding that both are crucial to the creative process. *Caring for uncertainty involves recognizing its value and our responsibility towards it.*

Generative uncertainties need to be carefully managed because they implicitly pose the crucial question of “why,” revealing insights that might otherwise remain hidden without the presence of disagreement or ambiguity.

Bomba, Menéndez-Blanco, Grigis, et al. [9] emphasize the importance of cultivating uncertainty within the assemblage, ensuring a rich, exploratory design process.

Arzberger, Lupetti, and Giaccardi [3] go further by providing methods to not only nurture but also deliberately produce uncertainties, keeping the design process dynamic. Reed, Benito, Caspe, et al. [65] advocate for resisting the urge to simplify indeterminacy into fixed conceptualizations, promoting the idea that we should "not observe what we don't need," thereby preserving the creative possibilities that uncertainties offer. This is particularly vital in systems that tend to formalize human practices, stripping them of their generative potential.

Even Dritsa and Houben [23] observe that, while it is necessary to manage uncertainty to some extent, completely eliminating it can render data uninteresting and non-generative. They highlight that a certain level of uncertainty is essential for maintaining the engagement and innovativeness of the design process.

5.3 New Uncertainties and New Space to Be Uncertain

The physical certainty of computing is also diminishing. As we move from tangible media to the nebulous realm of cloud computing and data centers, we lose touch with the physicality of our digital existence. The locations and jurisdictions of our data processing become obscure, adding another layer of uncertainty to our interactions with technology.

AI and machine learning introduce new uncertainties, particularly around agency, authorship, reliance, and bias. This space is explored by Bomba, Menéndez-Blanco, Grigis, et al. [9] in their blurred choreographies and by Arzberger, Lupetti, and Giaccardi [3] in their construction of machinically uncertain categorizations. These approaches challenge traditional notions of control and predictability, aligning with Reed, Benito, Caspe, et al. [65] in highlighting what is lost when we collapse these indeterminacies.

Labeling, a common practice in AI, swaps conceptual uncertainties for formal certainties, potentially obscuring deeper ambiguities. This shift demands a reevaluation of how we approach and understand these processes, as the uncertainty that machine learning has long tried to discipline rubs up against the cultural and social uncertainties that allow space for human individuality. Arzberger, Lupetti, and Giaccardi [3], in line with practitioners such as Jake Elwes [5] explore some of these new in-betweens as cultural appropriation meets categorical boundaries and human expression tangles with machine interpretation.

In conclusion, the threads of emerging uncertainties in design and algorithmic RtD practices weave a complex tapestry. They challenge us to rethink our approaches, to embrace the unknown, the probabilistic, and to navigate the shifting landscapes of technology and design with a thoughtful and critical eye. As we engage with these uncertainties, we uncover new possibilities for understanding and shaping the world around us. From this, *we get not just new uncertainties, but new kinds of space in which to be uncertain, as concepts and practices are projected from one place into another.*

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