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Human-centric analytics: collaborative design for mathematics, AI and data-driven insights

Christina J. Phillips[†]
Business Analytics, Liverpool Business School, Liverpool John Moores University, Brownlow Hill, Liverpool, L3 5UG, UK
[†]Corresponding author. Email: c.j.phillips@ljmu.ac.uk

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This paper introduces human-centric analytics (HCA) as a design paradigm for integrating mathematical models, data and human judgement into management decision-making. HCA addresses situations in which analytics must be understood, adapted and used within complex organizational settings, rather than treated as standalone technical artefacts. While human-centred design (HCD) offers useful principles for usability and participation, HCA addresses a different design problem. It focuses on the practical design and adaptation of analytical artefacts, techniques and processes, including the negotiation of model assumptions and appropriate levels of granularity. Drawing on a longitudinal case study in a pharmaceutical supply chain, the paper examines a series of analytics interventions involving forecasting, simulation, statistical analysis, visualization and data blending. Analysis of both successful and unsuccessful interventions shows how mathematical tools gained traction when they were developed through iterative engagement with users' work, expertise and constraints. The paper presents HCA as an empirically derived and theoretically grounded design paradigm, supported by an umbrella framework organized around four recurring design activities: structuring perceptions, structuring empirical data, overcoming resistance and evolving solutions. The framework supports flexible combinations of tools and techniques, enabling analytics to become technically grounded, contextually meaningful and integrated into organizational practice. As data-driven systems and AI become increasingly embedded in management, HCA offers an approach for designing analytics that augment human practice rather than bypass it.

Keywords: human-centric analytics; AI; pharmaceutical supply chains; decision making; analytics framework.

1. Introduction

Analytics can be defined in many ways, typically as a systematic process involving computing and mathematics. But what about the end-users? To make mathematically derived tools effective, decision makers need a basic foundation in mathematics, if only at a conceptual level. Yet, many potential users have limited exposure to mathematics or even a fear of it. How can we foster effective analytics use without alienating those who we seek to engage?

As Syntetos & Nikolopoulos (2024) emphasize, analytics needs to be applied in context. This includes not only the sophisticated and novel algorithms described by Tayur (2024), but also small-scale tools, methods, logic and transparent heuristic models that can structure judgement and augment human work (Katsikopoulos & Gigerenzer, 2026), while expanding users' confidence in analytics and AI. Algorithms have also become essential to management decision-making in organizations, giving rise to algorithmic management systems (AMS) that necessitate socio-technical design choices made with strategic organizational oversight (Zhang et al., 2025). Together, these points suggest a need for frameworks and methods that explicitly support the design of analytics within complex organizational settings.

Failure to consider the systemic, organizational and social effects of analytics systems can be catastrophic, as illustrated by the Robodebt programme in Australia (Rinta-Kahila et al., 2022) and the UK Post Office Horizon IT Scandal (Post Office Horizon IT Inquiry, 2025).

In the case of Robodebt, Rinta-Kahila et al. (2022) show how an algorithmic decision system, once embedded within organizational routines and governance structures, led to severe and unintended social harm. These outcomes arose not from a single technical failure, but from the way the system became integrated into organizational processes and decision-making. The organization continued using and defending these systems despite accumulating evidence of adverse effects.

This highlights the importance of understanding how analytical systems are designed and embedded within organizational contexts. It was within a different, but nonetheless complex and high-risk organizational context that we undertook this case study: a pharmaceutical manufacturer working toward 'swift and even flow' (Schmenner & Swink, 1998) in production planning and control.

In case study research such as this, theory often evolves in situ (Eisenhardt, 1989), as did the ideas that later informed what we term human-centric analytics (HCA), which focuses on the design of how humans, data and mathematical models work together, rather than on individual analytic artefacts. The manufacturer's complex supply chain meant that their preferred discrete lean tools had not achieved the desired smoother flow. We decided instead to adopt a more pragmatic conceptual approach to lean (Hines et al., 2004), driven by multiple mathematical insights and tools. The evidence gathered through the design and implementation of these tools was used to develop the ideas presented in this paper.

By studying both successful and unsuccessful interventions, we can gain a more nuanced perspective (Howick & Ackermann, 2011), which is the approach we applied in this case study. In a companion paper (Phillips & Nikolopoulos, 2019) show how action research can foster high involvement and enhance understanding in complex socio-technical systems such as forecast support systems (FSSs) in production planning and control. This study goes a step further by holistically examining all of the case study interventions, including what did not work, to understand the pathway to successful analytics implementation.

We found that in a complex setting like this, human involvement in the design process is essential for analytics to be informative and gain traction. We call this approach HCA, which, while not initially inspired by human-centred design (HCD) (Nielsen, 1993; Giacomin, 2014), emerged from our case study with similar attributes such as collaborative design iterations. Unlike HCD, however, HCA focuses specifically on integrating mathematics into human work by fostering a co-design process that encourages a dialogue between people, data and mathematical concepts. This process embeds learning and helps surface an acceptable level of detail and realistic parameters that support analytic reasoning and judgement.

Implementing analytics (used for decision making or insights) does not always require novel methods, but a lack of mathematical skills can hinder even basic applications. In an early volume of the Institute of Mathematics and its Applications (IMA) Journal of Management Mathematics, Bowen (1990) lamented the disconnect between a process orientation in operational research (often considered the foundational domain of analytics) and the more abstract orientation of pure mathematics. Bowen called for the community to model the process of integrating mathematics into practice to provide structure and insight. Recent work on fast-and-frugal heuristics addresses this gap from the perspective of decision making, showing how intuition can be analytically modelled and used in management practice

(Katsikopoulos & Gigerenzer, 2026). The growing role of AI adds further urgency to these questions of integration and use. Sanders (2024) argues that the management mathematics community must step up in engaging human users during what she describes as a short lived ‘inter AI period’. HCA responds to these connected concerns by emphasizing that the design process is as important as the end product. A well planned design process encourages contextualized, applied mathematics by fostering shared expertise and learning while creating opportunities for appropriate solutions to emerge. This process can also further our intellectual engagement with management practice (Tayur, 2024).

Analytics are useful in supply chains (Waller & Fawcett, 2013), providing foresight and improving decisions. Yet, many workers need skills to engage effectively with analytics (Liberatore & Luo, 2010; Ranyard et al., 2015; Vidgen et al., 2017). In our case, mathematics and data needed to supply timely, relevant intelligence to help people be proactive, improving both their day-to-day work and the overall strategy of the factory.

To achieve our goal of proactive analytics use, we applied multiple tools, including clustering, forecasting, simulation, statistics and accessible visualizations. These approaches served a variety of functions: furthering understanding of systems and sources of variability, augmenting work and supporting decision making. However, no generic theory or framework existed to couple these often-competing needs in what was a complex and highly dynamic manufacturing environment.

We propose HCA as a design paradigm for situations like those outlined above. A design paradigm is a framework that guides solutions to design problems (Braha & Maimon, 1997). HCA provides an archetypal approach to developing analytics that augment human work. It draws on concepts familiar from HCD, such as contextual understanding, iteration and reflection (Giacomin, 2014), but extends beyond them. Figure 1 illustrates how HCA differs from HCD, highlighting two distinct design requirements for analytics: (1) creating a dialogic space between human users and the data/algorithms deployed; and (2) achieving a mutually agreed level of system granularity, including, for instance, parameter choices and temporal aggregation. The concept and practice of HCA are discussed in depth in Section 5.

This study makes three contributions to research. First, it introduces HCA as a design paradigm for developing human-centred analytics. Second, it presents a practice-derived framework that supports the application of HCA in real-world contexts. Third, it offers empirical insights into how mathematics, data systems and managerial decision-making can be integrated in complex organizational environments.

The next section reviews literature on efforts to connect human actors with technical systems across disciplines. We then outline the case study context and describe how both the concept of HCA and its framework emerged through participatory inquiry. The penultimate section synthesises these elements, articulating HCA’s theoretical role and presenting the framework in structured form. The final section addresses limitations and points to avenues for further research.

2. Literature review

In this section, we discuss the foundational concepts of analytics and modelling, examining key characteristics needed to integrate analytics into management practice. Next, we review literature on mixing methods, noting how multi-paradigm approaches align with analytics design needs. We then investigate HCD across fields such as engineering, information systems and computing, as these share characteristics with analytics design in practice. Finally, we draw on literature from granular computing and mathematical abstraction to illustrate how these concepts contribute to analytics design.

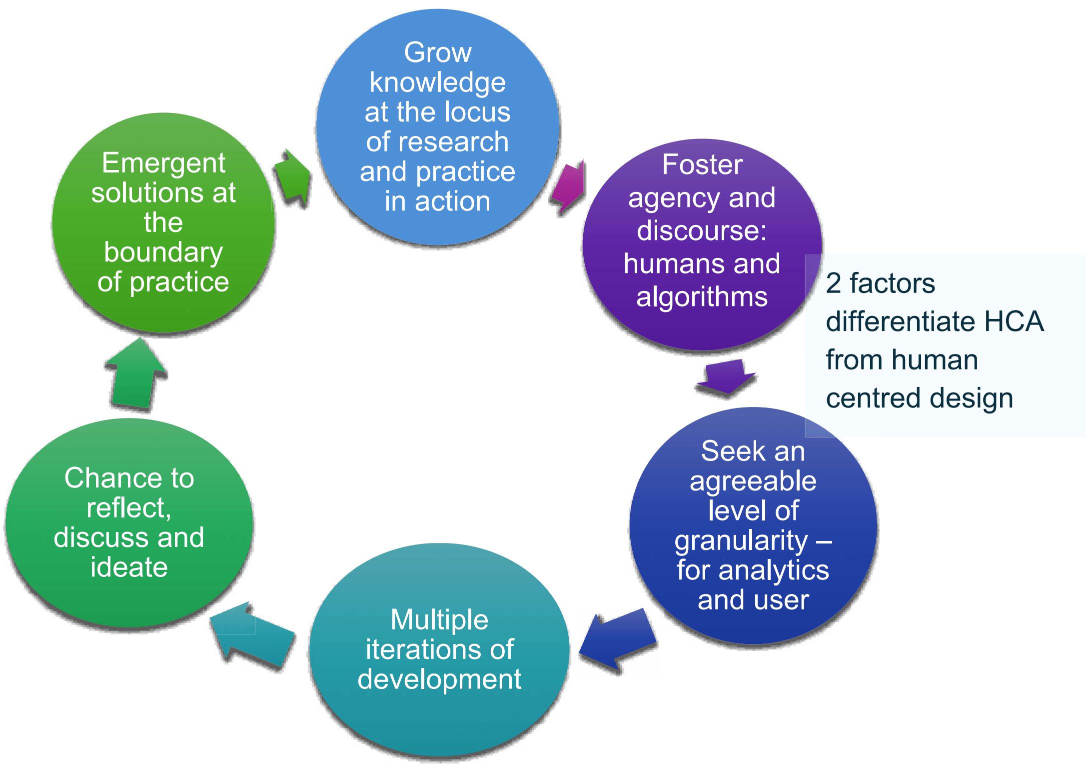

Fig. 1 Depicting the interconnected factors involved in HCA distinguishing it from HCD.

2.1. *Analytics: connecting mathematics, modelling and design*

Mortenson et al. (2015) define analytics as part of the broader paradigm of dianoetic management systems, those based on rational, data-driven decision-making using mathematics and computing. When using mathematics for predictive and improvement purposes, robust causal inference is essential and achieving this typically requires the involvement of subject matter experts, with detailed domain knowledge, throughout the entire analytics development process (Hernán et al., 2019).

Aspects of analytics are expressed through mathematical modelling techniques, such as time series, forecasting or simulation. Design, when seen as modelling and systems design, fosters high human involvement (Maier et al., 2014). In this framing, modelling as design provides form via mathematics or some other abstract code, such as causal mapping. It serves as a communication tool in the design process, helping participants work toward a form they can recognize and understand (Eckert et al., 2005).

This integrated perspective of modelling and design originates from a cybernetic approach in engineering design (Maier et al., 2014), where the importance of contextualized, iterative design and communication are noted, particularly in socio-technical systems (Wynn & Eckert, 2017; Piccolo et al., 2019; Zhang et al., 2025). Models, as bounded entities, can facilitate alignment among participants by fostering a shared understanding through a negotiated cognitive process. This potential has been noted by both design engineers (Maier et al., 2014) and operational researchers (Carlile, 2004; Franco, 2013; Luoma, 2016).

Luoma (2016) also highlights the need for thoughtful design when using models as decision aids. He advocates for models to attain a 'behavioural fit' by respecting work pace and structure. Models built this way are more successfully implemented because they are less disruptive, which reduces associated risks and potential conflict.

Summary 1: Mathematical modelling, when used as an analytical tool for decision-making, requires active involvement of experts to ensure robustness. In practice, this often evolves into a communicative design process involving iteration, reflection and contextual engagement, ultimately creating bounded objects that align with the typical work patterns of participants. These characteristics suggest a distinct design paradigm for applying mathematics when humans need to be highly involved.

2.2. *Structuring and surfacing user perceptions: mixing paradigms*

Including participants and using techniques that encourage them to articulate their individual worldviews can enhance the validity of mathematical and computational models. These processes foster user acceptance and can drive cultural change (Kotiadis & Mingers, 2006; Pessôa et al., 2015; Phillips & Nikolopoulos, 2019). Within Operational Research and Management Science (ORMS), frameworks and guidelines for multi-method approaches have been developed (Mingers & Brocklesby, 1997; Lane & Oliva, 1998; Pollack, 2009; Tako & Kotiadis, 2015). Some of these studies have used mixed methods to support information systems redesign or technology implementation (Pollack, 2009; Small & Wainwright, 2018) while others have created analytical artefacts, mainly in the realm of healthcare (Kotiadis & Mingers, 2006; Kotiadis et al., 2013; Pessôa et al., 2015; Phillips & Nikolopoulos, 2019).

Multi-method/paradigm use is inevitable in analytics, as human users interact with mathematically and computationally derived knowledge (Thomson et al., 2014; Conboy et al., 2020). Tako & Kotiadis (2015) provide a framework, PartiSim that explicitly couples soft systems methodology (SSM) (Checkland, 2000) with discrete event simulation (DES). Phillips (2021) notes that PartiSim's predefined goals and steps help human-centric approaches to simulation stay on track, provided that the rules are allowed to flex.

Lane & Oliva (1998) coin the term 'dynamic coherence' to describe the need to maintain consistency between behaviours alternately induced by suggested system changes or proposed causal effects. They explored the coupling of SSM and system dynamics (SD) using the politically sensitive and worldview focused process of SSM to confirm personal and social views, while employing SD modelling to assess system viability.

Pessôa et al. (2015), suggested their intervention may have more successfully integrated solutions if there had been greater stakeholder engagement throughout the modelling process. Another healthcare ORMS study used ethnography alongside SSM and DES, noting that it enabled the analyst to participate in an exploratory process informed by data observations (Lamé et al., 2020). Long-term engagement helped the analyst learn the context, becoming an accepted part of the process, thus improving communication and enhancing engagement.

(Phillips & Nikolopoulos, 2019) describe similar effects to Lamé et al. (2020), using action research and intervention theory to improve the use and understanding of an FSS. Their study focused on how action research enhances forecasting methodologies, while this paper examines how HCD principles emerge across multiple interventions, shaping analytics development beyond its use as part of the FSS.

PartiSim and SD are explicit multimethod approaches in OR, as is Multi-Criteria Decision Analysis (MCDA), which seeks to:

- 'Integrate objective measurement with value judgement,
- Make explicit and manage subjectivity' (Belton & Stewart, 2002) and
- 'Is as much about communication as decision-making' (Papamichail & French, 2013).

These same criteria apply to any HCD of analytics, since the goal is to make work processes and their associated decision systems (embodied in mathematics and analytics) transparent and supportive of other workflows, just as MCDA aims to do (Belton & Stewart, 2002). HCD should promote communication not only between human actors but also between humans and systems, data and mathematics, akin to MCDA (Papamichail & French, 2013).

Summary 2: Integrating analytics must bridge multifaceted human judgement and precise mathematical models. This requires well-defined techniques that help participants engage with data and algorithms to surface individual perspectives while exploring and expanding boundaries of understanding. This communication needs to bridge subjectivity and objective measurement.

2.3. *HCD for analytics and AI: bridging the divide*

The field of HCD encompasses designing for products, services and systems, ranging from business strategy (Brown, 2008; Giacomin, 2014; Gruber et al., 2015) to healthcare (Clarkson & Coleman, 2015) and computer systems (Maguire, 2001). Maguire (2001) provides a detailed overview of an ISO standard for HCD that guides development for interactive computer systems. Many of the features defined in that paper align with the findings from ORMS and design literature regarding involving participants and collaborative design, such as higher acceptance and fewer errors. Several of the characteristics these HCD papers describe overlap with those of analytics systems. Analytics differ, however, in that they operate at a secondary level, built on the software and technologies provided by computer science.

HCD's underlying philosophy is design thinking, which views design as a holistic and dynamic process involving the design in use and redesign (Kimbell, 2012; Giacomin, 2014). Many usability criteria in HCD align with the technology acceptance model (Venkatesh & Bala, 2008), such as ease of use, efficiency in use and ease of learning. HCD also emphasizes the importance of involving human actors at every stage, iterating on designs, adopting interdisciplinary approaches and clarifying roles and contexts.

An example of the limitations of HCD in analytics design comes from the Centre for Emerging Technology and Security which explores the challenges of integrating machine learning (ML) in intelligence analysis (Knack et al., 2022). The report highlights that the use of ML in characterizing and triaging information from large datasets is valuable when paired with human oversight. However, the 'black box' problem of ML models remains an issue, demanding transparent interpretation of model behaviour for highly varied users. The authors find that trust must extend beyond the ML outputs to the entire system, involving iterative prototyping with analysts to align system transparency and utility with user needs. This evolving collaboration and continuous calibration process points toward an approach that goes beyond typical HCD, where humans and ML co-create in an adaptive way that actively embeds learning in environments with varying levels of complexity.

Human-centric artificial intelligence (HCAI) focuses on the AI component of analytics systems, with particular emphasis on ethics and governance and AI's potential long-term societal impact. Garibay et al. (2023) frame HCAI as a design challenge that moves beyond artefact and interface, incorporating system-level approaches in which well-being and oversight are placed to the fore. More recent work argues that AI systems are embedded within wider sociotechnical organizational systems and cannot be considered in isolation from social interactions and work processes (Herrmann and Pfeiffer, 2023). In this framing, human-in-the-loop designs become insufficient once AI systems are taken into use and embedded in everyday work without considerations beyond individual users.

At a more technical level, inclusion is often necessarily limited. For example, human-in-the-loop systems employing adaptive control of thought - rational (ACT-R) cognitive models that learn from users' interactions aim to speed up data exploration so that users can focus on decision-making (Liu et al., 2014). In doing so, they link individual human users and machines to create shared quantitative mental models (Thomson et al., 2014). These techniques are designed for tasks in which data and objectives are specified in advance. However, they do not incorporate methods for working with stakeholders to define tasks, clarify data needs or support experimentation with alternative analytical designs.

Summary 3: HCD can guide HCA by providing criteria and methods to make solutions and processes more user-friendly. However, HCA also requires the flexibility to experiment with different designs of mathematical tools, data and transparent explanations that are shaped by human feedback, creative exploration and learning in context.

2.4. *The importance of granularity*

Granular computing seeks to represent defined information in ways that fit with human experience and behaviour. Pedrycz (2018) declares a 'Manifesto for Human-Centric Computing', describing how granularity can abstract information to a level that is more accessible for both human users and algorithms. For decision support systems to foster iterative, consensus building processes, a human-centric design is desirable (Papamichail & French, 2013). Granular information, such as in fuzzy set theory and fuzzy numbers (Zadeh, 1997) can enhance these processes (Pedrycz & Chen, 2015). For instance, researchers used rough sets to create an multi-criteria decision model for spare parts classification, based on 'if ... then' criteria, finding it intuitively easier for end users and involving them throughout the process (Hu et al., 2017).

The concept of grain size mirrors that of 'bounded rationality' (Simon, 1997) and some have suggested that irrational human behaviour is due to granular thinking (Lorkowski & Kreinovich, 2015); when individuals can no longer process information, due to cognitive limits, they tend to make seemingly irrational decisions.

Designing decision aids requires careful attention to the user's needs and an ability to elicit preferences effectively (Munier, 2018). Analytics take many forms, from a mathematically derived decision model to 'what if' simulations or descriptive visualizations, so a suite of solutions and decision tools needs to be considered. In complex settings, simpler models, bounded by an appropriate level of granularity for both computation and understanding, can often be more informative and parsimonious (Robinson et al., 2014; Luoma, 2016). Recent work on fast-and-frugal heuristics reinforces this point, showing that simple, transparent decision models can perform well under uncertainty when they fit the decision context and the cognitive demands placed on users (Katsikopoulos & Gigerenzer, 2026).

For Maier et al. (2012), keeping it simple is a component of collaborative design. They see participative modelling as an evolving cybernetic system with a high requisite variety (the number of parameters required to perfectly model a task) (Ashby, 1956). As a dynamic and emergent process, participative modelling involves multiple stakeholder perspectives, necessitating well-structured, simple, yet varied methods to aid design. Again, this speaks of a need to have multiple analytical tools at hand.

Summary 4: It is often preferable to have a wide variety of simple models that fit well, enabling participants to collaborate effectively with mathematicians and analysts. This supports the co-creation of an acceptable granularity and parameter choice across actors, including the data and algorithms.

2.5. *Existing tools and techniques*

Action research offers a broad framework to encompass diverse situations and is used to design, study and improve sociotechnical systems (Baskerville & Wood-Harper, 1996; Mumford, 2006; Caniato et al., 2011; Phillips & Nikolopoulos, 2019). Design thinking has also effectively coupled a human approach with technical design (Kolko, 2015), supporting the generation of collaborative ideas (Gruber et al., 2015; Kolko, 2015; Groop et al., 2017).

One of the closest existing approaches to HCD for analytics is the business analytics methodology (BAM), which uses part of SSM (Checkland, 2000) to elicit worldviews of participants. Hindle and Vidgen et al. (2017) describe BAM as an opportunity to re-evaluate business models, highlighting how analytical devices co-evolve as data scientists and business analysts interact. Although older methods for collaborative analytics design exist, Hindle and Vidgen et al. (2017) note that these approaches are not maintained. Li et al. (2016) introduce the KDDA (knowledge discovery through data analytics) model using a 'snail shell' approach for iterative knowledge development from big data using design science as a methodology. BAM and KDDA focus on computational data mining and established analytics tools but do not emphasize the bespoke mathematical design aspects that are central to this paper.

The frequent use of techniques like SSM, action research and design science reflects the socio-technical nature of creating analytics. This has been studied extensively in information systems (Orlikowski, 2000; Vidgen & Wang, 2009; Allen et al., 2013; Cecez-Kecmanovic et al., 2014) and to a lesser extent in forecasting research (Oliva & Watson, 2011; Asimakopoulos & Dix, 2013; Phillips & Nikolopoulos, 2019). Interacting across socio-technical boundaries has been described as a structuring process (Orlikowski, 2000). Others emphasize temporal coordination, framing this interaction as a 'dance of entrainment' (Ancona & Waller, 2007), or as a performative 'dance of agency' (Pickering & Guzik, 2008). The mangle of practice (Andrew Pickering, 1995; Ormerod, 2014), with its performative view, implicates both the structuring noted by Orlikowski (2000) and the temporal entrainment noted by Ancona & Waller (2007). The mangle also provides insight into the behavioural dynamics observed by Lane & Oliva (1998), making it a useful lens for analysing our multiple cases.

Falco (2015) advocates for the use of HCA to enhance resilience in smart city design. Similarly, the UNDP (2014) report suggests HCA as a way to tackle long-term planning in developing countries. Neither source, however, specifies how HCA might be implemented or clearly defines what it entails.

More recently, Zhang et al. (2025) examine AMS, highlighting how analytics and algorithmic systems are becoming an integral part of management infrastructure. Drawing on recent literature, they argue that the choices involved in designing these systems are inherently socio-technical and strategically consequential. In particular, they emphasize how algorithmic systems intertwine material and social elements, treating algorithms as agentic components within broader human and organizational systems. This points to the need for careful attention to the necessarily co-creative design process.

Summary 5: HCA needs a careful and considered design approach to coupling methodologies and mapping socio-technical interactions. Although previous authors have suggested the need for HCA, they have not provided a concrete definition or approach for its application.

Taken together, these five observations suggest that designing analytics in complex settings requires bridging and negotiating across human, material and operational domains. Across the literature, there is consistent evidence of the need to: (i) surface diverse perspectives and tacit knowledge; (ii) account for organizational dynamics, acceptance and sources of friction; (iii) support iterative sense-making between participants and technical artefacts, including the co-development of conceptual models, parameter selection and system granularity and (iv) deliberately structure dialogue between model assumptions, data and user expectations. While each piece of literature addresses aspects of this challenge, none offers a consolidated approach to analytics design. These observations therefore point to the need for a more deliberate design paradigm for analytics that bridges the social and the technical, acknowledging human judgement, negotiation and iteration as core elements of the process. We define this as HCA, a design paradigm that integrates these elements and provides a framework for their practical application.

The next section outlines the context of the case study and describes the methods used.

3. The case and the methodologies

The case study spanned 4.5 years and was conducted in a multinational company, PharmaCo, a semi-process industry manufacturing biological products. PharmaCo's production involved unique ingredients and complex testing regimes, resulting in highly variable lead times. The project aimed to smooth production by defining family groups of items with similar behaviours while accounting for exogenous demand variation, and to identify other sources of reducible variability. This prompted a series of interventions, each with an analytics component, across multiple business functions and organizational hierarchies. Collating multiple instances of analytics use over a prolonged period enabled comparative analysis within a single firm. While this approach is less generalizable, it is also less heterogeneous than studies spanning multiple firms or industries.

We triangulated our findings using diary recordings of meetings and interactions, recorded interviews, secondary recorded notes and empirical data (all covered by a non-disclosure agreement), using action research as the overarching frame within which most activities took place. Action research allows heterogeneous temporal change to be examined in situ, where outcomes are influenced by ongoing learning and organizational change, through its emphasis on contextualized, embedded research practice and highly engaged participants (Baskerville & Wood-Harper, 1996). To meaningfully catalogue such change, it is necessary to make explicit the analytical lenses being used and the position of the researcher; otherwise, the account risks becoming anecdotal (Checkland & Holwell, 1998). When applied consistently across multiple interventions, this approach supports comparison through equivalent data collection mechanisms (Eden & Ackermann, 2018).

In this case study, we adopted the performative lens of the mangle of practice (Pickering, 1995; Pickering & Guzik, 2008; Ormerod, 2014, 2017). Recorded notes were also influenced by SSM as described by Checkland (2000), which was used during one of the interventions. The agnostic stance of action research avoids imposing a normative framework or predefined rules, treating research and practice as co-evolving. A reflexive approach was maintained throughout, and where this gave rise to instrumentalization by more powerful actors, as can occur in such settings, this was explicitly noted (Westling et al., 2014).

The researcher worked part-time within the company as a business analyst, with her role evolving over time, and participants were involved in reflection throughout the case. Initially, she was employed as a Knowledge Transfer Partnership Associate, tasked with applying mathematics across a range of problem areas. This role later extended into consultancy work and a PhD scholarship. As a result of this progression, the systematic use of action research and the mangle of practice began approximately two years into the 4.5-year study. While most recorded evidence reflects the mangle perspective, this lens was retrospectively applied to material collected prior to its formal adoption.

Analysis of the triangulated notes and data took place both during and after the research, focusing on identifying themes and patterns. Data-driven mathematical insights and visual analytics were often informed by this qualitative evidence, supporting more contextualized interpretations and enhancing communication. This approach to business analytics was adopted early in the project, as it gained traction with participants and enabled the researcher to discuss proposed mathematical methods in ways that were accessible and meaningful.

When improving the forecast, we used the method of forecast auditing (Moon et al., 2003). For participative simulation, we employed the PartiSim method (Tako & Kotiadis, 2015) alongside the Simul8 discrete-event simulation package, chosen for its accessibility to participants. (Phillips & Nikolopoulos, 2019) provide a detailed account of the use of action research to improve the FSS at

PharmaCo, illustrating how action research can be applied within forecasting, one of the most widely used predictive analytics domains in business.

For visualization, we used Tableau, R and Excel. Data wrangling was carried out using the Alteryx data blending and analytics package, chosen for the transparency it provides at each step. Data analysis and forecasting were conducted in R.

The mangle of practice view has the following parts:

- Bridgehead: Creative, unconstrained moves that suggest new directions for exploration.
- Transcription: Incorporation of new knowledge and creative moves into cultural practice, enabling changes that align with the bridgehead.
- Resistance: Systemic, social, political, material and technical constraints that oppose or modify the direction of the bridgehead.
- Accommodation: The strategies employed to overcome resistance, including adjustments during transcription.
- Filling: The smaller changes required to incorporate and consolidate the directed change after overcoming resistance.

For a more detailed discussion of the mangle in relation to practice, see Ormerod (2014, 2017). Pickering & Guzik (2008) offer additional examples of the mangle viewed through different lenses, suggesting that agile design, for instance, is a 'mangleish' process. Pickering (1995) provides an extensive discussion of the interplay between human and non-human agency, exploring how they shape one another. His analysis of the discovery of quaternions by mathematician William Rowan Hamilton illustrates how the mangle can capture the dynamics of mathematical invention. This suggests the mangle as a tool well suited to analysing attempts to integrate mathematics into practice, we do this with our case in the next section.

4. Mathematics in the wild: what worked and what didn't at PharmaCo

Using the mangle of practice as a lens, we examine the case study at PharmaCo, focusing on a series of analytics interventions undertaken over time. The majority of the interventions are summarized in Table 1.

4.1. *Early projects*

Initially, we used only Excel as our analytical tool and gathered data from multiple incompatible sources, which made deriving meaningful insights challenging. We therefore expanded our toolkit, adopting additional software to support data gathering and blending. Alongside this, we undertook early projects to assess data quality, helping to align people's understanding of the data with what was actually being recorded. This process surfaced differences in interpretation and supported shared understanding. The following two examples illustrate this.

Example 1: Visualizing Production Issues with Venn Diagrams.

We used logical operators in Excel, applying simple probability theory to create 'right-first-time' Venn diagrams. These visuals quickly highlighted issues in production and testing, enabling managers

TABLE 1 *Describing the interventions at PharmaCo.*

Intervention	Tools/techniques	Objective	Outcome
Initial use of excel for data analytics	Excel (manual data gathering from SAP and other sources)	Exploring demand fluctuations using manual manipulation and analysis of unstructured data.	Resistance due to incompatible data sources; moved to alternative software that could blend, analyse and visualize.
Venn diagrams for production and testing	Venn diagrams, probability theory in excel	Identifying major production/testing issues via visualization.	Quick identification of problem areas; management adopted the tool.
Simple ratios for production metrics	Simple ratios: ideal/actual metrics	Providing easily understandable metrics for daily use.	Ratios became central to daily meetings and decision-making.
FSS improvements	FSS, aggregated and de-aggregated data views	Improving demand visibility and aligning data with real-world patterns.	Better demand visibility, improved confidence in managing demand spikes.
Participatory simulation using PartiSim	PartiSim (SSM, DES)	Simulating and understanding system performance with participant involvement.	Increased participant engagement, smoother flow solutions emerged. Cross functional alignment improved. Changes made regarding decisions around sudden demand changes.
Addressing 'Cherry Picking' with control charts	Control charts in excel	Reducing variability in demand forecasting by filtering out noise.	Control charts were initially resisted but later adapted and used.
Use of MAPA for multi-temporal forecasting. CV for demand categorization.	MAPA algorithm for secondary forecasting. CV for quick identification of problem lines.	Enhancing forecasts by analysing demand at multiple temporal levels. Quicker decision making regarding forecast.	MAPA gained trust as it aligned with staff's experience. Provided a recognizable view of how level loading might look. CV used with knowledge to improve decisions around forecasting.
Sourcing new software for data manipulation	Tableau, R, Alteryx for data blending and analysis	Overcoming resistance from existing infrastructure and improving data flow.	PoC proved useful, leading to wider company adoption of new tools.
Developing S&OP process	Structured data blending for S&OP	Embedding analytics into day-to-day production planning and control.	Integrated faster data processes and reduced systemic inertia.

to focus on areas needing improvement. The solution was implemented in a spreadsheet that a manager learned to use and subsequently adopted.

Example 2: Developing Simple Ratios.

We developed different ratios to create accessible metrics such as the 'Ideal/Actual' ratio:

- $\frac{\text{Ideal}}{\text{Actual}} > 1$: Overrun.
- $\frac{\text{Ideal}}{\text{Actual}} < 1$: Underrun.
- $\frac{\text{Ideal}}{\text{Actual}} = 1$: On track.

These ratios were applied to a range of temporal and numerical measures. To avoid extreme outputs, very small actuals were either scaled or excluded. Comparing expected production time with actual duration became a regular feature of daily meetings.

These examples emerged as the analyst responded to the needs of a senior manager and planning staff. Observing their difficulties in interpreting the data prompted a trial-and-error process, in which material was presented, discussed and adapted in response. As viable designs emerged, this process facilitated discussion and collaborative learning through use.

4.2. *Improving the FSS*

Building on these early, locally grounded interventions, a series of improvements were made to PharmaCo's FSS, forming a central component of the case examined here. These developments are documented in (Phillips & Nikolopoulos, 2019), with a focus on the use of action research in forecasting, and improvements to FSS use. In this section the emphasis is on how improved forecast use and understanding emerged through iterations and design choices.

Early work enabled improved data collection and visualization at greater velocity and volume, allowing demand and production to be explored through aggregation and de-aggregation. This had a noticeable effect on staff perception, as noted by the Production Planning and Control Manager in a final interview:

> 'we are much more aware of the demand patterns on our products I think .... until we were seeing them ... the way you aggregated them up to see that we are in a relatively flat stable world .... changed a lot of people's perceptions I think ..... we have more confidence to leave the system after a demand spike ... the visual system has definitely helped us to see (the patterns) a lot'

This ability to analyse demand holistically and to adjust granularity both temporally and cross sectionally aligned with staff experience. Once the analyst realized people needed data that spoke to their experience, she went as far as systems would allow in data collection. This constituted a 'creative free move' in Pickering's terms. She broke the current practice and creatively applied knowledge, to develop more meaningful visual analytics.

These data also allowed secondary forecasting contextualized to the realities of planning work. The FSS had to accommodate predictions as far out as three years; with lead times of up to 12 weeks, it was frequently adjusted between forecasts. Meanwhile, demand planners actively monitored daily sales data to track stocks. The MAPA (Multiple Aggregation Prediction Algorithm) (Kourentzes et al., 2014) was useful in illustrating what happened when planning to different time horizons, as it aggregates and forecasts over multiple temporal levels. The MAPA input data included the demand that planners used and often reacted to; by reflecting their experience, it provided outputs that were easily understood and used.

The collaborative, iterative nature of the work enabled multiple teams, from quality to scheduling, to follow the design as it evolved, learning through experience. Although none of them felt they were particularly mathematically inclined, they all found the work easy to understand, and this made the subsequent changes in planning and scheduling much easier to implement and control.

Resistance emerged at multiple levels. Sourcing new software for data manipulation, for instance, faced obstacles from existing infrastructure and governance requirements. Standard company tools were either large-scale enterprise solutions or highly specialized systems whose costs outweighed their value to the business unit. In response, the analyst sourced alternative software and co-created proof-of-concept systems with staff, which were gradually transcribed into practice. This adaptive process reflects Pickering's notion of accommodation, as new methods coexisted alongside existing infrastructure during a period of gradual cultural shift.

Eventually, using the proof of concept (PoC) models and emerging company wide data infrastructures, we developed data pipelines and visuals using preferred company methods. Staff who were interested or who needed it most began transcribing the new methods into everyday operations, sparking a cultural transformation. This transformation emerged over the course of the 4.5-year engagement and was later identified by the senior manager responsible for the programme as its most significant outcome.

Focusing on the needs of planners and their manager unlocked data for business intelligence. A data stream so rich we would use it across many analytics interventions. We set up procedures to ensure that data continued being collected and collated at the same velocity and volume, while new metrics of days to sell and export splits contributed to substantial inventory savings.

Using simple models, we iterated toward an improved FSS in planning and control and created simple, effective metrics that were easily integrated as they resonated with local contexts. The eventual integration of these metrics and the PoCs is a demonstration of the 'filling' phase of the mangle of practice, as numerous smaller changes adapted and aligned the system with the emerging practice.

4.3. *Exploring level loading with participative simulation*

A key challenge in reducing variability was understanding the viability of level loading to achieve a smoother flow of work at PharmaCo. Highly variable product characteristics with uncertain lead times, plus erratic demand, required a deeper investigation. Analytics offered a way to explore 'what if' scenarios through a collaboratively designed simulation model. Other attendant analytics could provide valuable insights to enable co-designing for parameter choices.

We adopted the PartiSim framework, a human-centric approach involving soft systems workshops, conceptual modelling and experimentation. Later sessions used analytics as part of the workshop, which facilitated design as we could change parameters and experiment with the models. The workshops were a novel setting that fostered adaptive system use and encouraged staff to explore the models and data, getting to know each other's processes as the designs emerged. Model validation was quick, and staff who were involved took ownership of the designs.

Ideas and behaviours to help smooth production began to flourish as an offshoot of the simulation project. This was partly due to the 'what if' scenarios and largely due to the attendant analytics we had to use for setting the parameters and granularity of the model. This interplay of humans and machines is what Pickering calls a 'dance of agency', whereby staff began understanding, and creatively adapting to, the model constraints and parameters. The range of small and varied analytical devices, including visualizations and statistical findings, opened pathways for communication between data, mathematics and people, facilitating co-evolution between the model and participants' understanding.

The slowest part of the project was the conceptual modelling, but this surfaced important perceptual differences and revealed deficiencies in the data. Statistical analyses, unsupervised ML and visual analytics opened pathways for communication between data, mathematics and people, facilitating co-evolution between model and the participant's understanding. The PartiSim project had a profound effect on the way that demand was managed, but it could not overcome the cherry-picking effect.

4.4. *The cherry picking effect*

Staff identified a recurring phenomenon they termed ‘cherry picking’, where some customers would take large amounts of the ‘best’ batch of a product. Sometimes the ‘best’ was a batch they had purchased previously; at other times it was any batch with enough stock to cover their needs within the expiry period. Each new batch was subject to destructive testing and calibration by every customer, so it often drove purchase behaviour. Sometimes the customer was a warehousing point, and this determined the ‘best’: not necessarily the one with the longest shelf life but the best batch size for their projected sales. Despite the demand planners' determined efforts managing batches, the behaviour caused highly erratic demand profiles.

We attempted multiple approaches to control both the cherry picking and the way planning staff reacted to the demand spikes. As the senior materials manager observed:

> ‘We have to stop them reacting to every little spike .... I know we are hurting ourselves by creating more variability’

Control charting was suggested by the analyst since this distinguishes between noise and signal. Working together, the analyst and the senior manager developed an analytical tool using Excel to generate charts for use by the demand planners. However, despite seeing the potential, the demand planners never used the Excel sheets. After the company updated to new software, one of the demand planners started using the mathematics for management by exception three years later.

This delayed adoption illustrates what Pickering refers to as the bridging process, as old practices must be adapted to accommodate the new. The control charting needed to be fit for purpose and have a behavioural and systemic fit. Despite perceiving the charting tool as useful, the demand planners found ease of use low until the material and systemic aspects changed enough to accommodate it. Only then could they adapt what they had learned into the new systems. In retrospect, had we included the planners from the start, we may have overcome the resistance sooner by co-evolving a solution.

When we did include users from early on, such as in the exploration of the FSS, analytical devices provided contextualized mathematics that enhanced understanding, learning and acceptance. They also provided the seeds for effective communication tools, created by the people who would use them and used across departments. An example was one of the production planners using Tableau visualizations to talk to the quality teams at the other end of production. At first, she built data views and presented them without engagement, which didn't get traction. After being coached in the human-centric approach, she created very similar views but did so with the quality team's involvement. These co-designed visual analytics were used and became a sought-after information and communication tool.

4.5. *Using the coefficient of variation and translated research*

The demand planners began using the coefficient of variation (CV) to quickly sift out problematic items. The CV identified product lines that were the most difficult to forecast and manage, such as those with regular cherry-picking or intermittent demand. The analyst explained how to categorize demand for managing cherry-picking by exception, a goal that all of those involved felt was worth pursuing and this surfaced discussion about the CV as a potential measure. The simple method of categorization comes from Syntetos et al. (2005) who use the squared CV and a measure of 'lumpiness' to categorize intermittent demand profiles. The planners adopted the CV calculation, rapidly selecting profiles to focus on, and were warned about what would happen with profiles that had a near-zero mean.

Working with the analyst, planners became aware of problems associated with managing intermittent demand and adopted more caution when setting forecasts for these lines. Nikolopoulos (2021) notes how highly erratic demand profiles, like those on the cherry-picked lines, can be dealt with using intermittent demand approaches, having made a choice as to which are peaks over threshold. Staff at PharmaCo intuitively recognized this connection as they tried to deal with both cherry-picked and intermittent profiles. In-house forecasting systems favoured approaches that aggregated and disaggregated past demand for prediction. This led the analyst to use the Nikolopoulos et al. (2011) ADIDA (Aggregation Disaggregation Intermittent Demand Algorithm) study to explain why certain methods worked better on occasions. This new knowledge helped planners make informed decisions about when to override the automatic system forecasts.

4.6. *The bullwhip effect*

The cherry-picking effect had significant repercussions throughout PharmaCo's supply chain, particularly given that some raw ingredients required lead times of up to three years. This induced volatility was costly and created a bullwhip across the system, amplifying variations in demand (Kahn, 1987; Lee et al., 1997). While the analyst was keen to model and further investigate these effects, progress was hindered by difficulties in communication and alignment across groups.

Different actors held different operational understandings of demand. For the analyst, demand was conceptualized as the order-up-to quantity used to update the system at each forecast horizon. For planners, demand referred to sales orders, while for the support team in the USA, it was recorded as nightly transactions between the forecasting and ERP systems. Attempts were made to transcribe knowledge across these boundaries in order to obtain congruent data, but geographical distance and the cognitive load associated with planning limited progress.

At the same time, the senior manager prioritized smoothing the production system and viewed the bullwhip analysis as an effort without immediate operational value. Although analytically well motivated, the work did not align with existing priorities or staff engagement. This managerial focus became a key material actor shaping the direction of the intervention, and the bullwhip analysis was not pursued further.

Rather than proceeding with a technically attractive but weakly grounded intervention, knowledge from existing research on the drivers of bullwhip was selectively transcribed into practice and used to inform supply chain decisions at PharmaCo. The episode illustrates how analytically plausible approaches may fail to gain traction when they are insufficiently aligned with participants' experience, language and priorities.

This tension also reflects a broader challenge in analytics-led interventions. Analysts are often drawn to methods in which they hold expertise, a tendency described as the practitioner's dilemma (Corbett et al., 1995). In this case, the analyst's interest in pursuing bullwhip modelling did not align with how demand was understood, prioritized and acted on by those involved. The decision not to pursue bullwhip mapping reinforced the value of using multiple, simple and contextually grounded models, even where more sophisticated analyses are available.

4.7. *Sales & operations planning*

Creating a new sales and operations planning (S&OP) process was among the final analytical artefacts developed at PharmaCo. It built on the data, relationships and shared understanding established through earlier iterations. For the S&OP process to be workable, data blending needed to be rapid and prior work on data collection and integration had already reduced friction in supplying and combining data from multiple sources. Efforts to overcome system inertia elsewhere in the organization had also accelerated the pace of change, shaping the system in response to emerging requirements. Within this context, empirical data and practitioners' experiential knowledge were brought together to support the development of an S&OP process that could be sustained during a period of wider organizational change.

Decisions about granularity were informed by earlier work on the FSS and by features of the existing S&OP arrangements. By this stage of the project, it was apparent that approaches which actively engaged participants and aligned with their ways of working were more readily adopted. The S&OP redesign therefore proceeded through an explicitly participative and iterative process, with potential solutions trialled and refined over time. Tools and processes were introduced at a pace that was acceptable to those involved and gradually embedded into routine practice. This marked the first point in the project at which a deliberately articulated HCA design approach was enacted, drawing directly on insights generated through the earlier interventions.

4.8. *Analytics that did not work*

The bullwhip mapping and the control charting were not the only analytics that did not work. Midway through the case study, we experimented with visual analytics by using a weekly data stream transformed with algorithms unfamiliar to the planners. Initially, staff weren't given the chance to collaborate and it wasn't until we held workshops with accompanying training packs that they were introduced to the analytics. The manager and the analyst designed the tools based on their perception of the planners' needs, which the manager found useful for decision-making. They thought that by creating time to engage, using workshops and information packs, with room for feedback, they were doing HCD. The lack of collaboration in defining the needs of the planners, however, resulted in visualizations designed primarily for strategic, long-term insights, rather than the practical, day-to-day challenges they faced.

A more collaborative approach from the outset could have yielded better designs if supported by an effective process of domain structuring. Excluding the planners created a resistance to alignment, as we had missed the chance to 'mangle' practices together. This process would have allowed us to adopt and accommodate the temporal and contextual requirements of all participants—not just the manager and the analyst.

We missed the opportunity to embed mathematical learning and grow knowledge while collaboratively designing visualizations that worked to provide insights, alerts and communication devices. In this instance, the absence of early collaboration limited opportunities for a 'dance of agency' (Pickering, 1995) between material and non-material actors. A meaningful dialogue between participants and the mathematical tools being developed did not happen in this case. Negotiating parameters and granularity required time, creativity and reflection over iterations of design.

5. Discussion

5.1. *Defining HCA*

The case study demonstrates the need to bridge the gap between systems that provide intelligence and the people whose workflows they should enhance. This aligns with Summary 2 in the literature review, which notes that integrating analytics must bridge multifaceted human judgement and precise mathematical models. Katsikopoulos & Gigerenzer (2026) make a related theoretical move in their work on fast-and-frugal heuristics, showing how intuition can be analytically modelled rather than treated only as a source of bias or error. As AI becomes more embedded in management practice, Sanders (2024) also highlights the importance of engaging the humans who both use these systems and supply the data. Taken together, these arguments help position HCA, developed from the case evidence, as a design paradigm for making this integration explicit in practice.

HCA offers a design paradigm for analytics created by and for human users in complex and uncertain domains, explicitly connecting the social and technological elements of analytics. We propose a simple conceptual definition of HCA:

> 'Human Centric Analytics evolves effective designs for analytics by facilitating a meaningful engagement of human end users throughout the creation process'.

To clarify what distinguishes HCA from adjacent approaches, an analytics intervention can be considered human-centric when:

- human participants are involved throughout the design and evolution of the analytical artefact, not only at the point of deployment,
- mathematical models, parameters and representations are iteratively shaped through engagement with users' experience and context,
- analytics artefacts serve as tools for sensemaking and dialogue, not solely as outputs for decision-making,
- resistance and accommodation are treated as part of the design process rather than as implementation barriers and
- solutions are allowed to emerge through iteration rather than being fixed *a priori*.

We conceive HCA as a performative process, creating knowledge while evolving and building analytical artefacts and processes through collaborative design. It aligns with Summary 1 from the literature, as expert involvement fosters a communicative design process characterized by iteration, reflection and contextual engagement. The parameter choices and granularity focus become bounded as practice is shared (Summary 2), requiring thoughtful communication and time for reflection.

Theoretically, our study suggests that analytics developed in complex situations will integrate more effectively if designed with active user involvement, aligning with Summary 1. The process should be a decentred exchange, where each expert leads when their expertise is most relevant. This approach is not new to engineering design, computing or information systems, as HCD embodies it. However, HCA goes further, addressing unique issues in surfacing implicit systems knowledge, understanding data and integrating mathematical concepts, which highlights that HCD alone is insufficient (Summary 3).

Our case suggests that the HCA approach becomes most relevant when both data complexity and human involvement are high (see Fig. 2). In contexts of lower complexity, standardized or automated analytics may be sufficient. Where complexity is high but human involvement is limited, feedback-driven or ML systems can operate effectively. However, implementing analytics becomes more challenging as complexity rises due to increased cognitive loads (Browning & Sanders, 2012), prompting a more human-centred way of designing and working (Knack et al., 2022). When complex analytical environments require sustained human interpretation, adaptation and coordination, HCA provides the design approach through which analytics can illuminate complexity and produce tools that are contextually grounded and systemically aligned. This aligns with Katsikopoulos & Gigerenzer's (2026) discussion of ecological rationality, where the value of a decision model depends not on complexity or optimality alone, but

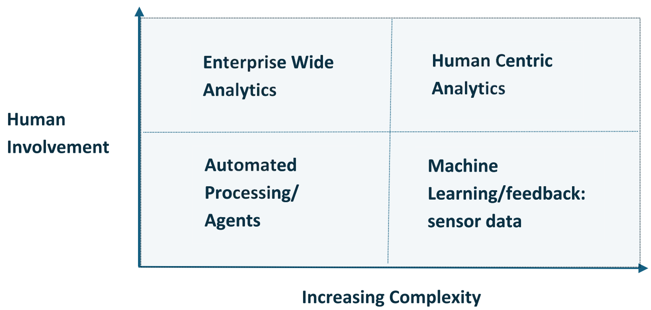

FIG. 2 Illustrating where HCA became most useful at PharmaCo.

on its fit with the decision environment. HCA takes a complementary design perspective, asking how analytical tools and representations can be shaped so that they become usable within the ecology of practice.

Our case study evidence indicates that analytics augmented human processes when:

- The design was participant led at every stage, with the analyst an equal participant (Summary 1).
- Solutions were allowed to emerge in a structured yet flexible setting (Summary 2, 3 and 5).
- A chance was given to reflect and redesign (Summary 1 and 3).
- Processes as well as data systems, people and solutions were able to flex (Summary 4).
- It caused minimum disruption to the flow of work by adapting to existing structures and systems (Summary 1 and 4).
- It was used to provide models for engagement and insight as well as end products (Observations 2, 3 and 4).

When we tried to get analytics working without a human-centric approach, it did not succeed. Initially, we thought handouts and workshops would be enough, not fully understanding what human centricity truly meant. We learned that HCA needs to be responsive, decentred, participative and iterative. It also needs to adapt to the changing roles and influences of all actors, both human and material. This supports Summary 5, highlighting the need for a thoughtful design approach when combining methodologies for HCA.

Humans shape how they interact with technology, rendering the surrounding processes open to interpretation, learning and change (Orlikowski, 2000). In HCA, human actions temper analytics and conversely, analytics influence human actions. This should continue until the system and designs suit the flow of work. The structure of any temporary balance is relatively less fluid; therefore, it is important to keep the system evolving until it reaches an effective state (Orlikowski, 1992; Hindle & Vidgen, 2017). This reflects Summary 1 on iterations and reflection in context, and Summary 2 in terms of bridging. Temporary equilibria also relate to supply networks as complex adaptive systems, which evolve to sit 'on the edge of chaos' (Choi et al., 2001). Hindle and Vidgen et al. (2017) also observed this phenomenon with respect to developing analytics, as the state in which a system must reside to innovate and allow solutions to emerge. HCA encourages co-evolution by giving users and data creators the freedom to make creative moves. Existing practices naturally resist, resulting in a back-and-forth adaptation until an acceptable outcome emerges. This illustrates Pickering's concept of the bridging process (1995, pp. 117):

> 'Practice has to take this form. The point of bridging as a free move is to invoke the forced moves that follow from it'.

Developing analytics via HCA incorporates them into the rhythm of existing practice as the speed of data delivery paces with user requirements. HCA also entrains practice when individuals start pacing their work with the emergent system (Ancona & Chong, 1996; Ancona et al., 2001; Ancona & Waller, 2007). Businesses often use analytics across units (Liberatore & Luo, 2010) to mediate supply chain boundaries (Oliva & Watson, 2011). They act as data objects that facilitate traversing individual frames to aid collaborative development (Pidd, 2004). This may explain why the work consistent with HCA helped functions align and encouraged the exchange of expert knowledge that previously hadn't occurred.

Structuring during HCA design requires abstraction to determine the optimal level of granularity. As stated in Summary 4, this is a process that tries to harmonise the boundedness of human cognitive representations (Brunec et al., 2018) with the symbolic limits of data, systems and analytics software. For instance, in PartiSim, participants and the modelling team work together to adapt the conceptual model toward a suitable and acceptable temporal and parameter structure for the DES model (Tako & Kotiadis, 2015).

These observations lead to a proposed philosophy for HCA:

Ontological: HCA represents a dynamic system that integrates humans, machines, mathematics and data. The design of this system evolves over time, emerging from reflexive yet structured interactions involving established rules and shared knowledge. It serves as a mechanism for enhancing both human and machine capabilities.

Epistemological: HCA involves structuring both implicit and explicit knowledge to create a mutually agreed level of abstraction, considering aspects such as granularity, heuristics, aggregation, or parameter choices. This abstraction can be embedded within analytics software or developed from conceptual models into mathematical solutions and insights that are readily understood and effectively utilized. Knowledge is continually generated as the process evolves.

Praxiological: The process of HCA is characterized by a decentred, iterative evolution of artefacts and knowledge, facilitated through mutual learning and a reflexive, participative approach to practice.

Figure 3 positions HCA at the intersection of analytics, human systems and domain exploration, showing that no single method defines HCA; rather, it emerges through the situated combination of approaches appropriate to the context. HCA is a design paradigm, a way of doing design. Methods that use iterative human centred development such as SD, MCDA and PartiSim can all be considered HCA methods. Rather than replacing existing methods, the HCA framework complements them, fostering an environment for collaborative analytics design. For example, we used action research in some parts of this study and employed PartiSim in others, which itself is an umbrella framework utilizing SSM—a framework derived using action research.

5.2. *The proposed framework to deliver HCA*

We have developed constructs for HCA, but these lack the structural support needed to guide implementation. For that, we developed the framework presented here. It is built on the cases studied at PharmaCo and on the research covered earlier. HCA has been used in diverse cases since this initial research, and we will draw on one of these alongside the case study and literature presented here to demonstrate how the framework fosters the approach.

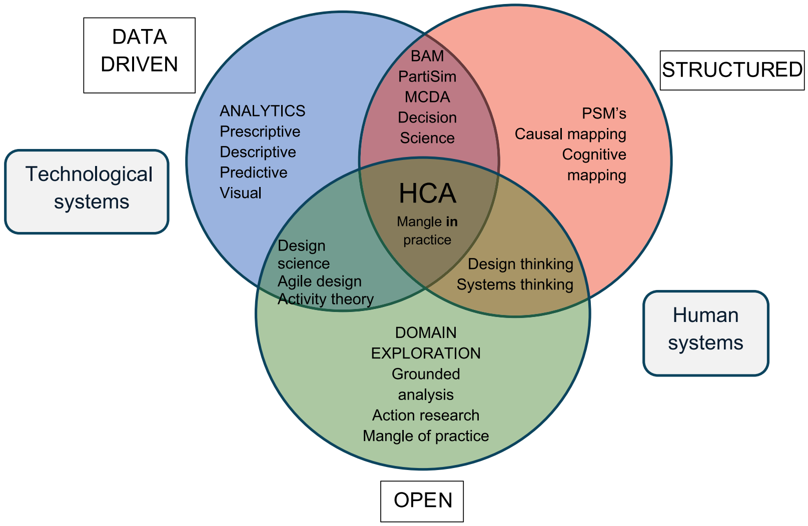

FIG. 3 The ecosystem of potential tools to perform HCA.

The four stages of the framework (see Fig. 4):

- Structure perceptions and gather implicit knowledge.
- Structure empirical data.
- Understand and overcome the resistance.
- Evolve solutions.

The process aims to create an emergent foundation and direction (the bridgehead) for change, working toward an integrated, acceptable solution.

At each stage, we recommend using the ‘Mangle IN Practice’ approach (Pickering & Guzik, 2008) to catalogue and analyse the ongoing process. This viewpoint helped us to understand what worked, what did not, and to systematically record knowledge for future use.

- What is the emergent structure, and how is it changing the roles and dynamics of the actors involved, including both human participants and material artefacts? Are all participants in agreement? Catalogue any knowledge creation.
- Is a bridgehead of agreed change emerging? Develop project goals and timelines that adapt as the bridgehead evolves. Assess the potential added value and catalogue the changes occurring within the bridgehead due to resistance and accommodation.
- What knowledge is being transcribed into practice? Are new things being learned or existing processes changing? What expertise is required to accommodate the bridgehead’s evolving direction? Are bespoke techniques necessary to move forward?
- What is required to fill in the gaps? Do these requirements extend beyond current boundaries? Are there any previously unidentified participants, either human or material, that should be involved?

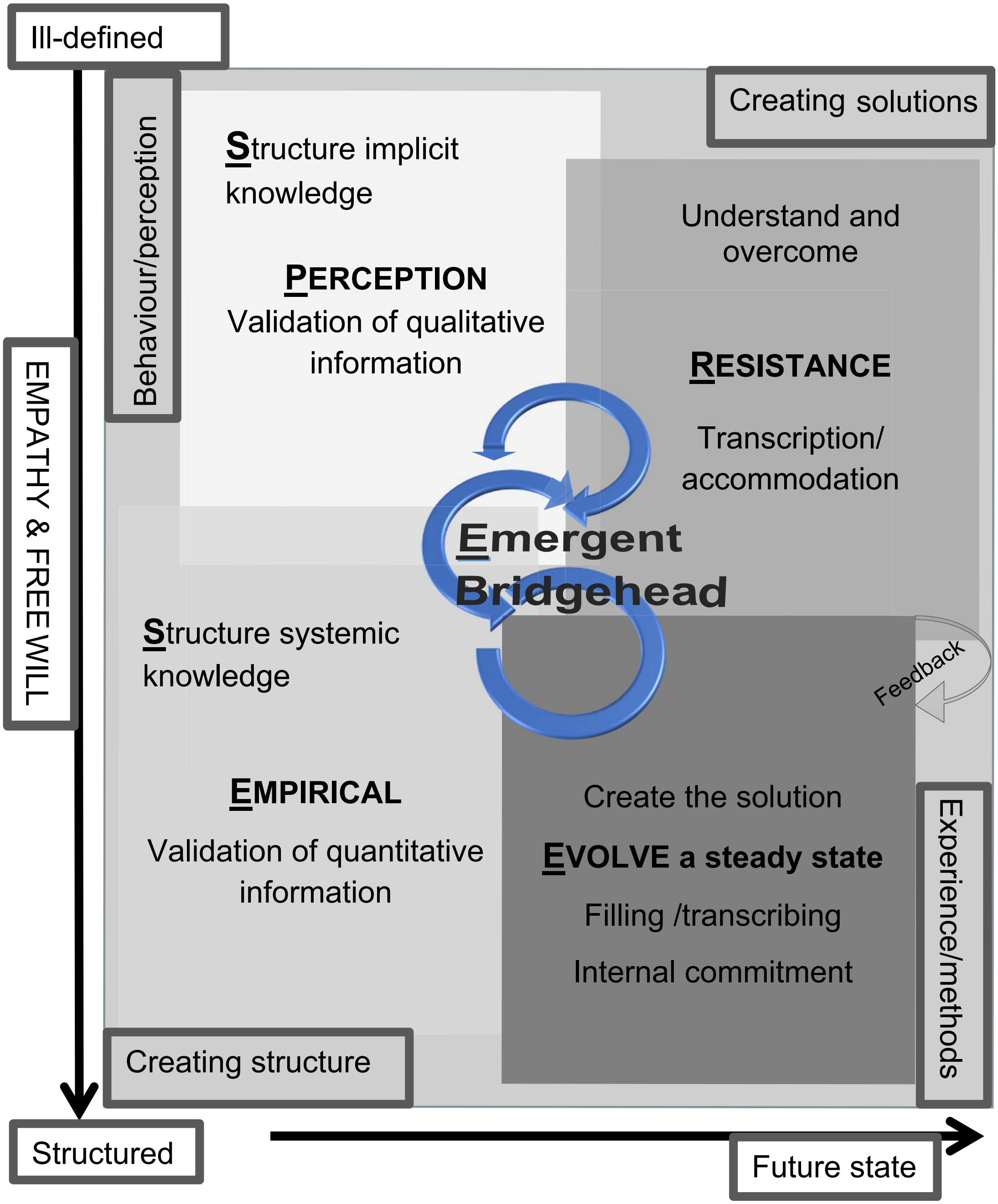

FIG. 4 The framework for delivering HCA.

5.3. *Structuring the domain—finding the boundaries*

Perception: Structuring the domain with respect to individual and group human views. This draws on the SSM collection of worldviews (or weltanschauung) (Checkland & Scholes, 1990) that involves surfacing different ways of viewing the world. This requires a facilitated process to explicate mental models, with findings triangulated through recordings, note-taking and documenting (e.g. sticky notes, rich pictures, etc.). We did exactly this during the PartiSim exercise, and for many of the small solutions, like the Venn 'right-first-time' diagrams, including whiteboarding, workshopping, listening and documenting. Action research helped to surface perceptions due to its sympathetic stance and focus on potential actions, as did SSM.

We wanted to apply this framework to an academic study using AI to understand information distortion during the COVID-19 pandemic, but it seemed this stage may be redundant: in that case the AI tool had already been chosen, natural language processing (NLP) and the project was already running when we were brought in to help foster engagement with patient groups. As we tried to understand perceptions, there was a profusion of design meetings to help us engage with the needs of the academics, health leader and patient group facilitator. In turn, the framework guided the group, and we decided to use the NLP labelling to gather the perceptions of the patient groups and to help give them some insight into the human aspects of AI, i.e. the labelling and training stages.

Empirical: Structuring the problem domain using data and available recorded knowledge. When using other types of analytics methodologies (e.g. BAM, forecast audit), data may already be available, along with a potential bridgehead of change. With HCA alone, opportunities arise to explore data sources and quality, conduct data mining and create simple explanatory models for insight. This is the moment to create, explore and validate information (Argyris, 1970). This is the stage of building in PartiSim where the team works toward a conceptual model with the attendant parameters and temporal structure. In our case this was a difficult task with differing perceptions of what was important, so we used many different visualizations and mathematical analyses to create a space for conversation between people, data and mathematics. This was where we started to work toward the granularity of the model by structuring around both individual perceptions and data availability.

Once again, in the NLP project, we thought this stage might be redundant at first, but using this framework prompted the idea of bringing the data and the patient groups together in deliberate, well-designed workshops. We could use the initial labelling data to prompt discussion, which led to us looking for new things in the data. As data was produced via the labelling and the NLP work, we brought that to the same patient groups for discussion in carefully designed, accessible workshops.

Which of these two phases of structuring comes first depends on the domain. Is a potential solution being investigated or is an ill-defined space being explored? If there is no clear structure or little reliable data, then perceptions can feed empirical data gathering. If the data are reliable and the processes are being questioned, then empirical data can alter perceptions. The outputs of the structuring phases are conceptual models or emerging granular levels that are acceptable to all parties and sensitive to the context.

Empathize: The role of the expert shifts with the project focus.

5.4. *Creating solutions—emergent bridgehead*

Resistance: This involves identifying constraints that cannot be changed and may feed back into structuring as it considers systemic and environmental constraints. In our case study, the main resistance came from existing information systems. The systems changed partly in response to our work as the need for alternative software became clear. By the time we worked on the new S&OP, we were able to use PoC systems on bespoke software that were then integrated into the main systems. Addressing resistance earlier might limit potential routes to solutions by stifling creativity. Overlooking it may cause integration problems in the final evolved phase. For example, if we hadn't known the IT systems would resist our S&OP solutions, we could have spent more time trying to get them to work, and if we had known there would be such strong resistance earlier, we may have given up trying to improve altogether. In the end, the process went from 3 days to 30 min, and it was quickly integrated into the company's preferred data and analytics systems once they changed enough to accommodate it.

In the NLP work, we knew that resistance was most likely to come from lack of understanding, so we were careful to design things in ways that spoke to human experience and that clearly laid out the steps involved. Unfortunately, the biggest resistance came from those who we were trying to help: those responsible for health messaging. This was largely due to them not being involved earlier in the process, and because we had already chosen the solution, AI. We were, however, successful at engaging patient groups and fostering discussion and learning around AI and misinformation.

Evolve: A working prototype is in use. Data needs have been addressed, and if they have not, the final artefact is adapted to cope with the system. Software and algorithms are sourced, learned and adapted. There may be many iterations before this phase settles into a steady state. Data gathered in earlier phases may need revisiting, emphasizing the need for effective qualitative data management. Pickering describes this as bridging. Creative free moves become tempered by the disciplined agency of established techniques, prompting the forced moves of transcribing from old to new.

When investigating the viability of production smoothing, we co-created a parsimonious simulation model that could inform senior management. They needed to make decisions around what to smooth and to see if level loading was viable; however, the final model was difficult for them to quickly understand as they had not been part of the journey. So, we worked with some of the Senior Leadership Team to refine the model to something that could be presented and digested in under 15 minutes. We took it down to a conceptual model with measurement points and ran different scenarios. Then drivers of variability and risks around smoothing, became clear. Although the final model was not used after this, many of the analytics that had been used along the journey were, providing the information that the model and modelling made clear was needed.

The entire HCA process integrates analytics by embedding data and mathematics skills where they are needed, growing them in context.

5.5. *The mangle of practice: studying the practice of management mathematics*

The mangle of practice reveals the structural and temporal dynamics of change involving people, processes and machines by observing their performative aspects. Pickering's use of the mangle of practice to examine Hamilton's discovery of quaternions provides insight into the human aspects of mathematical practice. He describes bursts of creativity, including Hamilton's moment of joy on Broom Bridge as he carved his eureka moment into the stone, followed by long hours spent integrating the idea into formal logic. Such an approach allows us to see mathematics as a human process. It is an ideal lens for understanding how people perceive and engage with mathematics. Adapting it into a Mangle IN Practice (Pickering & Guzik, 2008) creates a meta-methodology suitable for studying the socio-technical aspects of management mathematics. The need for this is increasingly urgent as analytics enter the 'Inter AI' period (Sanders, 2024) and organizations rely more on AMS (Zhang et al., 2025).

Pickering argues that the mangle offers a cybernetic view, weaving human practices with the material world (Pickering, 2002). This perspective may explain why HCA emerges as a distinctly cybernetic and performative paradigm, aligning with the lens through which we analysed our case. We believe that this influence arises from the emergent nature of the design process as we work toward mutually acceptable representations, in line with the work of Maier et al. (2012). It demonstrates the cybernetic aspect of modelling in design.

6. Conclusion

At the end of this case study, we interviewed senior management about their perception of the analytics interventions. Unexpectedly, the senior materials and operations manager, who had overseen the most substantial operational changes, identified culture change as the most significant outcome. In particular, he noted a shift across the site, with many departments moving toward a more inquiring and data-driven way of working. The following quote illustrates this perspective:

> 'There is no doubt that what we are seeing now in terms of operations ... the work that you've done (alongside others) ... it's been a fundamental in changing the culture of the site'.

This site wide culture shift was driven by iterated analytics interventions and opportunities for staff and analytics to come together. Through the design journey, knowledge and skills were built as work was progressively augmented. Co-creating understanding helped staff to manage the transition toward swift and even flow, with data providing a shared point of reference. Achieving this required humility and a willingness to listen, and change tack, by both the business analyst and the managers championing the work.

Efforts to integrate analytics that did not foster participant engagement, or that relied on pre-designed artefacts, were unsuccessful. In this case, we initially took our cue from management and introduced potential solutions through workshops and training materials. Even with iteration, these ideas did not gain traction until they became useful to staff as a part of their ongoing work. A similar pattern was evident in the NLP case. The use of AI was part of the research remit, but the absence of any key decision makers in the initial stages meant the design did not evolve in ways that were usable for them at the end of the project. We were able to successfully involve patient groups in the design, but they were not the ones responsible for the final decision making process. In this respect, HCA addresses a design gap that HCAI identifies but does not operationalize (Garibay et al., 2021).

What this case highlights is that analytics and mathematics now sit between human judgement and organizational action (Zhang et al., 2025). As a result, the socio-technical design challenge is no longer confined to interfaces or processes (Orlikowski, 2000), but to the analytical layer itself. A common risk in analytics initiatives occurs when those who are expected to use the outcomes are not involved in their design. If the systems surrounding analytics use, and the people who work in them are not considered prior to and during design, the resulting system can be left brittle, with issues such as validation, governance and integration emerging as possible failure points (Rinta-Kahila et al., 2022). HCA addresses this risk by involving end users throughout design, so that these considerations are shaped alongside use rather than imposed afterwards. In doing so, it provides a practical means of bridging human judgement, analytics and organizational action.

Many of the concerns addressed by HCA have been examined across decades of work on socio-technical systems, decision making and modelling research, but typically been treated in isolation. HCA reframes and unifies these strands as a design problem centred on analytics in use. In doing so, it closes a gap between theories of human judgement, organizational design and the practical development of analytics within everyday work.

HCA would benefit from further empirical testing across different organizational settings and use cases. In this study, the design paradigm emerged from a single longitudinal case involving multiple analytical interventions and was subsequently explored through a contrasting application. Future research could examine how HCA operates in other data-intensive contexts, particularly where analytics mediate decision making across organizational boundaries or over extended time horizons, such as in infrastructure development, healthcare systems design and sustainability initiatives. Future research may also explore the skills and organizational capabilities required to enact this bridging role in practice.

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Conflict of interests

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Declaration of statement

All material presented has been approved for publication in accordance with the author's non-disclosure obligations.

Data availability

Any data beyond what is reported here is not publicly available due to the firm's preferred anonymity.

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