What Got Us Here, Won't Get Us There

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Augmented Intelligence in Service Design. Developing an AI-Powered Assistant for Enhanced Efficiency and Big Data Utilisation

Nasser Bahrami

PhD Candidate in Design, ImaginationLancaster, Lancaster University, United Kingdom
E-mail: n.bahrami@lancaster.ac.uk

Abstract[1]: As emerging technologies continue to shape our world, service designers must navigate the complexities and debates that arise by revising their methods and embracing a mindset of lifelong learning. This article proposes a practical roadmap for developing an AI-powered assistant that can help service designers create more customised solutions, minimise uncertainty, and view data as a catalyst for creativity rather than an obstacle. Augmented intelligence fosters human-machine collaboration and yields positive outcomes that are not achievable independently. However, it is crucial to be prepared before undergoing a paradigm shift.

Keywords: Service Design, Mapping, Big Data, AI Assistant, Augmented Intelligence

Introduction

The rapid evolution of big data, robotics, and artificial intelligence has profoundly impacted human interactions and daily life, resulting in complex consequences and a redefinition of experiences and boundaries. As technology advances, revisiting and refining service design methods grows increasingly critical. Design methods, like other scientific research methods, are a result of collective core cognitive processes and the management of pragmatic, sophisticated conditions (Farrell & Hooker, 2013, p. 701). Therefore, service designers must concentrate on addressing design problems as systems of relationships and enhancing their understanding of technologies and support systems (Kozubaev, 2018). This approach enables them to create more customised solutions, minimise uncertainty, and view data as a catalyst for creativity rather than an obstacle (Feinleib, 2014, p.59).

Furthermore, to address workplace challenges successfully, they need to consider AI as a new stakeholder with unique conditions while recognising it as a tool (Mhanna & VanAntwerp, 2018). As emerging technologies continue to shape our world, service designers must navigate the complexities and debates that arise. This demands a significant commitment to becoming lifelong learners who can

[1] The content extracted is from an ongoing PhD research project, which has undergone continuous revisions and refinements to ensure accuracy and relevance.

adapt to the ever-changing landscape. By embracing this mindset and focusing on innovative strategies, service designers will be better equipped to address the challenges of skyrocketing digital transformation.

Methodology

A Practical Roadmap

By delving into design cognition, researchers can gain insights into designers, design teams, the design process, the progressive development of design artefacts, and, ultimately, the users of these artefacts. Over the past six decades, scholars have made significant efforts to understand the interplay between these processes and their interactions (Hay et al., 2020). The prospect of harnessing this knowledge to create an intelligent assistant system is both captivating and formidable.

1. Turning Maps into Algorithms[2]

The amalgamation of maps and algorithms sets forth an effective strategy to streamline service design and delivery. Maps, being human-oriented and visually interpretive, help in grasping complicated procedures and promote cooperation. On the other hand, algorithms add value through their precision, scalability, and automation potential. This transformation from maps into algorithms bridges these two distinct areas, uniting the empathetic comprehension of user experiences with the systematic efficacy of automated processes. The ensuing sections will shed light on the rationale for this merger and the path to accomplish this intriguing transition.

1.1. Why map?

Beyond just representing visual or physical aspects, maps in their various formats are versatile tools utilised for research, understanding the execution of ongoing activities, collecting individual narratives and experiences, drawing links between seemingly unrelated activities and organisations, and spotting opportunities for innovative methods of operation (White & Young, 2018, p.46). Deliberation in mapping[3] enables us to substantially represent the existing workflows of service designers. This significance is amplified when considering that maps function as collaborative tools, harnessing the collective intelligence of a diverse group of individuals such as leaders, team members, clients, and stakeholders. Each participant contributes unique perspectives and mental models regarding a service's operation and the user experience, thus fostering shared understanding and promoting collaboration among team members. Additionally, maps serve as boundary objects[4], providing a central space where all participants can exchange ideas and cultivate a unified vision. This alignment of goals and objectives reduces confusion and enhances the likelihood of success.

Maps facilitate comprehension of the complexity inherent in a service or product. By deconstructing a complex, multi-layered experience into smaller, more manageable stages, we can empathise with users and understand their experience from their perspective. This process leads to the identification

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[2] An algorithm constitutes a methodical process that, within a finite sequence of steps, yields the resolution to a query or the solution to a problem (Encyclopedia Britannica, 2022).

[3] The use of mapping isn't unique to service design; it's a borrowed technique with a much richer history. As Michel de Certeau highlighted, "The founding gesture is to make a map. It creates a space. It cuts out of the complexity of things a scene on which to draw the operations necessary to remake the world" (Hartnett, 1998, pp.288-289). Maps engage in a dialectic of what is and what could be, serving as metaphors from the earliest artefacts and mapping practices.

[4] Boundary objects are entities that possess sufficient malleability to adapt to the local needs and constraints of multiple parties utilising them, while simultaneously maintaining a consistent identity across various contexts (Star & Griesemer, 1989, p.393). This notion encapsulates the potential for collaborative scientific endeavours to transpire despite the absence of unanimous consensus (Bowker et al., 2016).

of pain points and opportunities for improvement, ultimately yielding a better service or product experience for users. Lastly, mapping aids in depicting the current situation, or "as is," empowering us to revise and reorganise components, relationships, and interactions to create a future state. As a diagnostic tool, mapping uncovers both advantages and drawbacks, as well as interdependencies and opportunities for mutual benefit, providing a foundation for subsequent potential improvements.

1.2. Why Algorithm?

Turning a design map into an algorithm can offer several benefits, mainly related to automation, scalability, and objectivity:

1. Scalability: Algorithms possess an innate capacity for easy scalability. When a service map is converted into an algorithm, it can be duplicated across multiple business units or branches with ease. This attribute is particularly advantageous in scenarios such as a franchise model or other extensive operations where uniformity in customer experience is vital.
2. Precision and consistency: Algorithms allow precise execution of tasks and ensure consistency. This can significantly improve the quality of service and ensure that every customer receives the same high level of service, regardless of which employee they interact with.
3. Automation: The translation of a service map into a programmatic algorithm opens the door to automation. By automating specific segments of the service, efficiency can be enhanced, the likelihood of human error diminished, and overall operational costs decreased.
4. Analysis and improvement: Algorithms can be analysed more easily than human behaviour. This makes it easier to identify bottlenecks and areas for improvement in the service map. It can also make A/B testing easier and more meaningful.
5. Personalisation: Algorithms can use data to adapt the service map to individual customers. This allows for a high degree of personalisation in service delivery, improving customer satisfaction.
6. Training and onboarding: An algorithm, meticulously crafted from a service map, serves as a practical tool for instructing new employees. It assists in quickly acclimating them to the service process, facilitating a smooth integration into the workflow.

However, it's important to note that design is inherently a creative and human-centred process. While algorithms can aid certain aspects of design, they cannot fully replace the need for human intuition, empathy, and understanding of user needs. Also, privacy and ethical considerations can limit the extent to which personalisation can be applied.

1.3. How to do it?

The inception of this phase entails an in-depth study of seven primary maps, specifically I) Empathy, II) Customer Journey, III) Experience IV) Value (by Cambridge)[5], V) Stakeholder VI) Service Blueprint, and VII) Ecosystem. However, these are not the only maps; service designers, considering the scenario and the purpose of the application, typically decide which maps, or the selected ones thereof, should be used. These maps, which have already been established and evaluated, serve as a reference for creating corresponding algorithms.

[5] Refer to https://www.ifm.eng.cam.ac.uk/research/industrial-sustainability/sustainable-business-models/tools/cambridge-value-mapping-tool/

The development of these algorithms involves identifying key components and interactions within each map. Subsequently, these elements are abstracted and the activities typically employed to form the map are broken down into a sequence of actionable steps. Each step is defined by its success criteria[6], acting as a gateway to the next one. They were later applied as a form of pseudocode[7] for the construction of a prototype in a chosen programming language.

The transition from maps to coded algorithms involves the following stages:

a) Abstracting/ breaking down activities into a series of steps
b) Defining success criteria for each step
c) Forming pseudocode

The first three steps were executed collaboratively by a human expert, namely the researcher, and a pre-trained Large Language Model[8] (LLM), in this case, ChatGPT versions 3.5 and 4.

d) Coded algorithm (Python programming language)

To prepare the corresponding algorithm for each map, more than 30 attempts have been made. Though the algorithms have significantly improved, the process continues in the pursuit of greater precision. The challenge lies less in the coding process and more in defining the steps and their success criteria clearly. The aim at this stage is to detail a process in a manner that is clear, precise, and compatible with machine interpretation. Since maps require an applied context to be meaningful, the efficiency of the algorithms must be evaluated using real-world scenarios that have previously been addressed using the maps. Comparing the algorithm-driven results with the outcomes of the original solutions provides a measure of their effectiveness. This approach has been trialled with one or two cases so far, indicating a need for more trials for a comprehensive evaluation.

2. Forming a Unified Algorithm

While it's undue to prepare all the existing maps for a given scenario, in the abstract, the more maps generated, the more holistic the understanding achieved. This opportunity can allow experts to discover linkages, patterns, and interconnections among the maps that may have previously been elusive. It also highlights an occasion for leveraging the potential of machine learning capabilities to learn and mimic what can be accomplished by human expertise.

Once the detailed steps for each map have been established, and the respective pseudocode formed, the broader picture can be pieced together. This can be achieved by comparing them, finding the overlaps and equal steps, recognising the required links, and merging the fragments. In other words, merging the algorithms and forming a well-evaluated, unified, but more extensive algorithm. Although

[6] Clear and observable key features, measures, or stages that need to be met.
[7] Pseudocode serves as a tool for detailing the logical stages of a process using simple plain language like English (Mahey, 2020, p.75). While working on prototype code, this storytelling technique provides clarity about the desired outcomes before the actual coding process begins (McElroy, 2016).
[8] A large language model (LLM) is a sophisticated deep learning algorithm capable of recognising, summarizing, translating, predicting, and generating text, as well as other types of content, by utilising knowledge obtained from extensive datasets (Lee, 2023). In the subsequent sections of this document, any reference to LLMs will signify existing pre-trained models.

the algorithm doesn't represent a specific map, it acts as a platform to cover all the maps that it is based on.

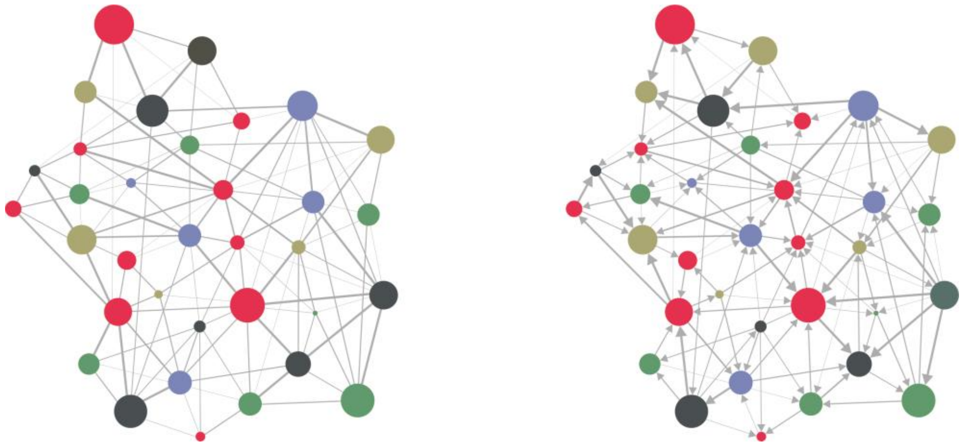


Image 1. An interactive dynamic spatial map, resulting from the integration of the unified map and the revised version of the brief, is presented as an imaginary illustration.

Given that the applied maps cover different scales and perspectives, ranging from micro to macro, and vice versa, this unified algorithm provides a more inclusive approach to the mapping system. The result would be a dynamic network graph, a step away from traditional two-dimensional flat maps.

The development of a unified algorithm is currently underway, orchestrated through repeated interactions between the human expert and some LLMs – especially ChatGPT[9] and Bard. The models' high inferential capability, fuelled by training on extensive data sets, provides remarkable potential. However, the active involvement of humans remains an essential component in deriving more meaningful and trustworthy results - at least up to the present point.

By utilising this algorithm, we can better trace and study the impacts of each decision at various levels by adjusting the scope- zooming in or out- much like observing the ripple effect after dropping a drop of water but in a spatial view. In addition, by providing the required information, the algorithm enables us to change the point of view selectively, such as shifting the perspective of a specific stakeholder to another one. On the other hand, this capability to change the point of view makes us aware of which details are already missed or have not been seen and should be elicitated. Furthermore, the unified algorithm also, presents an enhanced opportunity to apply the systems thinking approach, acknowledging the interdependent elements of a system and their interactions. Such adaptability aids in cultivating a deeper understanding of a situation, and in turn, fostering more informed decision-making. This can result in improved outcomes for all stakeholders and contribute to the development of more efficient business models.

Last but not least, it's vital to remember that maps, and subsequently algorithms, assist us in gaining a deeper understanding of the issue or situation, and they illuminate what is required. They allow us to discern how various elements are connected and how the unknown correlates with the data, giving us an inkling of a potential solution. However, actualising this solution requires formulating a 'plan' (Pólya, 1990, p.5), which goes beyond the current step.

3. Revising the Design Brief

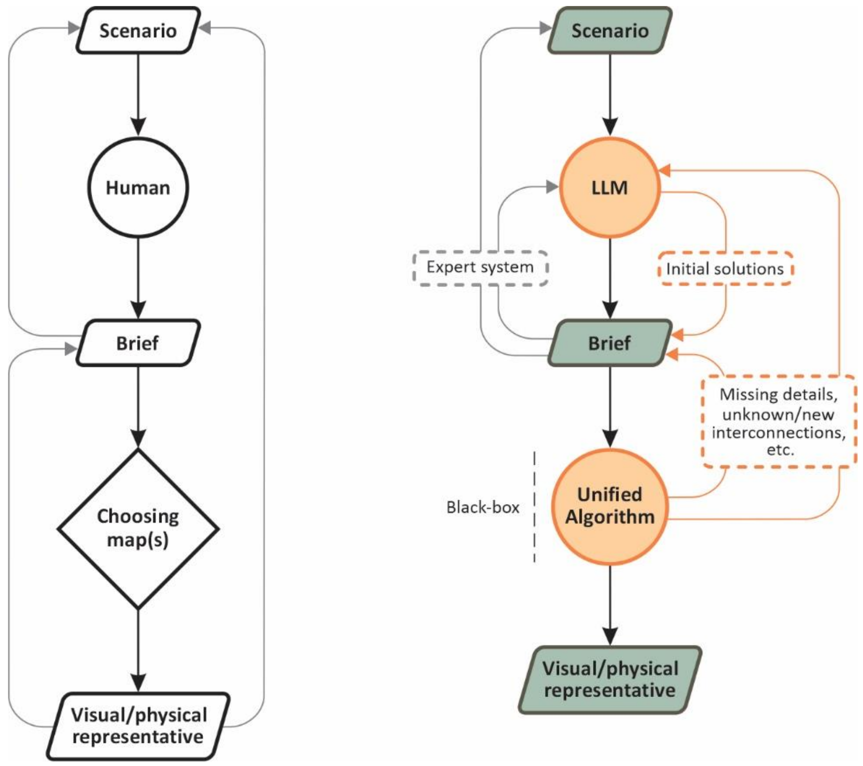
The Design Brief can be considered one of the most striking references for determining how to feed the algorithms- it supplies vital information that can be used as input within the algorithms. Once we have established a scenario, including a target future, and criteria for success such as Key Performance

[9] Through a Chrome extension, ChatGPT can get access to internet as well.

Indicators (KPI), and related metrics, we have the basic ingredients for beginning to ask useful problem questions (Hurson, 2018). The brief details keep us related to the real world and its limitations.

Before implementing the data, it's crucial to specify the essential details to be extracted as inputs, and to clearly define the nature of outputs and expected outcomes within the brief. This approach aids in ensuring that the algorithms can effectively meet the needs of the target audiences, whether in the form of a service, product, or strategy and deliver customised value. In order to effectively supply the unified algorithm, the current methods of briefing/ the brief documents need to be revised to ensure they are compatible with the requirements of this unprecedented method. This stage is currently in progress, and efforts are ongoing to complete it effectively and efficiently including the necessary details and components.

As we are going to use the brief to train machine learning (ML) models as well, particular attention should be given to aspects, the ones routinely not remarking them, including i) user action (the recommended method to cover their need), ii) ML system output, iii) ML system learning, iv) training dataset[10] needed v) key features needed in the dataset, vi) key labels needed in the dataset, and finally vii) data source key user's questions (People + ai guidebook, 2019) which, usually indirectly, related to the functional and non-functional dimensions of the platform. The details should be described succinctly and vividly; however, possibly labels you need to go deeper[11].



Flowchart 1. The comparison of the simplified traditional model of service design mapping with the augmented version through applying the unified map and revised brief.

[10] At present, one of the limitations in implementing AI and machine learning techniques in design processes is the lack of access to the necessary large datasets required for effective model training. It is crucial to acknowledge that the unavailability of sufficient data can still impede the performance and generalizability of the models. Consequently, addressing this data scarcity issue remains a significant challenge in fully realising the potential of AI and machine learning in the design domain.

[11] At the first glance, the complexity of this subject may appear daunting to designers. Nevertheless, it is crucial to remember that this field encompasses a multi- and/or interdisciplinary domain. Consequently, it is imperative for designers to acquire the requisite competencies prior to entering any specialised area.

Consequently, with the appropriately refined structure in place, the consolidated algorithm operates as an integrated system. Depending on specific inputs, desired outputs, and expected outcomes for each use case, it allows for the tracing of data flow and the interplay between different components. This facilitates the discovery of previously unnoticed connections and patterns, as well as the identification of gaps in detail. Additionally, the algorithm can be structured to trigger a response from a specific segment, akin to the logic that underpins decision trees. In doing so, designers are given the opportunity to create a feedback control mechanism, prompting them to re-evaluate their data collection and assessment methods.

Finally, by considering the nature of the black-box in both the LLM and the unified algorithm, alongside a high level of 'responsible AI' considerations, to provide an appropriate user experience for both service designers/design consultants and their clients, establishing a sense of 'manufactured normalcy' is essential. However, it's crucial for individuals to critically examine the idea and make conscious choices about how they engage with it[12].

3.1. Design Problems, Design Methods

In accordance with prevailing thought, the majority of problems tackled by designers fall under the category of 'wicked problems' which defines as social system problems that are ill-defined, characterised by confusing information, multiple clients and decision-makers with conflicting values, and where the ramifications throughout the system are thoroughly confusing (Buchanan, 1992, p. 15). If significant challenges such as reliability, infrastructure, and trustworthiness can be addressed effectively, in this domain, AI has the potential to demonstrate its superior capabilities[13] and provide substantial support to solution providers.

As illustrated in Table 1, these advantages can enable service designers to expand their capabilities through two primary approaches: automatable and/or difficult to automate. Nevertheless, owing to the inherent characteristics of the methods and activities, most can predominantly be augmented or involve a combination of both automation and augmentation. So, this would be mainly in the direction of forming a (strong) 'augmented intelligence' that fosters human-machine collaboration, yielding positive outcomes that would be unattainable by either humans or machines independently (Hurwitz, 2019, p.3). Appropriate augmentation can lead to numerous benefits, such as enhancing creativity, increasing user responsibility, and fostering a sense of fulfilment. The objective of augmented intelligence is to complement and enhance, not replace (IEEE Digital Reality, n.d.).

[12] In the context of utilising advanced AI such as LLMs, Jaokar (2023) presents a set of worthy principles readily applicable to this domain. It is not a source of information for areas we are unfamiliar with. Designers must exercise caution when using AI for unfamiliar topics and seek further verification from reliable sources. It might be employed to hypothesise about what we don't know about. Accepting these outputs as potential creative avenues, designers can explore new possibilities. However, these AI-generated ideas must be subject to the same rigorous validation and testing as any other unproven hypothesis before being implemented.

[13] Generally speaking, AI is potentially better when I) the fundamental experience necessitates recommending diverse content to distinct users, II) the central experience demands forecasting future occurrences, III) personalisation will enhance the user experience, IV) user experience necessitates natural language interactions, V) the requirement to identify a broad class of entities that is too extensive to enumerate each instance, VI) the need to discern infrequent events that are incessantly evolving, VII) an agent or bot experience tailored to a specific domain, and VIII) the user experience is not contingent on predictability. In contrast, AI is conceivably inferior when i) the paramount aspect of the core experience lies in its predictability, irrespective of context or supplementary user input, ii) the expense of errors is exceedingly high and surpasses the advantages of a marginal increase in success rate, iii) users, clients, or developers necessitate comprehensive understanding of all processes occurring within the code, iv) the expeditiousness of development and market entry takes precedence over all other factors, including the potential value derived from AI implementation, and v) individuals explicitly express their disinclination towards automating or augmenting a particular task (People + ai guidebook 2019).

Core activities	Activities			Task Groups
Research	Data Collection	Desk research	Preparatory research	2, 3
			Secondary research	2, 3
		Self-ethnographic approach	Autoethnography	2, 1, 3
			Online ethnography	2, 1, 3
		Participant approach	Participant observation	2, 1, 4
			In-depth interview	2, 1, 4
			Contextual interview	1, 2, 4
			Focus group	1, 2, 4
		Non-participant approach	Non-participant observation	1, 2, 4
			Cultural probes	1, 2, 4
			Mobile ethnography	1, 2, 4
	Data visualisation and analysis		Building a research wall	2, 3, 4
			Creating personas	2, 3, 4
			Mapping journey	2, 3, 4
			Mapping systems	2, 3, 4
			Developing key insights	2, 3, 4
			Generating jobs-to-be-done insights	2, 3, 4
			Writing user stories	2, 3, 4
			Compiling research reports	2, 3, 4
Ideation	Pre-ideation methods		Slicing the elephant and splitting the ideation challenge	1, 2
			Ideas from journey mapping	1, 2
			Ideas from system mapping	1, 2
			"How might we ...?" questions from insights and user stories	2, 3
	Generating many ideas		Brainstorming and brainwriting	1, 2, 3
			10 plus 10	1, 2, 3
	Adding depth/ Diversifying ideas		Bodystorming	1,2, 3, 5
			Using cards and checklists	1, 2, 3
			Ideation based on analogies and association	1, 2, 3
	Understanding/ Clustering/Ranking		Octopus clustering	2, 4
			Benny Hill sorting ("Thirty - Five")	2, 4
			Idea portfolio	2, 4
			Decision matrix	2, 4
	Reducing options		Quick voting methods	1, 2, 4
			Physical commitment	5, 2
Prototyping	Service processes and experiences		Investigative rehearsal	2, 3
			Subtext	2, 3
			Desktop walkthrough	2, 5
	Objectives and environments		Cardboard prototyping	2, 5
	Prototyping for the digital		Rehearsing digital services	2, 3
			Paper prototyping	2, 3, 5
			Interactive click modelling	2, 3, 5
			Wireframing	2, 3, 5
	Ecosystems and value		Service advertisement	1, 2
			Desktop system mapping (a.k.a. Business Origami)	2, 4
			Business Model Canvas	2, 3, 4
	Further methods		Mood boards	1, 2, 4
			Sketching	2, 3
			Wizard-of-Oz approaches	2, 3, 4
Implementation	Change management		Know how people change	1, 2, 3, 4
			Understanding what will change	1, 2, 3, 4
			Beliefs and emotions	1, 2, 3, 4
			Key tactics of change	1, 2, 3, 4
	Software development		Preparation	1, 2, 5
			Idea board	1, 2, 3
			Ideation and mini-sprit	1, 2, 3
			Research	1, 2, 3, 4
			Software prototyping	1, 2, 3, 4
			Build	1, 2, 3, 6
			Release	1, 2, 4
	Service design/ Product management		Imagine	2, 3
			Define	2, 3, 4
			Support/Use	1, 4, 5
			Realise	1, 2, 4, 6
			Retire/Dispose	2, 4, 6
	Service design/architecture		Needs assessment	1, 2, 4
			Mindset change	1, 2, 3
			Testing	1, 4, 6
			Creation	2, 3, 5
			Monitoring	1, 4
			Building	3, 6

Task Groups	
1 Interpersonal	Difficult to automate
2 Creative & decision -making	Difficult to automate
3 Information synthesis	Difficult to automate
4 Information analysis	Automatable
5 Unpredictable physical	Automatable
6 Predictable physical	Automatable

Table 1. Categorising service designers' core activities into automatable & difficult to automate, adapted from (Stickdorn et al., 2018) and (AlphaBeta, 2017).

4. Prototyping

It is crucial to acknowledge that the corresponding algorithm developed for each map, as well as the unified algorithm, are initial prototypes. Before incorporating them into our everyday work with clients, a comprehensive evaluation process must be conducted. This evaluation ensures that the algorithms are effective, reliable, and aligned with our clients' specific needs and requirements.

Given the forward-looking nature of the project, the utilisation of the 'diegetic prototype' method and the 'critical design' approach have proven to be not just beneficial, but also crucial.

4.1 Evaluating the Prototype

To evaluate the two sets of algorithms - the corresponding algorithms developed for each map and the unified algorithm - a comprehensive and iterative process is required. This process involves presenting various design scenarios, modifying the details iteratively, and examining the results. By comparing and analysing the solutions and processes employed by both human users and the platform, errors and failures can be detected and resolved, leading to continuous improvement. This evaluation process serves a dual purpose: providing an onboarding experience for service designers and conducting user research to better understand their behaviours, needs, and motivations. Transparently responding to inquiries fosters trust and gathers valuable feedback from users, enhancing the evaluation process.

In addition to scenario-based evaluations, it is crucial to consider the evaluation of components, requirements, processes, and user experiences. This ongoing evaluation helps make informed decisions regarding the trade-off between precision and recall, ensuring that the algorithms are optimised for their intended purposes.

Now, let's delve into the shared and unique considerations when evaluating these algorithms:

Shared Considerations:

A. Defining evaluation metrics: Both types of algorithms require clear and meaningful metrics aligned with their objectives. Key metrics, such as accuracy and efficiency of generating results, should be established. For example, when evaluating a relevant algorithm for an Empathy Map, the metric could be the accuracy in capturing and categorising user emotions and needs. Similarly, for the unified algorithm, a metric could be the accuracy in combining insights from multiple maps to provide comprehensive recommendations.

B. User experience and feedback: Gathering feedback from service designers is crucial for both sets of algorithms. Conducting usability tests, surveys, and interviews with service designers using AI-augmented tools, such as a Customer Journey Map algorithm, provides valuable insights into their experience, efficiency gains, and the quality of insights provided. This feedback helps identify areas for improvement and ensures a user-centric approach.

C. Ethical considerations: Ethical implications such as fairness, transparency, and privacy apply equally to both types of algorithms. As per the 'Ethics guidelines for trustworthy AI' by the European Commission, a reliable AI should embody the following principles: a) being lawful, which entails respecting all applicable laws and regulations, b) being ethical, by adhering to ethical principles and values, and c) being robust, both from a technical standpoint and while considering its social environment (European Commission, 2019). Evaluating how the algorithms handle user data, ensuring transparency in decision-making processes, and incorporating mechanisms for human oversight are essential to address potential biases and maintain ethical standards[14].

Moving on to the unique considerations for each type of algorithm:

Corresponding algorithms for each map:

1. Map-specific performance: Evaluating the performance of an algorithm tailored to a specific map is critical. For example, assessing an algorithm for a Service Blueprint map based on its accuracy in identifying touchpoints and customer interactions ensures that the algorithm effectively represents the service components and their relationships within the map.
2. Comparison amongst maps: Comparing the effectiveness, efficiency, and usability of comparable algorithms for different maps allows us to understand if certain maps benefit more from AI augmentation. For instance, comparing the performance of AI-augmented Empathy Map and Stakeholder Map algorithms can shed light on which map benefits more from AI augmentation.

Unified Algorithm:

1. Holistic performance: The objective of the unified algorithm is to synthesise and integrate insights from various service design maps to offer a comprehensive view. For instance, its capacity to coalesce insights from an Empathy and a Customer Journey Map is fundamental in generating a broad understanding that takes into account user needs and the entire service trajectory.
2. Adaptability and scalability: The unified algorithm needs to adapt to complex and varied service design challenges while handling large amounts of data. Evaluating its ability to handle changes in the service scope, incorporate new data, and provide accurate and relevant insights is essential for its successful implementation.
3. Beyond-Human Capabilities: Assessing the unified algorithm's performance in complex scenarios that surpass human capabilities[15] is important. Its ability to identify patterns or correlations in large datasets from multiple maps can uncover valuable insights that might have been overlooked by human analysts.

In addition to these considerations, long-term monitoring and iterative improvement play crucial roles in evaluating and enhancing the algorithms:

a) Long-term monitoring: Continuous monitoring of AI-augmented prototypes in real-world settings is essential to evaluate their long-term performance and impact. For example, monitoring an AI-based energy management system's effectiveness, adaptability to changing usage patterns, and potential cost savings over an extended period allows for data-driven optimisations and improvements.

b) Iterative Improvement: The evaluation process should be viewed as an iterative cycle of feedback, analysis, and improvement. Incorporating user feedback, expert insights, and evaluation results helps refine the algorithms iteratively. Continuous optimisation of AI-augmented features, refining the algorithm's logic, enhancing

[14] Frameworks such as Fairness, Accountability, and Transparency (FAT) or Ethical Impact Assessment (EIA).

[15] The restrictions of the capability of the human brain to process information and the requirement of artificial intelligence to be inside its boundaries are depicted by the human window — a concept first presented by the late Donald Michie. A solution is required to be ideal with regard to correctness, grain size, executability, and comprehensibility if it is to lie inside the boundaries of the human window (Kopec et al., 2014, pp. 25-26).

data inputs, and improving the user interface contribute to enhancing the algorithms' performance.

How It Works

Flowchart 2 depicts a streamlined model, representing merely one of the countless possibilities, which exemplifies the efficacious integration of AI and machine learning techniques to augment conventional design processes. By narrowing down the scope, this use case scenario focuses on a specific method—'design thinking'—rather than attempting to encompass the entire process.

By utilising the mapping method based on the unified algorithm discussed earlier, a more comprehensive understanding of the current situation (as is) can be obtained during the 'Empathise' and 'Define' steps. This, in turn, facilitates the ability to depict a desirable future and comprehend the requirements during the 'Ideate', 'Prototype', and 'Test' phases.

Each decision, encompassing those related to service design, is subject to a set of constraints and interrelated or independent variables that must be meticulously considered to optimise profits and/or minimise losses- these are known as objective functions- and are a significant driver of the user experience. Nonetheless, sometimes this process can become intricate and complex.

The "Felicitous Design Concept"[16] serves as an illuminating example, elucidating this complexity. This concept harnesses the synergistic potential of existing theories, specifically Societal Marketing and Persuasive Design, to delineate the foundational principles for developing an effective solution/design as a product, process, and strategy. The concept categorises three integrated reversible levels, each involving three main considerations (a set of variables). The arrangement and accompaniment of each level component are in such a way that, in addition to performing their roles, they prepare a vital platform for the next stage. It is worth mentioning that each consideration at each level can be applied to different degrees and with respect to the requirements of each case; nevertheless, it is impossible to ignore any of them (Bahrami & Aryana, 2019). Consequently, designers find themselves in predicaments analogous to dispute resolution, where they must astutely navigate the trade-offs among diverse variables, assigning weight to them commensurate with their significance and relevance.[17] To solve this, we can apply a two-layer method, one among so many possible ways. Firstly, in classical programming, as the symbolic AI paradigm, humans input rules (a program) and also data to be processed in accordance with the rules, and outcome answers. However, in machine learning, humans input not only data, but also the answers anticipated from such data, and the outcome of the rules. Following this, the rules may be applied to new data in order to obtain original answers (Chollet, 2021, p. 4). Furthermore, employing techniques such as 'multi-objective optimisation' can empower a system to make optimal decisions while navigating trade-offs between two or more conflicting objectives[18] while utilising big data.

Despite the effectiveness of techniques like transfer learning and weakly supervised learning, which make use of limited and imprecise sources or pre-trained models to fine-tune them for specific tasks, the challenge of data scarcity remains unresolved- I have not found a solution yet. Therefore, it becomes imperative to consider specialised methods for gathering data. For instance, during the

[16] Refer to www.tandfonline.com/doi/abs/10.1080/14606925.2019.1595021

[17] Our perception of these should be founded on a well-measured balance of both analytical and systems thinking contingent upon the particular circumstances at hand. This could help us to look at the situation inclusively and unbiasedly.

[18] Measuring results and quantifying uncertainty in qualitative studies can be a significant challenge. Acquiring the necessary capabilities is essential. One helpful resource is "Quantifying the Qualitative: Information Theory for Comparative Case Analysis" by Drozdova and Gaubatz (2017) published by SAGE.

Ideate phase, the efficient application of the method necessitates a substantial amount of annotated data—put simply, a considerable number of available scenarios with their respective outcomes.

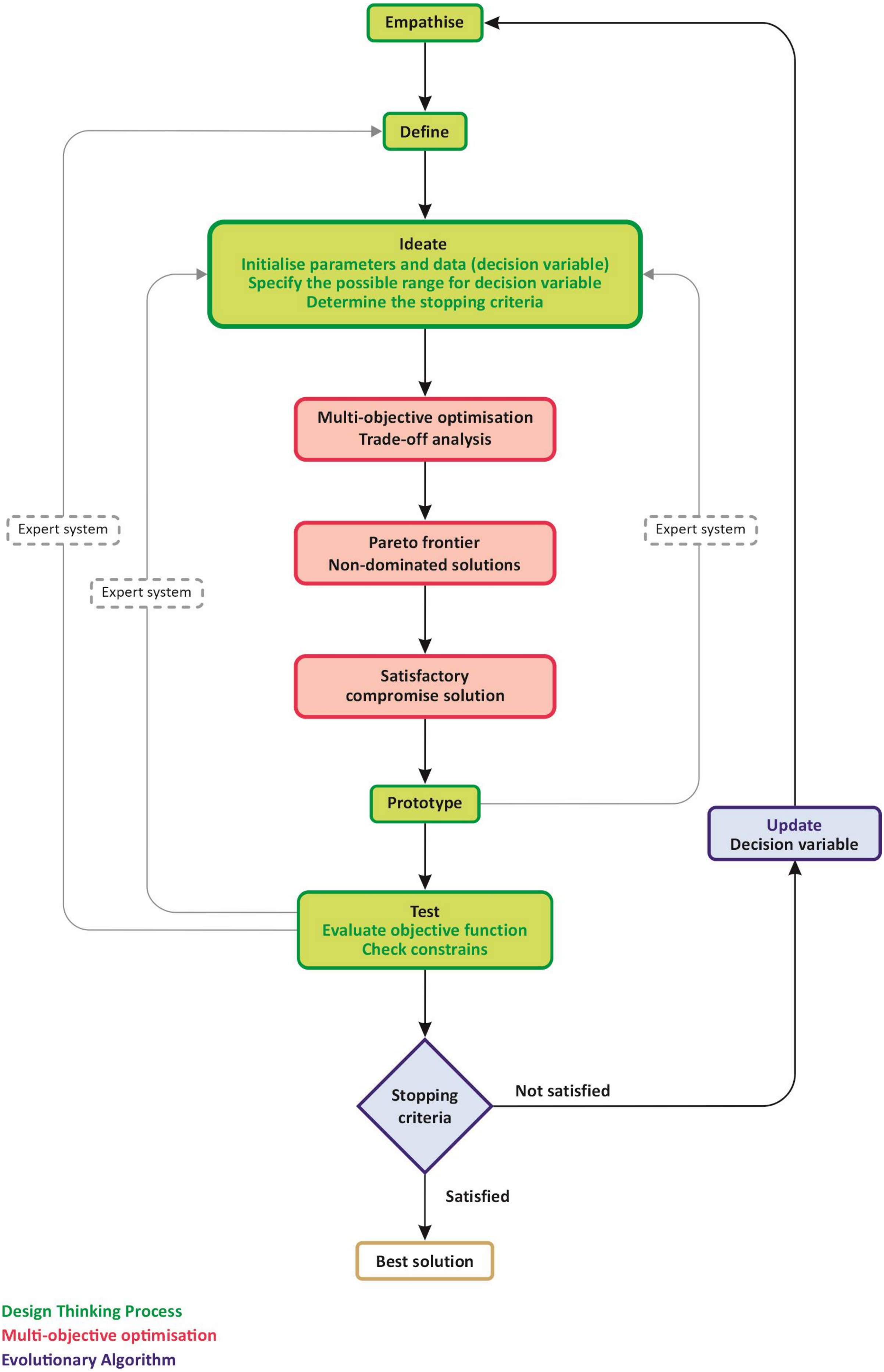
Whether you apply augmentation, automation or a mixed method, you need to use algorithms. An algorithm is a set of rules or procedures that needs to be followed in problem-solving operations, including calculations (Gonfalonieri, 2019) that define what needs to be done and how to do it. However, any unpredictable factors, the interplay of indicators or changes in the context can change the game. Therefore, confronted with numerous inefficient solutions. Moreover, we have no option other than repeatedly revising the procedure. The required reforming and rearranging of the algorithm and components could take weeks to sift through the data. Also, some specific methods such as Evolutionary Algorithms (EAs)[19] are effective and heuristic search techniques which have strong attributes and adaptability whose purpose is to capture extensive solutions to complicated optimisation problems (Galvan et al., 2003, p. 573). Moreover, incorporating the 'Human-In-The-Loop'[20] approach in conjunction with evolutionary algorithms can significantly enhance iterations, expedite the process, and improve the quality of outcomes in terms of both effectiveness and efficiency.

As additional contemplation is applied and the system undergoes further training, the development of innovative and increasingly efficient models for formulating solutions becomes more viable. Recognising that stopping criteria should be defined and tailored according to each unique situation is crucial.

Undoubtedly the propositional foundation should be purified further in future studies.

[19] Evolutionary algorithms are stochastic search methods that emulate the metaphor of natural biological evolution. These algorithms work on a population of potential solutions and employ the principle of 'survival of the fittest' to progressively generate improved approximations of a solution" (Pohlheim, 2005, p.3). EAs are typically used in optimisation problems, machine learning, and in fields where exact solutions are not feasible.

[20] The concept Human-in-the-loop machine learning consists of various techniques that integrate human cognition and artificial intelligence in applications utilising AI. The primary objectives usually involve one or several of the following aspects: i) enhance the precision of a machine learning model, ii) accelerate the attainment of the desired accuracy level for a machine learning model, iii) merge human and machine intelligence to achieve the highest level of accuracy, and iv) employ machine learning to augment human tasks for improved efficiency. Annotation and active learning serve as the foundational elements (Monarch & Manning, 2021, p.7).



Flowchart 2. A simplified model to augment design thinking, adapted from (Plattner et al., 2010), (Di Somma et al., 2015, p.299) and (Ketabchi & Ataie-Ashtiani, 2015, p.197).

Discussion

During the implementation of the proposed methodology, several challenges were encountered that shed light on the complexities of integrating AI and machine learning (ML) into service design practices. This section discusses some of these challenges and explores potential strategies for overcoming them.

Interdisciplinary collaboration emerges as a prominent challenge in this project, requiring a close-knit synergy among experts from different majors and disciplines, including service design, AI, and data science. However, achieving effective collaboration and constructive conversations among these diverse experts can be challenging due to the need to build trust, foster mutual understanding, and bridge the gap between different professional languages and perspectives. To address this challenge, it is essential to exercise patience, maintain open communication, and establish a shared vision of the project's objectives and potential impact.

Another significant contemplating point pertains to the scarcity of relevant data for training machine learning (ML) models. Data plays a crucial role in training AI algorithms and enabling them to make accurate predictions. Nonetheless, obtaining high-quality and diverse data specific to service design can be difficult. Service designers must explore strategies to elicit, gather and curate relevant data, potentially through collaborations with organisations and stakeholders. Additionally, considering the use of synthetic or simulated data can supplement the limited real-world data. Solving the challenge of data scarcity requires resourcefulness, creativity, and a willingness to experiment with alternative data sources and generation techniques.

By providing designers with powerful tools and insights, augmented intelligence has the potential to revolutionise service design by enhancing efficiency, enabling customisation, and facilitating collaboration. Integrating AI algorithms into the design process can lead to a shift towards a more data-driven and evidence-based approach, complementing the creativity and intuition of designers. This has the potential to result in the development of innovative, human-centric services that better address societal challenges and improve the quality of life.

Nevertheless, the impact of the AI-powered assistant extends beyond the design practice and raises ethical considerations. Ensuring fairness, transparency, and accountability in the use of AI algorithms is crucial. Designers must be mindful of potential biases in the data and algorithms and take steps to mitigate them. Ethical considerations should be integrated into the design process to protect privacy, handle sensitive information responsibly, and prioritise the well-being of users.

To fully understand the impact and effectiveness of these emerging opportunities, user studies and evaluations should be conducted. Engaging with designers and stakeholders will provide valuable insights into their experiences, perceptions, and the actual outcomes of using the assistant. This user-centric approach will contribute to refining the assistant's capabilities, addressing limitations, and continuously optimising its performance.

Looking towards future work, advancements in technology and the emergence of new methodologies will create opportunities to enhance algorithms, expand the range of maps and design methods covered, and incorporate more sophisticated machine learning techniques. This iterative process of development and improvement ensures that the AI-powered assistant remains relevant, effective, and adaptable to evolving design needs and challenges. However, it is vital to establish the required philosophical platforms to understand, accept, and take ownership of these advancements.

Furthermore, it is important to clarify that although Language Models (LLMs) trained on big data were applied in this research, the direct incorporation and amalgamation of big data into the proposed models have not been achieved at this stage of the research. This limitation highlights an avenue for future research and development in order to fully harness the power of big data in the context of this study. This is the beginning, not the end.

Conclusion

As we approach a paradigm shift, it is vital to consider our readiness level. Neglecting this aspect can turn a promising opportunity into an Achilles heel. Let's face it, are we as prepared as we are excited? During this transformation, the revision and reconstruction of infrastructures, particularly the educational system, play a pivotal role. Providing essential training and nurturing a curated set of skills and competencies increase the chances of successful adaptation to new circumstances.

While the integration of AI may displace certain jobs, particularly in analytical roles, it opens up an array of new opportunities. This shift, painful as it may seem, is a call for us to explore the full range of possibilities that human-machine integration offers (Huang & Rust, 2018). Similar to human teams, the strength of collaborating with an AI lies in how the individual and computer complement each other; the most skilled players and the most powerful AIs do not necessarily guarantee the best results when paired (De Cremer, 2021). This symbiotic relationship between humans and AI can lead to the emergence of new design methodologies and approaches that were previously unattainable.

Incorporating frameworks like post-phenomenology[21] into insights from Socio-Technical Systems[22] (Rosenberger, 2018, p. 188) can help harmonise the relationship between humans, technology, and the world. These perspectives can help us navigate the complexities and opportunities that this brave new world presents.

As we navigate this transformation, a key insight is that the ability to ask the right questions is critical to harnessing the full potential of AI. The goal should not be to deliver ready-made solutions for every problem but to equip individuals with the tools and skills to construct their own solutions. This necessitates a strong commitment to critical thinking, developing fusion skills, and fostering a culture of lifelong learning. And learn how to collaborate with colleagues from different fields. An opportunity for a new generation of silent designers.

Finally, the advent of AI, with its potential to either match or supersede human capabilities, poses a significant challenge to our traditional understanding of humans as unique beings with the highest moral status (Gordon & Nyholm, 2021). As we confront this challenge, our approach must be guided by a commitment to harmonious human-AI integration, the continuous development of relevant skills, and a willingness to adapt to the changing landscape.

However, it remains a question whether this integration can be considered part of human beings' evolution, but not in a biological aspect.

[21] In philosophy of technology, the post-phenomenological approach studies technology in terms of its role in the association between the human being and the world (Aydin et al., 2019).

[22] STS approach acknowledges the intricate interplay between individuals and technology within workplace settings (Stranks, 2007, p. 100).

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About the Author:

Nasser Bahrami
PhD Candidate in Design at ImaginationLancaster, Social Design Analyst (Senior Research Associate), and member of the Centre for Mobilities Research (CeMoRe), Lancaster University, United Kingdom