

Navigating Design, Data, and Decision in an Age of Uncertainty

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Abstract

The Future of Design Education working group on technical systems argues that the approach to handling data — the methods used, and the expectations for outcomes — can transform design practice. In contrast to design's past defined by a lack of accessible data, today's rapidly evolving age of data abundance informs the choices available — the decision space — with far-reaching consequences for organizational, social, and environmental well-being. The shifting design landscape requires new tools and techniques to navigate this data age effectively. This paper proposes a new curricular approach that intersects data, technology, and design to create an environment where students can evaluate their roles and impact, and interact effectively through data with humans and computational collaborators. This data-oriented curriculum includes foundational technical skills proficiency, data analytical skills, rhetorical skills for arguing with data, interdisciplinary design studies, and a focus on designing for society. It embraces the complexities and opportunities of the data age, and acknowledges the inherent uncertainty in this new landscape. The aim is to prepare the next generation of designers to create data-informed, human-centered, ethical, and sustainable designs, thereby fostering an inclusive, equitable, and sustainable future.

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- 1 Jeff Leek, "The Four Eras of Data," *Simply Statistics*, December 15, 2016, <https://simplystatistics.org/posts/2016-12-16-the-four-eras-of-data/>.
- 2 Thomas P. Hughes, "The Evolution of Large Technological Systems," in *The Social Construction of Technological Systems: New Directions in the Sociology and History of Technology*, ed. Wiebe E. Bijker, Thomas Parke Hughes, and Trevor Pinch (Cambridge, MA: MIT Press, 1989), 51–82.
- 3 Roberto Verganti, Luca Vendraminelli, and Marco Iansiti, "Innovation and Design in the Age of Artificial Intelligence," *Journal of Product Innovation Management* 37, no. 3 (2020): 212–27, <https://doi.org/10.1111/jpim.12523>.
- 4 Leek, "Four Eras of Data."

Introduction

The field of design is at a pivotal juncture. Longstanding traditions are being reconfigured by technological advancements—generative artificial intelligence (AI), new human computer interactions (HCI) paradigms, ubiquitous computing, and the Internet of Things (IoT)—and the unprecedented speed, scope, and diversity of data they generate. The transition from an era of data scarcity—characteristic of the period when the design field emerged—to data abundance today, significantly redefines the terrain for designers.¹ Ever more precise data collection and actuation shadows every person and environment today. This process is visible and invisible; it involves every physical and digital experience, with ever-increasing precision and frequency, both with and without consent. The heuristics that have long been used to analogize this new data reality as a force of nature or new materiality to be exploited no longer reflect the unparalleled challenges and opportunities that now emerge through data.² This transformative change in tools, methods, targets, and outcomes is fundamentally reshaping the landscape of design research and implementation.³

Historically, the field of design emerged and developed when data was not as abundant as it is today. It was an era of data "poverty."⁴ The societal and technological circumstances of the early twentieth century shaped the epistemology, methods, and mindsets of the design field. However, the contemporary era has been transformed by rapid socio-technical developments. These are typified by the prevalence of such technologies as generative AI, recommendation algorithms, advanced computer vision, and persistent data capture. There is a need to reassess these historical foundations. Traditional ways of understanding and practicing design may no longer be entirely relevant, appropriate, or sufficient.

The current situation is now undergoing a paradigm shift. The emergence of design disciplines such as service design, UX and UI design, and speculative design, and a growing focus by all designers on complex societal issues have spurred a reevaluation of the relationship between design and data. The boundaries between consumers and producers, between physical and digital experiences, and between collective and individual experiences are blurring. The need for designers to engage with data has never been greater. And, as designers work in larger and more diverse opportunity spaces—often with more experimental and indirect approaches—the need for data-enabled methods and certainty becomes ever more critical to the future of the discipline.

A Short History of Data in Design

Design educator and practitioner Jay Doblin (1920–1989) quipped that the design process was like "cutting cubes out of fog." The metaphor captures how twentieth century design practice and process attempted to enforce certainty on ambiguous and incomplete information. Designers were expected to approach these problems methodically, reducing perceived complexity towards a justified "solution."

The inception of the design field was intrinsically linked to the industrial revolution. The wave of industrialization in the nineteenth and twentieth

- 5 Jay Doblin, "The USA Theory of Design," *Home Appliance Builder* (1964): 10–13, available at https://findings.library.iit.edu/repositories/2/archival_objects/4165.
- 6 Stephen M. Stigler, *The History of Statistics: The Measurement of Uncertainty before 1900* (Boston: Harvard University Press, 1990).
- 7 Lennard J. Davis, ed., *The Disability Studies Reader*, 5th ed. (New York: Routledge, 2016), 2–6, <https://doi.org/10.4324/9781315680668>.
- 8 Henry Dreyfuss, *Designing for People* (New York: Simon & Schuster, 1955).
- 9 Bess Williamson, *Accessible America: A History of Disability and Design* (New York: New York University Press, 2019), 149–54.
- 10 Ton Otto and Rachel Charlotte Smith, "Design Anthropology: A Distinct Style of Knowing," in *Design Anthropology: Theory and Practice*, Reprint ed., ed. Wendy Gunn, Ton Otto, and Rachel Charlotte Smith (London: Bloomsbury Academic, 2013), 1–29, <https://doi.org/10.5040/9781474214698.ch-001>.

centuries, including process mechanization, materials development, and product standardization, set the early priorities of the design field. Design education reflected these industry needs, with many schools focusing on technical skills and aesthetic principles to meet the demands of industrial production.⁵ The data relevant to this type of design expression was physically measurable, empirical, and deterministic: material properties, process refinements, and operational costs.

Simultaneously, other fields were making progress in understanding and managing uncertainty. In the social sciences and decision science, groundwork was being laid for statistical thinking and decision-making in uncertain situations. Belgian astronomer, mathematician, statistician, and sociologist Adolphe Quetelet first described social and behavioral phenomena with numbers, pioneering the use of statistical methods in the social sciences.⁶ Quetelet used measurable centers—averages, medians, and modes—to construct dangerous ideas of normal and ideal human behavior, presaging many of the unsophisticated heuristics used by today's social scientists and designers.⁷ In the same period, the concept of correlation and regression to the mean emerged, becoming vital statistical tools. These works led the way for more sophisticated statistical modeling, facilitating nuanced interpretations of social phenomena and more informed decision-making in uncertain contexts.

As the statistical methods grew increasingly powerful, these approaches permeated disciplines beyond the social and decision sciences. The ability to manage uncertainty and make informed decisions based on numerical insights and measurable correlations provided a new type of certainty for designers grappling with the complexities inherent to their work. This transitional era saw cross-pollination, with techniques and insights shared between disciplines and adapted to new contexts. Statistical methods inspired the design field to refine its methods, especially in the early days of the Modernist movement.

Modernists placed emphasis on a new type of data for design. "Human factors," emerging from anthropometry and psychometry studies—and best encapsulated in the discipline-shaping works of Henry Dreyfuss—allowed designers to leverage new kinds of data focusing on expected behavior, perceptual faculties, and the body and spatial conditions of their audience.⁸ This Modernist impulse saw the first partial borrowings of a recognizable statistical science into design, with an emphasis on means and extremes, but without an appropriately modeled understanding of variance, bias, or dynamics. Data was seen as fixed points to embed into design decisions relating to scale, materiality, and contextual use. Homogeneous audience samples and averages were used to represent diverse populations.⁹ Data-driven design practitioners had at-hand and justifiable answers to usability uncertainties, seeding much of design research to come.

By the late twentieth century, the ongoing integration of social sciences into the design field further evolved the design field's understanding of data and its application. Methods from anthropology, psychology, and sociology were adopted into design research, bringing a new focus on understanding user behaviors, experiences, and contexts.¹⁰ This evolution, marked by the emergence of practices like experience design, human-centered design, and service design, championed empathetic and participatory methodologies, often rooted in ethnomethodological or humanistic approaches. This

	Period	Design + Data	Decision Science	Social Science	Soft Tech	Hard Tech
Late Industrial Age	Mid-19th century to early 20th century	Emergence of consumer research and product optimization	Development of linear programming and decision theory	Adoption of empirical methods and surveys	Development of early operating systems and compilers	Advent of transistors and electronic computing
Information Age	Mid-20th century to late 20th century	Rise of user experience research and digital product design	Integration of AI and machine learning into decision-making models	Proliferation of digital data collection methods and computational social science	Rise of the Internet, development of web technologies and databases	Invention of microprocessors, growth of personal computing
Digital Age	Late 20th century to 2010s	Data becomes integral to the design process, guiding strategic human decision-making and problem-solving	Use of big data analytics and advanced machine learning algorithms	Rise of social media analysis, network science and digital ethnography	Advent of cloud computing, mobile apps, and AI software	Progression to quantum computing, advanced AI hardware

Figure 1
An era analysis of the evolving role of data in informing decision-making and problem-solving. © 2023 the authors.

introduced greater complexity into the design process. The data extended beyond averages or extremes to encompass detailed, multifaceted insights into people's lived experiences, preferences, and expectations. Design was not only focused on shaping material reality, but also on understanding and influencing human behaviors and experiences. The design field wrestled with this nuanced data about complex social contexts alongside the inherent uncertainties of measuring human behaviors and social systems.

While the integration of social science methodologies into design represented a significant evolution in practice, it also illuminated the complexities of cross-disciplinary adaptation. The co-opting of social science, intended to enrich design practices, inadvertently diluted the hallmark methodological rigor of these disciplines. Designers of the era were primarily problem-solvers, crafting aesthetic and functional solutions suitable for industrial-scale production. Consequently, the translation of social science-based methodologies into design practices was approached through a problem-solving lens, without a thorough understanding of the foundational philosophies, theories, or intentions of these originating fields. Methodologies were borrowed and applied superficially, without full appreciation of the deep-seated principles that give them structure and rigor. This led to, in many cases, oversimplification or misinterpretation of the foundational principles of the social sciences—principles refined over years of methodological development.

This scenario has become a recurring phenomenon in the design field, as the integration of new data-oriented practices can lead to a commoditization of foundational methodologies. This pattern underlines a significant concern: while design has made strides in incorporating methods from related fields, it often falls short of fully understanding, preserving, and evolving these methods, especially in the context of rapidly evolving data and technology landscapes. As data becomes more central to design, this issue remains pertinent.

Figure 1 summarizes an era analysis of the evolving role of data in informing decision-making and problem-solving. Tracing our historical legacy

- 11 Nigel Cross, "Expertise in Design: An Overview," *Design Studies* 25, no. 5 (2004): 427–41, <https://doi.org/10.1016/j.destud.2004.06.002>.

not only gives us insight into how we have arrived at the current juncture but also equips us with the necessary tools to navigate the challenges of today with intentionality. The integration of data and technology into design represents an ontological shift reflecting our rapidly evolving societal and technological landscape. Today, designers contend with data that is vast in quantity and inherently uncertain. Data is now a crucial and intrinsic part of the design process. It is entwined within the systems and experiences that designers create. Journeying deeper into this data age necessitates the reshaping of our practical and educational presumptions to ensure that design remains not just relevant, but effective and responsible as well.

Design Decisions in the Age of AI and Data

Design evolves in tandem with broader societal and technological shifts. This entails reimagining how we understand and incorporate data and technology into design practices and educational curricula. This transformation also entails a thorough reimagining of how we understand and incorporate data and technology into design practices and educational curricula, marking a shift from static and authorial to more fluid and emergent design methods and processes.

In this context, the “decision space” concept takes on new significance.¹¹ The mechanisms by which designers identify and analyze design problems, formulate strategies, and make decisions, must now accommodate a rapid proliferation of data. The design process must navigate vast arrays of information, comprehend complex, continually evolving systems, and shape experiences within the socio-technical contexts these systems foster. Design evolves beyond problem-solving, transforming into a practice of creating meaningful experiences within the dynamic interplay of data, technology, and society.

Traditionally, designers navigated the decision space through a mix of intuition, experience, and expertise. The data age introduces a more nuanced approach. Data transforms from a decision-making resource to an integral, contextual component of the design process—a collaborator. Designers no longer merely use data to *inform* decisions; they create systems and experiences in which data is an inherent and embedded element. Evaluating the natural characteristics of data—error, precision, confidence, certainty, and variance for example—are new, powerful mechanisms to gauge the appropriateness and efficacy of a design practitioner’s work.

This perspective aligns with the earlier discussion about a design orientation toward uncertainty. It recognizes that design decisions often emerge from navigating the ambiguity and uncertainty that pervades the design process. Instead of attempting to dispel this “fog,” a data-enabled approach is about allowing the fog to remain “foggy,” accepting the inherent complexities and uncertainties as integral parts of the design process, and reacting with algorithmic intelligence and computational speed to constantly changing circumstances and definitions.

In the context of machine learning and artificial intelligence (AI), these new mindsets and approaches are more relevant than ever. Conventional distinctions between quantitative and qualitative data—never a clear line—immediately break down when data is fed into an AI training algorithm. While

- 12 Janelle Shane, *You Look like a Thing and I Love You: How Artificial Intelligence Works and Why It's Making the World a Weirder Place* (New York: Voracious/Little, Brown and Company, 2019), 170.
- 13 Viktor Mayer-Schönberger and Kenneth Cukier, *Big Data: A Revolution That Will Transform How We Live, Work, and Think* (Boston: Mariner Books, 2013).
- 14 Susan Leigh Star and James R. Griesemer, "Institutional Ecology, 'Translations' and Boundary Objects: Amateurs and Professionals in Berkeley's Museum of Vertebrate Zoology, 1907–39," *Social Studies of Science* 19, no. 3 (1989): 387–420, <https://www.jstor.org/stable/285080>.

simple enumerated quantitative data provides a basis for statistical analysis and model training, qualitative data, such as survey results, voice and sound recordings, and photographic and video logs, can also be transformed into quantitative representations through various encoding techniques. Natural language processing algorithms convert textual data into numerical vectors for analysis. Similarly, image recognition algorithms convert pixel data into numerical forms to recognize patterns and identify elements in the image. AI merges the formerly distinctive spaces of quantitative and qualitative data, treating both as valuable inputs that can lead to more comprehensive, self-improving, and accurate predictive models. The data which designers have long associated with their expertise can be made numerical, opening up new tools, methods, and intervention vehicles.

AI similarly blurs the distinction between correlation and causation. Designers often focus on identifying high-impact leverage points, pinpointing causative factors to guide design interventions. AI models can identify correlation and causation patterns within data sets.¹² However, these models are typically tuned to finding small correlations. While training, an AI model might observe that as one variable increases, another also increases, or as one increases, another decreases. Based on those patterns, the evolving AI model will adjust its weights to reward those relationships. However, determining causation, which asserts that a change in one variable is the cause of a change in another, is more complex and typically beyond the direct capabilities of most contemporary data-driven systems.¹³ While AI architectures can attempt to make causal inferences through specific architectures and technical decisions, AI itself does not intrinsically distinguish between correlation and causation. While AI can uncover patterns and associations within data, human interpretation and judgment are crucial in establishing causal relationships. This requires a mindset change in designers working with AI- and data-enabled tools, and greater rigor and attention to data quality, relationships, and structures.

This paradigm shift involves reshaping practices and reevaluating our philosophical stance towards knowledge, its acquisition, and application. The challenge is not just simplifying complexity, it is about embracing and leveraging this complexity to inform our design decisions.

New Mindsets for Students and Educators

As design education and practice transition from the data poverty to data abundance, designers must adapt by integrating new mindsets, models, and tools that acknowledge the complexity and uncertainty of the design landscape.

- 1 **Integrating Diverse Disciplinary Perspectives:** In the data age, practitioners—whether designers, planners, strategists, or anyone involved in shaping change—can no longer assume the role of an omnipotent author, steering the course of action independently within their chosen decision spaces. They must be part of a larger system of humans and non-human interpretive stakeholders. This demands a shift from a solitary, autonomous approach to change-making, towards one that is open and collaborative, bridging the gap between design, technology, data science, and other disciplines. Datasets are critical boundary objects,¹⁴

- 15 Craig R. Fox and Gülden Ülkümen, "Distinguishing Two Dimensions of Uncertainty," *Journal of Risk and Uncertainty* 35, no. 2 (2007): 107–21.
- 16 W. Ross Ashby, *An Introduction to Cybernetics* (Chapman & Hall, London, 1956), 202, <http://pcp.vub.ac.be/books/IntroCyb.pdf>.
- 17 Marta Braun, *Picturing Time: The Work of Etienne-Jules Marey* (Chicago: University of Chicago Press, 1992).

embodying collaborative, narrative, and procedural guidance for teams and processes.

- 2 **Embracing Complexity and Uncertainty:** Designers must view innate complexity and uncertainty of the design landscape as sources of inspiration and innovation. This includes understanding and accounting for different types of uncertainties, such as aleatory uncertainty,¹⁵ which arises from the inherent randomness of monitoring the world, epistemic uncertainty deriving from incomplete modeling and limitations in observation and unpredictability in certain aspects of the design process. This shift requires moving away from the 20th-century rationalist view of design as a problem-solving activity with clear, fixed goals towards a more flexible, adaptive approach that embraces ambiguity and change. Designs in this mindset will always be unfinished, incomplete, and unresolved, but will maintain the capacity to grow and change. This resonates with the cybernetic concept of "requisite variety," underscoring that our responses must be as diverse and adaptive as the challenges we confront.¹⁶
- 3 **Adopting a Systemic Approach:** Designers must consider the wider system in which their design operates, and how those systems would manifest in datasets. They must understand the interconnections and interdependencies within the system and consider the potential impacts and implications of their design decisions. This moves beyond a product-centric view of design to a more holistic, system-oriented perspective that considers broader socio-technical and environmental contexts. Data-enabled models, simulations, and synthetic data generation are useful mechanisms for exploring these systemic approaches.
- 4 **Engaging Datafication:** In an era where almost every facet of our lives generates data, designers must navigate these vast data landscapes responsibly. Data has become more than just a tool—it is a ubiquitous, incomplete, collaborative layer that permeates our societal fabric, influencing the systems and experiences we design. The era of Big Data is often used to describe this convergence, and itself is defined by its five "V"s. **Volume** denotes the enormous amount of data that is continuously generated in today's hyper-connected and surveilled world, posing challenges for storage, processing, and analysis. **Velocity** underscores the speed at which this data is produced and must be processed, from large intervals to near real-time streams. **Variety** reflects the diverse types of data available for collection and analysis, from structured datasets to unstructured or semi-structured data such as text, images, and videos. **Veracity** measures the quality, reliability, accuracy, and actionability of the data. Finally, **Value** relates to a data practitioner's ability to extract valuable insights from the data.

Cultural historian Marta Braun's concept of the "thickened present" speaks to this new reality, where perceptions and experiences are shaped and constructed through technology and cultural practices.¹⁷ In a world increasingly surveilled and recorded, every individual experience leaves a data trace. This expanded "thickened present" offers a new space for data-capable designers to explore, understand, and engage with, executing design comprehensively and responsibly.

- 5 **Thinking Probabilistically:** With the advent of AI and machine learning, the deterministic design mindset—rooted in the industrial era—must give way to probabilistic thinking. Data used in generative systems like large language models, generative adversarial networks, and neural networks is not measurable in the same way as material properties or human factors data. Instead, the data itself better matches the ambiguity inherent to design context—sensors reporting values with nulls and error bands, surveys with demographic variance, logs with temporal and measurement uncertainties, and simulations with ranges of outcomes. Systems built on these datasets embody these same limitations, and often take steps to fill in fundamental uncertainties with computational creativity. Data-enabled systems are more likely to seed new questions with probabilistic hypotheses, rather than provide discrete answers. Designers must leverage increased sensitivity to statistical techniques and numerical insights, in order to better regulate and integrate AI and other data-driven systems into their design interventions.
- 6 **Capturing Data in Design Works:** Designers have new roles as data collectors and aggregators, creating experiences that actively capture and generate data. This is reflective of the essential data feedback loop in AI systems, where data collected from user interactions and design efficacy feeds into the system, influencing future design decisions and continuous improvements. Designers must be mindful of which data to collect, ensuring its relevance to enhancing user experience and system performance. This new role must be viewed through an ethical lens to ensure the transparent collection and responsible use of data to respect privacy and maintain trust. When experiences are inclusive and accessible to a wide range of users, regardless of their identity, abilities, socioeconomic status, or geographical location, the data collected is more representative and comprehensive, enhancing the predictive capabilities and performance of the system.
- 7 **Recursive Iteration:** Effective data-oriented designs internalize an ongoing, cyclical process of data collection, analysis, action, and further data collection. Every user interaction with the system is a potential source of data to enrich the learning of the AI, leading to more personalized and effective design solutions.

Tools and Techniques for Data-Enabled Design

It is important to reconsider design education paradigms. How do we prepare the next generation of designers to navigate the data-oriented landscape? The answer is a curricular approach that intersects data, technology, and design, preparing students to think critically about their role and impact.

Traditional queries like “Which programming language should I learn?” or “What device should I prototype for” are losing relevance for design students. The emergence of AI and associated technologies represents a convergence of formerly distinct technology categories, diminishing the importance of traditional technical development skills. The rise of data science, with its

unique tools and methodologies, is transforming design research and implementation with large language models like ChatGPT and related transformers like the image generator DALL-E 2 being used in research, prototyping, and design development contexts. Designers must equip themselves with new tools and techniques to leverage these technological developments and navigate the data age proficiently.

- **Data Sourcing and Capture:** Understanding various types of data acquisition is instrumental in designing with data. Data is often available in open datasets and application programming interfaces (APIs, simple protocols for computationally accessing data stored on web servers) but rarely is it usable or comprehensive without mining, manipulation, or aggregation with other data. When open data is inadequate, sensors, web scraping, surveys, computer vision, social media mining, and other capture mechanisms help designers build appropriately-structured datasets.
- **Data Structures:** Singular data points are not useful on their own, and must be structured to facilitate comparison amongst many elements in a group. Data structures—such as arrays, graphs, time series, trees, matrices, and key-value pairs—provide data-oriented practitioners with an associated set of operations, transformations, simplifications, and visualization frameworks. For designers, data structures are of critical value for research and insight mining, but the structures themselves also provide narrative and analogical utility for data storytelling. The creation and manipulation of data structures is fundamental in the field of computer science and engineering, having a profound impact on the efficiency and effectiveness of any digital architecture. In multidisciplinary contexts, the choice of data structure can serve as a useful boundary object between design and adjacent disciplines, facilitating effective collaboration centered on data.
- **Data Analysis and Manipulation:** Data analysis skills enable designers to identify actionable and confident insights, informing decisions and shaping design strategies. They allow designers to test hypotheses, identify trends, discern meaningful patterns and correlations, cluster and group elements, understand behaviors, forecast the future, and assess the impact of their designs. Skills in descriptive statistics are vital for interpreting the results of user testing, ensuring audience representativeness, as well as evaluating the training conditions, performance, and error of AI systems. Statistics is the natural language of probabilistic and systemic thinking and is often the biggest obstacle for students to overcome.
- **Algorithms and Simulations:** Algorithms break down complex problems into parts that can be independently managed and completed. This systematic approach is useful in tasks involving repeated or sequential operations involving data. Thinking in algorithmic terms can help create efficient, repeatable, adaptable, and sensitive data processing methods. Simulations allow designers to test, iterate, and improve their designs in a risk-free environment, ensuring the efficacy, usability, and robustness of their designs. Algorithmic thinking and simulations often reveal natural dependencies and limitations, fostering continuous learning, improvement, and innovation.

- 18 Annika Wolff et al., "Creating an Understanding of Data Literacy for a Data-Driven Society," *The Journal of Community Informatics* 12, no. 3 (2016): 16–17, <https://doi.org/10.15353/joci.v12i3.3275>.

- **Creating Design Assets with Data:** Data visualization, physicalization, and sonification are powerful tools for communicating complex data-driven insights. Data visualization is the graphical representation of data such as charts, graphs, or maps. Data physicalization adds a dimension, giving form, tangibility, and materiality to data. Sonification uses audio to convey information or perceptualize data. All of these techniques make data more accessible for more informative, engaging, and empathetic design experiences.
- **Data Storytelling:** How datasets are simplified, mined, and represented in narrative form can significantly influence our ability to communicate their contents to stakeholders and users. Designers can elevate data interpretability by mastering techniques such as data visualizations, data journalism formats, and interactive simulations. Communicating data is not only concerned with representing the data accurately. Instead, it might focus on projecting possible future scenarios, educating a viewer on the relationships between variables, simulating alternatives and counterfactuals for advocacy purposes, and identifying patterns that might not be immediately evident.¹⁸ Designers should also be aware of how different narrative vehicles can be interpreted, and the potential biases these interpretations may carry.

Integrating the tools of data science into design is an invitation for designers to recognize and utilize their unique position at the intersection of various disciplines. By leveraging their creative prowess and values-driven motivation, designers working with data responsibly will continue to play a crucial role in shaping experiences and society amidst data abundance and ambiguity.

Navigating the Intersections: Suggestion for a Curriculum Combining Data, Technology, and Design

The innovative curricular strategy outlined below (Table 1) is devised to develop acumen in data-focused design education. Aimed at cultivating adeptness at the intersection of data, technology, and design, this curriculum emphasizes five critical domains:

- 1 Foundational technical skills: sourcing and working with data
- 2 Data analytical skills: using algorithms to identify patterns
- 3 Rhetorical skills: arguing and advocating through data-enabled insights
- 4 Interdisciplinary design studies: using data as a collaborative boundary object
- 5 Designing for systems: using computational support to better understand complex dynamics

Each underscores the significance of mastering new technical competencies, discerning the social implications of data and technology, and grappling with the ethical dimensions of design decisions. This pedagogical model underlines the necessity of a comprehensive perspective, one that seeks

Table 1 Curriculum recommendations.

1. Foundational technical skills: sourcing and working with data	What design students should know: • Various types of data and data structures. • Creating datasets by hand, and thinking about sources from which to collect data, including sensors and external databases. • How traditional data capture techniques like surveys and trend analyses can be combined with contemporary approaches like sensors, large public data sets, web crawling, and simulated data for insight generation. • How data visualization and analysis tools (such as Excel and Tableau) support design work and communication of design insights. • Basic dataset building and programming concepts and techniques. What design students should do: • Approach common human behaviors with a data science lens. • Write and execute code in Python, a widely-used programming language. • Use combinatorics and permutations to understand a design decision space comprehensively with computational assistance serving as a gateway for conversation about AI support in design practice. • Extract insights and knowledge from data with statistical and computational methods — analyze and interpret data to make informed decisions. • Create preliminary prototypes of products or services — test and refine design. • Assess the limitations of contemporary and near-future technologies — make informed design decisions based on this assessment.
2. Data analytical skills: using algorithms to identify patterns	What design students should know: (concepts and theories) • Information science — The creation, representation, organization, and use of information, including concepts such as data quality, data privacy and security, and data literacy. • Open data — The concept of making data publicly available, accessible, and usable for informed design and decision-making, including principles of data transparency, data sharing, and data collection. • Descriptive statistics — Summarizing and describing data using measures of central tendency (mean, median, mode), variability (range, standard deviation), and visual representations (histograms, box plots). • Inferential statistics — Generalizing about a population based on a data sample, including concepts such as hypothesis testing, estimation, and confidence intervals. • Probability — Chance and random events and their impact on predictions and simulations. • Data mining — Discovery of patterns and insights from large data sets using clustering, association rule mining, and decision trees. • Machine learning — The use of algorithms enabling computers to learn from data and make predictions or decisions, including supervised learning, unsupervised learning, and reinforcement learning. • Data cleaning — Identifying and correcting inaccuracies, inconsistencies, and missing values in data. What design students should do: (skills and behaviors) • Data collection and sourcing — Collecting and sourcing data ethically and accurately in a representative manner. • Data access — Accessing and using public data sources, including government, academic, and non-profit organizations. • Data structures — Organizing and storing data efficiently and effectively for use in analysis. • Data manipulation and analysis — Cleaning, transforming, and analyzing data using tools and techniques like Excel, Tableau, and programming languages like Python.

- **Data modeling, simulation, and prediction** — Creating models, simulations, and predictions based on data and the limitations and uncertainty associated with such predictions.
- **Statistical methods** — Applying descriptive statistics (e.g., measures of central tendency and variability, visual representations) and inferential statistics (e.g., hypothesis testing, estimation, and confidence intervals) to summarize and generalize about data.

3. Rhetorical skills: arguing and advocating through data-enabled insights

Constructing persuasive and well-researched arguments with data, as well as the skills required for effective communication of design decisions with data visualizations, rhetoric, and narratives.

What design students should know: (concepts and theories)

- **Rhetoric** — Theories and techniques of persuasive communication important for understanding how to craft effective data-supported arguments and narratives.
- **Communication design** — Principles for the visual representation of information and ideas.
- **Data representation and visualization** — How to effectively represent and visualize data in an informative, persuasive, and accessible way to a diverse audience.
- **Narrative theory** — Theories on the structure and meaning of stories to create compelling data narratives that convey complex information in an engaging and accessible way.
- **Technical writing** — Writing and presenting technical information and ideas (e.g., white papers and presentations) clearly and concisely.

What design students should do: (skills and behaviors)

- Effectively represent and visualize data in a clear, informative, and persuasive manner using tools such as chart, graphs, maps, and other graphic forms.
- Explore data physicalization and signification to create engaging and accessible experiences.
- Apply principles of design to the effective visual representation of information, including typography, color, and composition.
- Tell stories with data, paying attention to narrative structure, storytelling techniques, and visual representation.
- Write clear and concise technical reports, whitepapers, and other materials.
- Present clear and concise communication — representing data in visual aids and storytelling techniques — to engage and persuade an audience.

4. Interdisciplinary design studies: using data as a collaborative boundary object

Considering how datasets can represent complex systems, be manipulated by human and non-human collaborators alike, and be shared amongst multiple disciplines and stakeholders.

What design students should know: (concepts and theories)

- **Science and technology** — Theories of how science and technology shape society and how society shapes science and technology.
- **Systems theory and cybernetics** — interdisciplinary frameworks that examine complex phenomena as integrated wholes as well as individual parts.
- **Human computer interaction** — The design of interactive computing systems and the relationship between humans and machines, including the study of human factors and ergonomics.
- **Design rhetoric** — Theories of persuasive communication and the role of design in shaping public opinion and decision-making.
- **Data policy and governance** — The ethical, legal, and policy implications of data use and management, including the examination of data privacy, security, and access.
- **Modeling and social change** — The use of models to understand and communicate social and technological change, including the role design plays in shaping these changes.

What design students should do: (skills and behaviors)

- Critically analyze and evaluate the social, cultural, and technological impact of design decisions on individuals and society.

- Analyze complex systems and their interactions, including interplay among design, technology, and society.
- Design for people's needs, desires, and limitations.
- Design the rhetoric of presentations to inform public opinion and decision-making about reasons for change and why participation is necessary.
- Design interactive computing systems that are user-centered and that account for human factors and ergonomics.
- Justify the ethical, legal, and policy consequences in the use and management of data.
- Model and project possible trajectories of technological and social change and the implications for design.

5. Designing for systems: using computational support to better understand complex dynamics

Addressing the responsible design of data and technology-enabled products, services, and systems, as well as their impact on society and the environment.

What design students should know: (concepts and theories)

- **Ethics and values** — Ethical and moral principles guiding decisions in design and technology, including privacy, security, access, sustainability, well-being, and equity.
- **Cultural studies and analysis** — Norms, values, and practices shaping society, defining diverse cultures, and forming design responses.
- **Sociology and systems thinking** — The interdependency of natural, social, and technological systems and the role design plays in their interactions.
- **Speculative design** — Exploring possible futures and the potential of design to bring them into being.
- **Data-driven activism** — Using data to drive social and political change, including visualization and storytelling to communicate complex information and engage various audiences.

What design students should do: (skills and behaviors)

- Apply ethical and moral principles in decisions about design, technology, and the use of data. Do no harm.
- Analyze and account for cultural norms, values, and practices in design decisions. Privilege cultural diversity and specificity over universal, one-size-fits-all solutions.
- Analyze internal and external systems relationships and interdependencies, as well as effects of change in these relationships on society and the environment.
- Explore possible futures and the impact of technological change on society and the environment and of social change on technology.
- Use data to drive social and political change.

to integrate the technical, analytical, and social aspects of a data-centric design approach.

In our rapidly changing digital era, design education is no longer confined to traditional disciplinary boundaries. Across the globe, institutions like the College of Design at North Carolina State University are pioneering curricular experiments that champion a data-centric, multidisciplinary approach (Figure 2). A driving force behind this shift is the linking of real-world industry partnerships into the academic arena, providing students invaluable access to data analytics, challenges in optimization and scalability, and the opportunity to influence the way data is captured, processed, and utilized to craft meaningful human-centered experiences. This transitional phase calls for a novel pedagogical approach, one that prepares

The Graphic/UX Design program in the College of Design at North Carolina State University has a ten-year co-teaching partnership with analytics software company SAS. A spring semester project negotiates a data-driven design challenge for upper-level undergraduates that supports the goals of the bachelor's curriculum. Project histories span issues such as identifying the overuse of opioids, tracking bias in mortgage lending, and ethical concerns in the applications of AI. Across time, the project has enjoyed oversight by NC State Department Chair Tsailu Liu, Design Professor and author of *Big Data, Big Design* Helen Armstrong, SAS Senior Director of Product Experience Christine Browning, and SAS Director of Product Design Rajiv Ramarajan. Following each year's presentation in the SAS auditorium, students receive feedback from SAS employees in a lobby networking café.

For the 2023 spring course, the teaching team of SAS Product Design Manager Macklin Frazier and NC State Design Assistant Professor Jarrett Fuller asked students to reduce food waste in the supply chain of a fictional multinational food distribution company through the conceptualization of a data-driven system. SAS identified potential users as a logistics manager, data scientist, and corporate executive. They required the system to: visualize current situations through historical and real time data; simulate and enact responses to changing and unpredictable environmental, equipment, and human resource conditions; and generate reports for shaping future action. The proposed system employed networked hardware and software; sensor technology in company equipment, farms, and produce; public databases and AI projections of evolving weather conditions and changes in transport routes; digital twins and interactive mapping simulations; and AI for assessing confidence in a variety of response scenarios. Real-time and historical data had to be exportable to a variety of reports and students reflected on new questions raised by the system design.

Work began with shared analyses of the situation; supply chain, workflows, interacting and unpredictable variables, available technologies, and comparable systems. Students explored feature sets and wireframed interface strategies with SAS. They worked in five teams, each responsible for one activity with access to ongoing SAS advice and resources. Although visualization was an important aspect of the work for which their communication design education prepared them, the purpose of the project was not simply the look-and-feel of charts and maps. Students focused on how integrated dynamic data fed visualizations and the relationships among displays in informing and assessing possible action under the urgency of time and

limitations of available resources in the field of operations. By purposefully tracking the journeys of different perishable foods and geographic locations, student teams defined the data parameters the system had to address.

Student presentations included a two-minute video of the group's high-fidelity prototype and slides that framed the situation under a series of exploratory questions.

- Team Liatrix' scenario involved receiving orders for its kombucha (fermented tea) products and shipping them to warmer regions of the country than ever before. Their system uses a pinnable tracking dock, adaptive visualizations powered by predictive analytics, and smart alerts based on AI confidence.
- Team Hive addressed unpredictable equipment breakdowns in transporting avocados from Mexico to points in the Southeastern US. Their customizable dashboard uses a filtering system and intuitive scaling, intelligent alerts that weigh options and enact choices, and live tracking that follows trucks and predicts arrival times.
- Teams Sunny Side and Orchid focused on large-scale environmental events that could disrupt the production and delivery of eggs in the Northwestern US and rice from the company's Telangana farms in India to the US. Sunny Side uses digital twins of the live system that integrate real time and projection data. It automates some remediation strategies based prior human responses to similar conditions. Orchid explores alternatives to cartography that remove response-slowness noise in the display of AI-generated recommendations for both mobile and desktop applications.
- Team Report Farm developed a continual monitoring system that alerts employees to under-performing components of the supply chain. It builds real-time reports, using pre-generated, editable templates and conversational interfaces and pulls data from IoT sensors in the field.

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Figure 2
A case study in the student design of a data-driven system. © 2023 North Carolina State University and SAS Institute Inc.

students with a rigorous foundation in statistical and probabilistic thinking, novel capabilities in simulation and AI, and a sensitivity to the ethical considerations that arise from integrating data into the design process. As these curricular experiments mature alongside the technologies and opportunities that enable them, we will observe how these innovative practices are re-shaping the face of design education, equipping the designers of tomorrow with the tools and perspectives they need to excel.

A Renewed Vision for Design

The integration of data science and design represents a critical paradigm shift in how we educate and prepare future designers. With our world becoming increasingly data-enabled and interconnected, designers must now consider their roles within larger systems, navigate complexities and uncertainties, capture and analyze data responsibly and comprehensively, and learn to leverage vast amounts of data for dynamic design solutions. By merging diverse disciplinary perspectives, adopting a systemic approach, and thinking probabilistically, designers will thrive in the emerging era of data and AI.

A curriculum that intertwines data, technology, and design will play a pivotal role in this shift. By equipping students with foundational technical skills, sensitivities to data quality, data analytical abilities, rhetorical skills for advocating data-driven insights, and the capacity to use data as a collaborative boundary object, future designers will be prepared to interface with the complex challenges and systems that define all impactful design work.

The intersection of design and data science, while offering new challenges, also presents significant opportunities. By understanding and adopting these new mindsets and skills, today's students will be prepared to shape the future of design and to have a meaningful impact on our increasingly complex, data-centric world.

Declaration of Interests

There are no conflicts of interest involved in this article.

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