**Topic**:

Flood-Risk Prediction (Germany and the Netherlands)

**Instructions**:

Need minimum 400 words

Need 3 APA References

Need 3 **Contributions** (Not Responses) (150 words minimum each)

(Use uploaded document for the Contributions)

**Initial post 1**:

There has been a lot of debate surrounding the topic of correlation of humans and technology, specifically in the context of which entity should drive the analysis of data. This can be seen in the machine learning sphere as well. Two broad categories of machine learning algorithms are supervised learning and unsupervised learning approaches. As one can infer, the major difference between the two is the aspect of human knowledge. While the former trains the machine learning models using human knowledge (supervised), the latter instead relies solely on the machine learning algorithms to detect patterns and extract features from the data. It is important to lead with the point that neither class of algorithm fits all the cases, and a choice between the two is usually determined by the type of application and the nature of the problem. However, studies show that supervised learning approaches have expressed a higher level of accuracy in classification and regression problems. In order to understand the disparity here, we have to dig a little deeper into the inner workings of these models. Let us begin with the creation of these machine learning models. The core of machine learning is an entity called the neural network. This is aptly named because its operation is similar to that of a neuron in the human brain. The process of “training” a neural network is identical to the idea of teaching an infant to recognize shapes and different colors. The neural network is fed a bunch of images or categorical datasets that represent an exhaustive dataset. This is the point where supervised and unsupervised learning approaches take different paths. Supervised learning relies on annotated human key points in these datasets that the network can use as initial knowledge to begin the learning process. As the iterations progress, the network extracts higher-level features and starts becoming more responsive and better at detecting the target features in a new image or dataset. Unsupervised learning, however, differs here because there is no human knowledge fed into it. The machine learning algorithms in the network are responsible for extracting first-stage low-level features and merge them to form high-level features.

**Initial post 2**:

Computation models are being used in decision making process to test the effectiveness of the proposed policy and to make further changes based on the outcome of the model. Technology usage in decision making has been increasingly used to make policy better and it was being applied to public policy making as well. The outcome of the model is determined by the data that is given to the model when it is being tested. When a policy in being implemented and technology is being used to influence the decision-making process, it should be evaluated whether technology that is being used is biased towards the outcome or data that is given to the model to test is biased. When technology is considered that are various kinds of opinions regarding the technology of who is controlling it whether it is humans, or the technology is controlling humans and whether technology is considered neutral or biased effecting the outcome of the opinions raised (Smith & Marx, 1994; Scharff & Dusek, 2003). To evaluate the values of the technology and data that are considered for testing are evaluated from different case studies. Based on the research, it is observed from the actors involved that the data which is considered neutral towards outcome have similar kind of goals that they need to perform and when data is considered biased it is observed that the actors involved have different perspectives towards the goals. When the technology is considered, when the political goals of the technology ownership and actor match, the technology is considered as trusted and neutral whereas when the goals of the technology ownership and actors goals differ then the technology is considered biased (Moody & Gerrits, 2015).

**Initial post 3**:

Computational models are becoming increasingly popular in public decision making. Public decision making takes place in an erratic, complex world. Increasingly, public decision makers deploy computational models in order to make sense of the possible consequences of decisions. Such models are rarely available off the shelf and are often developed for specific cases. As such they are tailor-made and the process of building and using the models becomes an integral part of the public decision-making process. Public decision makers struggle with too little time to make well-informed decisions (Lee, E. A., & Sangiovanni-Vincentelli, A., 1998). Computational models bring the promise of shedding light on the object of decision making. The assumption is that a computational model is a valuable free tool that will provide a neutral oversight of all available alternatives with their consequences. Computational models of decision making assume that the following five processes are carried out at the time the decision is made: representation, action valuation, action selection, outcome valuation, and learning (Rangel, A., Camerer, C., & Montague, P. R., 2008). However, it is important to recognize that computational models are normative because of they cannot mimic full reality and instead reflect the developers and users ideas. It is important to recognize that the data and the relationships between variables are of a complex nature. This means that it is possible models used by different actors generate entirely different outcomes. It is not as much a design flaw of the model but rather a consequence of the complexity of data and models. Policymakers should be aware of the details and uncertainties of the model, modelers should communicate these more accurately. This will lead policymakers to be more specific in what they ask modelers to design and it will help them interpret results in a way policy-making could improve.