# PhD Study #4: Refining the ML/DL Argument for the SensorAble Project

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**Abstract**

Is Machine Learning/Deep Learning (ML/DL) a *technological necessity* when implementing SensorAble or is it something to be *investigated* because of its potential? Should ML/DL be implemented because it permits processing large quantities of multimodal data enabling modelling of autistic neurocognitive processes that well relate to distractibility and anxiety? Or would interventional prototyping using old-fashioned Artificial Intelligence (AI), Bayesian theory or a hand-crafted rule be preferable?

Following Participant Public Information (PPI), can ML/DL techniques permit greater understanding of how disruptions occur and properly align/prepare the groundwork for an interventional prototype? Would heuristics, data mining, or perhaps some other statistical approach adequately provide evidence proceeding a design? With the constellation of supervisors who have invested in this project, can fundamental science properly situate SensorAble in a broader vision that creates practical tools? It is one thing to understand and model a problem. It's another to simply design/build. Doing the latter may inform the user, but how does it guarantee that other stress factors, ethical issues and newly created anomalies aren't inadvertently introduced?

*Keywords: Autism Spectrum Condition, Attention, Focus, Machine Learning, Deep Learning, Multimodal Learning Analytics, Distractibility, Anxiety, Focus.*

## 1. Introduction

Heterogeneity often confounds understanding phenomena in autistic study. Themes as diverse as causality, genetics, behaviour, socialization and communication all suffer as a result of the dissimilarity in problem-solving. Regarding sensory predisposition, variants exhibited by a spectrum of responses to environmental, physiological and interventional responses widely diverge.

A proposed solution used to capture an appreciation of unique fingerprints affecting stimuli stems from: (i) principally grounding user-generated content, evidence and phenomena; and then, (ii) following this harvest by dialling-in appropriate neurocognitive supports.

While artificial intelligence (AI) offers great potential in serving a technical role in the latter process, there are limitations, perceptions and ethical issues—to say nothing of practical basics—that beckon us not to embark on a prototyping mission, but to suspend interventional development in favour of closely capturing and understanding facts first.

## 2. Looking backward: multimodal learning analytics

There is a scholarly legacy of sensor utilisation to capture synchronised, individually created and responsive activities *in situ* that are related to physiological and ecological stimuli (Spikol et al., 2018). These fall beneath the banner of Multimodal Learning Analytics (MMLA), which aims to understand and optimise learning process predominantly wrapped within educational contexts (and not neurocognitive ones).

While the majority of these studies interrelate technologies to a largely scholastic framework, there is every reason to suggest the probable allowance of MMLA to cognitive neuroscience—particularly with relation to autistic distractibility, focal-attention and physiological symptoms (e.g. anxiety).

In fact, MMLA has produced "virtual learning environments, mobile applications, and student-response systems, which are rapidly becoming part of the everyday educational landscape" and may well lead to newer systems that provision interventions that analyse, respond to and alter/filter an individuals' highly stimulating environment (Ibid., 2018, p. 366).

Multi-dimensional systems may include pupillary, face and bodily movement tracking, audiometric, biosensors and the resultant log and user files related to both biological responses and environmental cues. Researchers have: (i) classified data points with acceptable accuracy rates, (ii) extended records in support of classroom teaching, (iii) analysed complex streams from divergent sources, (iv) predicted performance based upon statistical analysis, and (v) featured reduction algorithms to advance the state-of-the-art (Grover et al., 2016; Preito et al., 2016; Ochoa et al., 2013; Schneider & Blikstein, 2014; Worsley, 2014).

Historically, classification models applied to MMLA illustrate superior precision. These are well documented across predictive performance (Giannakos, Sharma, Pappas, Kostakos, & Velloso, 2019), complex evaluation (Di Mitri et al., 2017) and human decision-making processes (Cukurova, 2019); all of which constitute cognitive enhancing techniques.

While MMLA may provide a deeper understanding of disruptive stimuli by capturing hi-fidelity multimodal inputs and signal processing, the ability to coalesce and evaluate multi-sourced data using machine learning may clear a pathway toward greater understanding of sensory patterns experienced by autistic individuals.

Originating distinctive facets of autistic heterogeneity creates a magnitude of information that may be mined best by traditional and deep learning techniques. These "capture the complexity of learning through data intensive approaches" (Worsley, 2012; Siemens & Baker, 2012; Spikol et al., 2018, p. 367).

As Cukurova mentions: most MMLA "approaches aim to provide explicit and comprehensible ways of presenting information to learners and teachers to make them more informed in their decisions. This positioning differs significantly from the multimodal machine learning approaches that aim to automate the decision-making process itself" (Cukurova et al., 2019, p. 3034). Hence, could not MMLA combined with machine learning assist autistic individuals by better informing them through alerts, filters and haptic coaching?

Extending MMLA beyond educational spaces may lead to predictive cognitive items and other related procedures. The feasibility to alert, filter or otherwise coach "at-risk individuals" through sensory challenging moments may provision insight and nurture proper, ethically harvested and resourceful solutions.

Machine learning approaches (e.g. neural networks and traditional regression approaches) may one day classify MMLA data to the advantage of autistic

## Creating new Research Questions combining SensorAble to Multimodal Learning Analytics, Machine Learning and Deep Learning

Q.1.: Can analytic classifications support modelling responses to ecological and biological cues resulting in decreased distractibility and anxiety with increased focus among autistic individuals?

Q.2.: What are the relative accuracies of multimodal analytic models in classifying environmental and physiological stimuli and their relation to the heterogeneity among autistic individuals?

Q.3.: What sensor features from ecological and physiological data are good predictors of distractibility, anxiety and focus?

Q.4.: Can the exploration of different supervised machine learning approaches accurately classify MMLA data and contribute toward their predictive quality and high accuracy necessary to craft alerts, filters and coaching that increases attentional focus whilst decreasing distractibility and anxiety?

Q.5.: Can a new line of MMLA research provision new ways of understanding heterogeneous phenomena related to reactivity and responsiveness to ecological and physiological distractors?

## 3. A way forward: applying MMLA to SensorAble



 

individuals and engineering challenges related to SensorAble aspirations. In so doing, projects may leverage big data to “devise naturalistic assessments which would be, at the same time, social, ecologically valid, more inclusive as to the types of knowledge they measure, and enabling real-time evaluation in realistic tasks, either off or online" (Blikstein, 2013, p. 9).

Hence, SensorAble aims to (i) *examine and correlated* MMLA data among audiometric, pupillary, inertial movement and biological responses to environmental cues and their effect on distractibility, focus and anxiety; (ii) *mine* data points to reveal patterns that are applicable to heterogeneous responses; and, (iii) *extract* predictive data creating filters, alerts and coaching that aids individuals with greater focus in disruptive and anxiety-producing environments (Schneider and Blikstein 2015).

## 4. Heuristic versus analytic processes

If we are able to properly extend MMLA to a neurocognitive space, we must equally understand and sensitize ourselves to the *decision-making processes* exhibited by a heterogeneous autistic community that contends daily with ecological and biological cues.

The literature indicates two generalized methods of decision-making or executive-functioning processes. The methods of selecting and successfully monitoring behaviours that facilitate the attainment of a chosen goal rely on either *heuristics or analytic practises*.

Research purposes that heuristics operate automatically and autonomously with the individual exhibiting little to no conscious control (Kahneman & Frederick, 2002). Analytics, on the other hand, proceed in a more stepwise fashion through both deliberative and conscious awareness (Betsch, 2008).

Heuristics, therefore, carry a consequence requiring the individual to exercise less time and labour when reaching a decision. This, however, is tempered by significant bias resulting often in inadequacies and miscalculations. Analytics juxtapose heuristics and require an individual to operate at slower, more methodical approach occasioning evaluative standards routinely free from preconception or preference.

Relating to AI, Bayesian theory and logistic regression may be categorised as analytical methods. While there is a limit to their purpose and distribution, a benefit lies in their clarity (Russell & Norvig, 1995).

## 5. MMLA Research questions applied to SensorAble research

This then leads us to the crux of incorporating MMLA into SensorAble research; specifically: how can research questions be adapted to MMLA, DL/ML and this project? Here are five proposed interrogations:

- Can analytic classifications support modelling a response to ecological and physiological stimuli resulting in decreased distractibility and anxiety accompanied by increased focus among autistic individuals?
- What are the relative accuracies of multimodal analytic models in classifying environmental and physiological stimuli and their relation to the heterogeneity among autistic individuals?
- What sensor features from ecological and physiological data are good predictors of distractibility, anxiety and focus?
- Can the exploration of different supervised machine learning approaches accurately classify MMLA data and contribute toward their predictive quality and high accuracy necessary to craft alerts, filters and coaching that increases attentional focus whilst decreasing distractibility and anxiety?
- Can a new line of MMLA research provision new ways of understanding heterogeneous phenomena related to reactivity and responsiveness to ecological and physiological distractors?

## 6. Limitations, perceptions and ethics

Of great ethical concern is whether or not MMLA should be coupled with deep learning, machine learning or AI. Are unpremeditated by-products created as a result of implementing machine learning? The literature suggests that cognitive enhancement, replacement or assistive technology appear preferable over automation/replacement of human functionality (Cukurova et al., 2019).

Understanding the depth and breadth of systems within the context of at-risk populations, their ability to achieve autonomy and an expansion in quality of life is critical. Similarly, “we also need to identify the potential unintended consequences of these systems” (Cukurova et al., 2019, p. 3032)

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