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Research Statement

The principle focus of my research program is the investigation of neural systems that underlie human reasoning, with particular interest in determining the complexity of cognitive mechanisms involved. Specifically, my research program will partner electroencephalography (EEG) with computational modelling in two streams: i) to determine the cognitive mechanisms involved in reasoning, and ii) to expand existing computational models of reasoning.

Stream One: Cognitive Mechanisms of Reasoning

Research Question*: What complexity of cognitive mechanisms are involved in reasoning?*

Intuitive reasoning is fast and effortless but can lead to mistakes, while rational reasoning is slow and accurate but takes considerable effort. We rely on intuitive reasoning for the majority of our decisions as it most often leads to an acceptable outcome, yet it can fail us when decisions require more thought and consideration. In these instances, we turn to rational reasoning. As such, there is an intimate balance between intuitive and rational reasoning where we operate to conserve energy until we must exert effort when faced with a difficult decision. But how do we decide whether to reason intuitively or rationally?

One model of reasoning, the Expected Value of Control (EVC) model (Kool et al., 2017), posits that the recruitment of reasoning systems (intuitive versus rational) is determined by an assessment of costs and benefits. If the benefits outweigh the costs, effort is exerted to reason rationally, but if the costs outweigh the benefits, effort is withheld to reason intuitively. In line with the EVC model, my research has posited that the crossroads between intuitive and rational reasoning is cognitive control wherein there is an increased need for control as one reasons more rationally (Williams, Kappen, et al., 2019; Williams, Ferguson, Hassall, Wright, et al., 2021; Williams, Oorschot, et al., 2021).

Cognitive control, however, is not the whole story. Rather, I've found that mechanisms of attention, working memory, and long-term memory interact with cognitive control during reasoning, as evidenced by the complexity of involved neural signals (Williams, Kappen, et al., 2019; Williams, Ferguson, Hassall, Wright, et al., 2021). As such, when investigating reasoning, it is imperative to adopt a network science approach rather than focusing on individual mechanisms in isolation. Correspondingly, my research program will investigate the interactive complexity of cognitive mechanisms involved in reasoning as informed by EEG-derived neural signals.

Stream Two: Computational Modelling of Reasoning

Research Question: *What computational architecture can holistically define reasoning?*

Indeed, reasoning has been computationally realized. For example, a computational description of the EVC model integrates a drift-diffusion model within a high-level cost-benefit architecture (Musslick et al., 2019). Alternatively, the Predicted Response Outcome (PRO; Alexander & Brown, 2011; Vassena et al., 2020) model draws from reinforcement-learning principles and describes the separation of reasoning systems to be driven by the discrepancies between expected and actual decision demands – specifically, the degree of discrepancy is proportional to how rationally we reason. These and other models come with different assumptions of underlying cognitive mechanisms; however, often adopt single mechanistic explanations of reasoning rather than accounting for the full complexity of processes involved.

In 2021, I assessed EVC and PRO model assumptions by comparing neural signals to model predictions (Williams, Ferguson, Hassall, Wright, et al., 2021) – a method I've also applied in other research fields (Williams et al., 2017; Williams, Hassall, et al., 2019). Although the EVC and PRO models are thought to be mutually exclusive, I found concurrent evidence for both – signifying that neither alone could explain the full complexity of reasoning. I concluded that it was conceivable to align both models in that EVC predictions function to reactively resolve the decision at hand while PRO predictions function to proactively update expectations and optimize future decision making.

Correspondingly, there is a need to expand current models of reasoning by integrating the full complement of necessary cognitive mechanisms. As such, my research program will expand and integrate existing models by drawing on neural signals derived as humans' reason. One expansion I have begun to pursue, for example, integrates the EVC's cost-benefit assessment with the PRO's expectation updating mechanism to explain how predictions of costs and benefits are adjusted across experience (see progress here).

Research Practices

Altogether, my research program partners EEG with computational modelling to explain the complexity of cognitive mechanisms involved in reasoning. However, the success of this program demands my adoption of rigorous research practices – namely, my commitment to inclusivity, open science, and collaborative initiatives.

First, the consideration of equity, diversity, and inclusion in my research is of primary focus. By recruiting diverse participants, I will ensure my findings are sensitive to individual differences (e.g., gender, ethnicity), and thus generalizable to a large population of people. Similarly, I find it important to build a laboratory with a diverse team of researchers as I value how different perspectives and experiences will improve the laboratory environment, interpretations of findings, and applicability of research to society.

Next, I believe that open and transparent science is necessary to achieve proper scientific rigour. I now have three publications where the data and scripts are freely available and have made this my new standard (Williams, Ferguson, Hassall, Abimbola, et al., 2021; Williams, Ferguson, Hassall, Wright, et al., 2021; Williams, van Oorschot, et al., 2021; see my OSF profile). For example, I provide data and analysis scripts of 500 participants alongside methodological guidelines to further standardize EEG practices (Williams, Ferguson, Hassall, Abimbola, et al., 2021). Similarly, my research program will endorse replication initiatives independently and through collaborations with the EEGManyLabs and other similar groups.

Finally, science is quickly moving away from isolated research groups and into vast collaborative networks as the combination of diverse expertise propagates creativity in research beyond what could be accomplished by an expert alone. I have a rich network of both academic and industrial collaborators and have worked on projects ranging from predicting participant semantics with computer scientist Dr. Alona Fyshe (Foster et al., 2021) to using brain-computer interfaces to control technology with L3 Harris Inc. (see my similar work here). I'm excited to bring my collaborative network to the department and to offer my skills and knowledge in new collaborations both within and outside of the department.

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