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Harmonizing human-AI synergy: behavioral science in AI-integrated design

Dirk Van Rooy ✉ and Kristof Vaes

University of Antwerp, Belgium

✉ dvanrooy@gmail.com

Abstract

This paper explores the role of integrating behavioral science to refine human-AI interaction, essential for ensuring safety and efficiency. Advocating for empathetic, user-centric design, the paper illustrates how behavioral insights can effectively inform AI-integrated designs, making AI applications more intuitive and ethically aligned with diverse human needs. This approach can ultimately enrich interaction across systems, fostering a more harmonious human-AI synergy.

Keywords: artificial intelligence (AI), behavioural design, human-centred design, ethics, interaction design

1. Introduction

The application of behavioral science to design has deep historical roots, tracing back to the late 19th and early 20th centuries when researchers began systematically studying human behavior and cognition: Max Wertheimer's groundbreaking research on visual perception, has had a profound influence on design, emphasizing the importance of understanding how people perceive and interpret visual stimuli (Wertheimer, 1912). Insights from the mid-20th century on operant conditioning have steered design thinking, especially in creating systems that motivate desired behaviors through reinforcement, a concept explored by Deterding (2012) and Wenker (2022). Donald Broadbent's research on selective attention has significantly impacted the development of user interfaces that highlight pertinent information, reducing cognitive overload (Broadbent, 1958). The concept of mental models, as articulated by Norman (2013), has been pivotal in creating interfaces that are intuitive and align with user expectations. While behavioral science principles have long guided design, one could argue that with the emergence of AI driven systems, their relevance has increased.
The advent of AI in autonomous systems like self-driving cars, smart homes, and AI-powered chatbots has brought a paradigm shift in industries ranging from transportation to healthcare. These systems, designed to function autonomously with minimal human input, rely on sophisticated algorithms for decision-making. Human-Machine Interaction (HMI) in this context has evolved rapidly, becoming crucial in systems where human oversight is still necessary (De Fazio et al., 2022). The integration of AI amplifies the need to understand human behavior for designing effective interactions (Cross & Ramsey, 2021). For instance, research shows that excessive system feedback can overwhelm users, leading to reduced performance and over-reliance on automation, the "out-of-the-loop" problem (Endsley & Kiris, 1995). Such insights have proven to be critical in designing AI-integrated interfaces in autonomous vehicles and smart homes (Choi & Ji, 2015; Lee et al., 2015). Similarly, AI chatbots and virtual assistants rely on understanding user intent and conversation dynamics, where research on human language processing informs interface design and highlights user tendencies to anthropomorphize AI

systems (Kuhail et al., 2023). In military applications, AI-integrated autonomous systems pose challenges in workload management and decision-making for human operators. Studies on the impact of automation on trust, situational awareness, and accountability are shaping the design of these systems to ensure effective integration and utilization (Endsley & Kiris, 1995; Norris, 2018; Sparrow, 2009). The growing focus on cognitive and behavioral factors in AI-component systems underscores the complexity of applying behavioral science in design (Hopko et al., 2022; Krausman et al., 2022). The challenge lies in translating abstract behavioral concepts and theories into practical design solutions, often requiring interdisciplinary collaboration. A practical approach for design practitioners could be to start with the more applied aspects of behavioral science, and in particular the difference between different types of cognitive processes (Voyer, 2015). Building on this historical context, this paper's main thesis emphasizes the growing significance of behavioural science in AI-driven system design, particularly in understanding and applying cognitive processes. The subsequent sections explore the integration of behavioural science in AI interface design, beginning with a discussion of Kahneman's Type I and II cognitive processes and their application in AI systems. We then examine challenges in implementing these concepts in AI-driven systems, and present two case studies to illustrate the practical application and challenges of applying cognitive dynamics in AI systems: One on AI-enabled unmanned aerial vehicles (UAVs) focusing on the balance between human control and AI autonomy, and another on adaptive human operator interaction with autonomous systems in high-stakes environments like navigation control rooms. The paper concludes by offering insights and recommendations for effectively applying behavioural science principles in the design of AI systems, emphasizing the need for a nuanced understanding of human cognitive processes.

2. Cognitive dynamics in AI interface design

Kahneman's influential work on fast (Type I) and slow (Type II) cognitive processes (see Table 1), offers an insightful framework that is especially relevant toAI interface design (Kahneman, 2013). It might be useful to clarify these concepts in some detail, for those unfamiliar with behavioral science:

- Type I thinking is fast and instinctual, used for quick decisions like catching a ball or responding to simple queries. It relies on heuristics, which are mental shortcuts that speed up our decision-making but can lead to biases. For example, reading about a local robbery might cause you to overrate the risk of crime, a result of the availability heuristic. In AI interface design, this understanding helps create intuitive systems that support swift, effortless decisions, capitalizing on our tendency for rapid, automatic thinking, while avoiding the need for detailed analysis in every situation. The aim is to enable immediate, efficient AI interaction.

Table 1. Characteristics of system 1 and system 2 and application in AI design

Type	Characteristics	Key aspects	AI design application
Type 1	Automatic. Instinctive, rapid, operates subconsciously.	Uses heuristics (mental shortcuts), susceptible to biases	Align with users' mental models and cognitive maps for intuitive interaction
Type 2	Controlled, slow, limited capacity and conscious	Involves careful processing of information, evaluating options, &considering consequences	Facilitate analytical mindset with information and tools for data analysis and decision making

- Type II thinking is deliberate and conscious, utilized for complex decisions or problems requiring meticulous scrutiny, like challenging math or evaluating job offers. In AI interface design, the facilitation of Type II thinking is a critical consideration. AI interfaces should be structured in a way that supports and encourages this analytical mindset at appropriate times by providing detailed information and tools for thorough analysis. This allows users to weigh options and understand consequences, crucial in high-stress or intricate situations. AI interfaces should thus balance immediate responses with the facilitation of deeper, reflective decision-making where necessary.

When integrating these concepts into AI interface design (see Table 1), the goal is thus to strike a balance that caters to both types of thinking. This means creating interfaces that allow users to make efficient, instinctive decisions when appropriate, minimizing the cognitive load for routine tasks. At the same time, the interface should provide the necessary tools and information for more considered and analytical decision-making when required. This balance is crucial for effective interaction with AI systems, especially under pressure or in situations that demand a high level of accuracy and thoughtfulness (AlKhars et al., 2019; Nurse et al., 2022).

2.1. Interplay of cognitive biases and thinking types

Closely related to the literature on Type I and II thinking is the research into cognitive biases. Cognitive biases typically refer to systematic patterns of deviation from norm or rationality in judgment, and are integral to our understanding of decision-making processes (see table 2 for an incomplete list). These biases are strongly associated with Type I thinking. For instance, the anchoring bias, where initial information heavily influences subsequent decisions, often plays out in Type I thinking, as it operates under quick, automatic processes (Meppelink et al., 2019). Similarly, the framing effect illustrates how decisions are influenced by how options are presented, and is also linked to quick, heuristic-based judgments. For example, people tend to be risk-averse when decisions are framed in terms of gains, but risk-seeking when framed as losses (Tversky & Kahneman, 1981). This bias is particularly relevant in AI systems involving risks or options, such as financial investment or healthcare choices (Stea & Pickering, 2019; Tversky & Kahneman, 1981). Social proof, where people follow the actions of others particularly in uncertain situations, is leveraged extensively in systems that utilize user-generated content, such as online reviews or ratings (Cialdini & Jacobson, 2021). Furthermore, the strategic use of defaults in interfaces showcases how preset choices can significantly influence decision outcomes. Studies such as Johnson and Goldstein's work on organ donation demonstrate the power of defaults in shaping user decisions and behaviors, a principle that has been effectively applied in various design contexts, including AI-powered recommendation systems and online forms (Johnson & Goldstein, 2003; Mertens et al., 2022).

Table 2. Cognitive biases

Cognitive bias	Description
Confirmation bias	To look for or to interpret evidence to support prior hypothesis rather than look for disconfirming evidence.
Anchoring effect	To rely heavily on one piece of information when making decisions (usually the first piece of information acquired: the 'anchor').
Availability bias	Judgments of likelihood or percentages based on ease of recall (greater 'availability' in memory) rather than on actual probabilities.
Framing effect	To draw different conclusions from the same information, depending on how that information is presented.
Loss aversion	To view losses as looming larger than corresponding gains.
Sunken-cost fallacy	To allow previously spent time, money, or effort to influence present or future decisions.
Social proof	Also often referred to as the Bandwagon effect. To do (or believe) things because many other people do (or believe) the same.

The exploration of cognitive biases within the frameworks of Type I and Type II thinking offers valuable insights into the complexities of human decision-making. Understanding these biases is crucial, not just for identifying the limitations and strengths of human cognition, but also for shaping the way we interact with technology. As we will argue next, we can derive design principles from our understanding of cognitive biases and thinking processes that can inform the design and functionality of AI systems. Behavioural science provides a rich repository of knowledge that can be leveraged to enhance the intuitiveness, efficiency, and overall effectiveness of HMI. By applying these insights, we can develop AI interfaces and systems that are more in tune with human cognitive processes, potentially reducing errors, enhancing user experience, and paving the way for more seamless and productive interactions between humans and machines.

3. Case studies

Human-Machine Interaction (HMI) design, traditionally centered on usability principles like efficiency and effectiveness, is increasingly informed by behavioral scientific insights (Ferreira et al., 2020; Jeffries & Wixon, 2007; Zaharias & Poulymenakou, 2006). Operators of autonomous AI-driven systems often rely on quick, intuitive decisions. However, these decisions can be influenced by biases. Confirmation bias, for instance, might lead an operator to ignore important warning signs if they contradict their belief in the system's reliability. Similarly, anchoring bias can cause operators to give too much weight to the first piece of information they receive, potentially leading to flawed decisions. Increasingly, we see examples of how human behavioral insights are being applied to HMI to either investigate and/or mitigate the impact of cognitive biases.

3.1. Case Study 1: AI-Enabled Unmanned Aerial Vehicles (UAVs)

A recent example of advanced autonomous systems in action involves the Robotic Autonomous Platform for Tactical Operations and Reconnaissance (RAPTOR) unmanned aerial vehicle (UAV). The FOCUS AI-enabled autonomy software enables the UAV to autonomously locate, track, and identify targets with minimal human supervision, underscoring the growing importance of autonomous systems in strategic operations. The adaptability of SSCI's software across various UAV sizes and for multidomain operations also expands the scope of AI's application, enabling a wide range of tactical operations from surveillance to direct engagement. While this adaptability is technologically impressive, it simultaneously broadens the ethical implications of AI in military contexts.

Figure 1. The Robotic Autonomous Platform for Tactical Operations and Reconnaissance (RAPTOR) unmanned aerial vehicle (UAV)

With the increasing autonomy of systems like RAPTOR, new challenges emerge, particularly in the realm of decision-making and ethical considerations. The use of AI in such high-stakes scenarios raises questions about the balance of control between human operators and autonomous systems, especially in situations where rapid, critical decisions are necessary. In that respect, one of the key aspects of the RAPTOR project is its emphasis on human-machine collaboration. Although the UAV can operate autonomously, it is designed to function alongside human decision-makers, ensuring that crucial strategic decisions remain under human control. This approach aims to mitigate the risk of over-reliance on AI and maintains the centrality of human judgment in military operations.

As such, the RAPTOR case study illustrates the importance of incorporating behavioral science into AI development. Understanding human cognitive biases and decision-making processes is essential in designing interfaces and protocols that enhance the effectiveness of human-AI interaction. This is especially important in scenarios where operators must quickly interpret and act upon the information provided by autonomous systems. In terms of operational efficiency, the FOCUS AI-enabled autonomy software significantly reduces the cognitive load on human operators. By autonomously performing tasks like target identification and tracking, the software allows operators to focus on higher-level strategic planning and decision-making. This division of labor between AI and human cognition can lead to more effective and timely responses in dynamic battlefield situations. At the same time, it necessitates careful consideration of potential biases arising from rapid, intuitive (Type I) thinking, and how ethical performance in military AI systems requires a deliberate effort to counteract these biases and foster more reflective (Type II) thinking processes. As AI continues to evolve and integrate into various military technologies, the lessons learned from the RAPTOR project will be invaluable in guiding the development of future autonomous systems, ensuring they are effective, ethical, and synergistic with human oversight.

3.2. Case study 2: Adaptive Human Operator Interaction with Autonomous Systems (AHOI)

The Adaptive Human Operator Interaction with Autonomous Systems (AHOI) project recently received funding by Belgian Defense to explore and address the interplay between human cognitive biases and decision-making in the context of AI-driven autonomous systems. The work will focus on critical areas like navigation control rooms and other high-stakes environments where the synergy between human operators and AI systems is essential. At the core of AHOI's mission is the understanding that while AI systems offer remarkable capabilities in data processing and decision support, human operators bring to the table invaluable qualities of intuition, experience, and adaptability. However, human decision-making is also prone to various cognitive biases. By recognizing and mitigating these biases, the project aims to enhance the efficiency and safety of these interactions.

The research team has at its disposal a Full Mission simulator (FMS), which can simulate the various functional parts of ships as realistically as possible. More specifically, two bridge simulators will be used that provide a versatile but robust test bed for scenario driven research to explore key factors in human-machine teaming and interaction (see Figure 2).

Figure 2. Full Mission bridge simulator

The research will involve a series of experimental scenarios designed to study cognitive biases and their manifestations in real-time AI-human interactions:

1. Confirmation Bias: In a navigation room, if an AI suggests a new path to avoid collision, an operator might show confirmation bias by favoring evidence that supports the AI's suggestion, overlooking other data.

2. Anchoring Effect: When given an Expected Time of Arrival (ETA) by AI, an operator could stick to it due to the anchoring effect, not updating it despite new data like weather changes or engine issues.
3. Sunken-Cost Fallacy: If changing course to avoid bad weather means leaving a resource-heavy route, an operator may not do so, influenced by the sunken-cost fallacy, preferring to stick with the initial investment.
4. Loss Aversion: Faced with a minor system malfunction, an operator might overreact because of loss aversion and overestimate the potential consequences of this minor issue, possibly changing course unnecessarily.

Through these scenarios, the AHOI project will not only identify and study these biases but also develop AI systems capable of recognizing and counteracting them. The goal is to create AI interfaces that prompt operators to engage in more analytical, reflective thinking (Type II) in situations where intuitive, automatic responses (Type I) might lead to biased decisions. The AHOI project is positioned to make significant contributions to the field of AI and human interaction. By integrating insights from behavioral science into the design and functioning of AI systems, it can enhance decision-making processes in critical environments. The work will not only address the immediate challenges of cognitive biases in high-stakes settings but also pave the way for a future where human and AI collaboration is more harmonious, efficient, and safe. Overall, these case studies illustrate the practical implications of applying behavioural insights to HMI. Table 3 compares and summarizes key aspects of this approach in the two case studies. It highlights the differences in operational efficiency, cognitive bias consideration, and ethical considerations, among other factors, in each case study's application of behavioural science principles.

Table 3. Behavioural Insights in HMI: UAVs vs. AHOI

Aspect	RAPTOR	AHOI
Division of Labour	Al performs tasks like target identification and tracking, enabling human operators to focus on strategic planning and decision-making.	
Operational Efficiency	Reduction cognitive load human operators, leading to effective and timely battlefield responses.	Focus on enhancing the efficiency and safety of interactions between humans and AI systems.
Cognitive Biases	Understanding human cognitive biases in interpretation of information provided by AI.	Interplay human cognitive biases and decision-making in AI-driven autonomous systems.
Reflective Thinking	Encourages more reflective (Type II) thinking processes to counteract biases from rapid, intuitive (Type I) thinking.	Emphasizes the importance of balancing AI capabilities with human intuition, experience, and adaptability.
Ethical Considerations	Ethical performance in military AI systems requires a deliberate effort to maintain human judgment at the core of operations, guiding future development of autonomous systems.	
Focus on Specific Environments	Focus on dynamic battlefield situations.	Concentration on critical areas like navigation control rooms and other high-stakes environments.

4. Implications for human machine interaction

The two case studies mentioned above provide good examples of how behavioral scientific insights can enrich and improve HMI. Such case studies, together with other examples, allow us to generate some initial design considerations for HMI that consider the cognitive dynamics in human decision making (see Table 4 for an overview).

Table 4. HMI design considerations

Design Consideration	Description	Examples / References
Comprehensive Information Provision	Supply operators with comprehensive information, including data challenging system performance.	Healthcare, aviation (Eva & Norman, 2005; Lighthall & Vazquez-Guillamet, 2015; Kaempf & Klein, 2017)
Diverse Information Presentation and Decision Support	Utilize diverse information presentation methods and decision support tools to mitigate cognitive biases.	'Time-based de-anchoring,' human-Al collaboration (Rastogi etal., 2020; Eva & Norman, 2005; Lighthall & Vazquez-Guillamet, 2015; Kaempf & Klein, 2017)
Enhanced Decision-Making Tools Across Industries	Systematically evaluate options to improve decision quality in various industries.	Real estate, fishing management, preferential choice problems, algorithmic trading (Multiple references)
Heuristic Control Strategies for Cognitive Workload	Estimate cognitive workload, including physiological indicators like eye gaze, and employ real- time feedback mechanisms.	Eye tracking, EEG signals, (Aygun et al.,2022; Knisely et al., 2021; Pomranky & Wojciechowski, 2007; Yuh et al., 2022; Wiltshire et al., 2014, 2022)
Minimizing Perceptual and Informational Load	Reduce perceptual and informational load to prevent cognitive overload.	Directional cues in visual displays, augmented reality (Davis, 2007; de Melo et al., 2020)
Minimizing Interruptions for Enhanced Decision-Making	Interfaces that align with users' mental models & minimize unnecessary interruptions to streamline cognitive switching and enhance decision-making.	User interface design in healthcare and emergency services (Norman, 1983; Zhang & Patel, 2006)

Providing operators with comprehensive data is crucial in AI operations, including information that may counter expected performance. For instance, in healthcare, giving doctors extensive, varied patient data improves decision-making (Eva & Norman, 2005; Lighthall & Vazquez-Guillamet, 2015), a practice mirrored in aviation with detailed flight displays aiding pilots (Kaempf & Klein, 2017). Applying diverse information presentation and 'time-based de-anchoring' helps mitigate biases and enhance human-AI collaboration. Time-based de-anchoring strategy in this context is about using time allocation based on AI confidence levels to reduce the impact of anchoring bias and enhance the effectiveness of human-AI collaborative decision-making (Rastogi et al., 2020). Decision-making tools have advanced across sectors, with Clinical Decision Support (CDS) systems in healthcare aiding treatment decisions (George et al., 2000; Gong et al., 2017; Todd & Benbasat, 1991; Bhandari et al., 2008).

In human-machine interaction, heuristic strategies optimize cognitive resource management. Monitoring cognitive workload with physiological metrics like eye gaze (Aygun et al., 2022) and using real-time feedback (Knisely et al., 2021; Pomranky & Wojciechowski, 2007), alongside autonomous systems that respond to user states (Yuh et al., 2022; Wiltshire et al., 2014, 2022), improve performance. Cognitive load management involves reducing perceptual load and aligning interfaces with users' mental models to avoid cognitive overload, crucial in high-stakes decisions (Norman, 1983; Zhang & Patel, 2006; Davis, 2007; de Melo et al., 2020).

4.1. A note on training

Training is essential in managing unmanned vehicles, emphasizing the need for teamwork among operators. Experienced personnel sharing knowledge through regular debriefings sharpens decision-making and situational awareness, which translates to improved safety and performance (Thieme & Utne, 2017). The roll-out of Europe's first full-sized autonomous bus, CAVForth, exemplifies the ongoing need for adaptive learning in driverless technology (GOV.UK, 2020). Training programs that focus on recognizing and mitigating cognitive biases are also critical, impacting sectors from the military to finance (AlKhars et al., 2019; Sellier et al., 2019). Operators can then evaluate situations more objectively and make informed choices. Feedback mechanisms that offer performance metrics and real-time analysis play a significant role in the learning process, allowing for the identification of improvement areas and skill enhancement. This is particularly important in high-stakes fields such as military and emergency response, where decisions must be both rapid and accurate (Junger, 2018; Yu, 2016). Moreover, the training also benefits AI-driven systems. For example, cooperative reinforcement allows a team of Unmanned Aerial Vehicles (UAVs) to learn and adapt control parameters more effectively together than in isolation. This leader-follower dynamic not only expedites the learning curve but also ensures consistent performance, showcasing the synergistic relationship between human expertise and AI capabilities (Jardine & Givigi, 2021).

5. Conclusion

This paper has tried to provide an initial exploration of the integration of behavioral science principles into the development of AI-driven systems, with a particular focus on human-machine interaction (HMI). The research presented emphasizes the necessity for a holistic approach in design, one that considers not only the technological advancements, but also the cognitive and behavioral aspects of human operators. The discussion of various domains, including unmanned vehicle operation, military operations to finance, has hopefully illustrated the diverse applications of these principles. Based on that discussion, and two case studies, a number of design considerations were formulated dealing with decision tools and feedback mechanisms, while the role of training was also highlighted.

The intersection of behavioral science and Human-Machine Interaction (HMI) design represents a burgeoning area of research, but it is fraught with both potential and challenges. A key concern in this field is the adherence to ethical principles in relation to the respect of user privacy, autonomy, and dignity. This is demonstrated by studies like Lunter (2020), which highlight the inherent biases in facial recognition algorithms against specific racial or ethnic groups, leading to potential discrimination. Such findings necessitate the development of systems that encourage critical evaluation of provided information, as suggested by Nurse et al. (2022), and caution against over-reliance on algorithmic outputs. Furthermore, the proliferation of autonomous systems, such as vehicles collecting data on passenger behavior, presents privacy concerns. It is crucial to ensure secure data handling and use for intended purposes only. Heuristic control strategies, while beneficial in reducing operator fatigue and cognitive overload, also carry implications for liability in accidents. The ethical quandary extends to the manipulation of user behavior: While nudging and influencing behavior can yield benefits, it is vital to maintain a balance between persuasion and unethical manipulation. Upholding transparency, informed consent, and user empowerment is essential. While the ethical dimensions of HMI design, such as those related to user autonomy and data privacy, are critical, they are beyond the scope of this paper and warrant dedicated research. However, a human-centred approach to HMI, informed by a good understanding of human decision making, can help prioritise human values and address key ethical issues while ensuring a balance between efficiency and ethical integrity.

Overall, the integration of behavioral science into autonomous system design offers a number of pathways to better HMI. However, this integration is still in its early stages, and ongoing research is imperative for developing ethically grounded design strategies that leads to HMI design that is both ethically responsible and attuned to the complexities of human decision-making. By focusing on the nuanced understanding of behavioral scientific insights, and their limitations, designers can create systems that are not only effective, but also respectful of user autonomy and diversity.

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