A REVIEW OF BIAS IN DECISION-MAKING MODELS

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Abstract:A decision-making model solution is a dependent variable derived from independent variables, parameters and forcing functions. Independent variables collected in linguistic form require intuition which can be potentially biased. A collection of qualitative research papers on bias in models was perused to identify the causes of bias. Decision-making in the manufacturing, finance, law, and management industries require solutions from a complex assortment of data. The popularity of combining decision-making with artificial intelligence (AI) for intelligent systems causes concern, as it can be a predisposition to a true solution. A true solution avoids impartiality and maintains repeated results from a natural phenomenon without favoritism or discrimination. This paper appraised the development of the decision-making environment to identify the path and effect of bias on the variables used in models. The literature reviewed was associated with the design of a decision-making criterion rationalizing the application of variables. The influences on variables were observed with respect to the available resources, environment, and people. This list was further extended to consider the constraints of the resource, customer, network, and regulation fed to the structure. The involvement of bias was founded because of the need for rational decision making, cognitive misperceptions, and psychological principles. The study of variables showed the opportunity for a conscious bias from unethical actions during the development of a decision-making environment. In principle, bias may be best reduced with continuous model monitoring and fair adjustments. Ignoring these implications increases the chance of a bias decision-making model. It also influences the decision result and may be avoided with an ethical and fair quality review. The paper increases the awareness of bias in decision-making and guides actors to the identification and avoidance/reduction of bias effects. This may be a guide for the reduction of the model error to achieve a true solution.

Keywords: *Attributes, Decision-Making, Intelligent Systems, Status Quo Bias, Variables.*

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1. Introduction

Ration and intuition describe the overarching forms of decision-making. Rational decision-making logically compares the level of confidence against the worst [1] and intuitive decision-making provides quick solutions developed by instinct without logic [2]. For example, a production schedule requires data of a technical nature and the present status of a dynamic industry must be rationally analyzed. Each situation can achieve a straightforward solution once the persons involved have current valid information and uses the best method to process the solution. A sudden demand change may require intuition when insufficient and incompatible data is available. It will not fit in the rational logic and pressure of time schedules add to the need for immediate action. The accuracy of the method and information highly depend on the model and variables considered for the choices available. The general decision-making procedure (see Figure 23) contains a problem, symptoms, and behaviors. Constraints can be developed to forecast a theoretical desired state solely influenced by endogenous variables. Practical solutions are complicated by exogenous variables caused by influences out of the boundary [3]. This paper attempts to explore the effects surrounding variables from the conscious and unconscious mind.

2. Steps in Decision-Making

Decision-making models begin when an actor (an individual or team) desire change of an existing state after discovering a problem, Step 1of the General procedure for decision-making (Figure 23). The actor is required to plan (Step 2) and evaluate (Step 3) a change for this existing state or develop a procedure that would attain the desired state. During the decision-making process, most may confer that identifying differences between the existing and desired state can be challenging. In reality, the issues arise when more than one approach leads to the desired state, identifying additional issues to be included in the plan (Step 4). In hindsight, the actor usually notices that there is more than one method available (Step 5) and regrettably has to choose an option. Initially, it is important for the actor to realize that a change of states identifies the alternative methods and develops a procedure to select the most appropriate method.

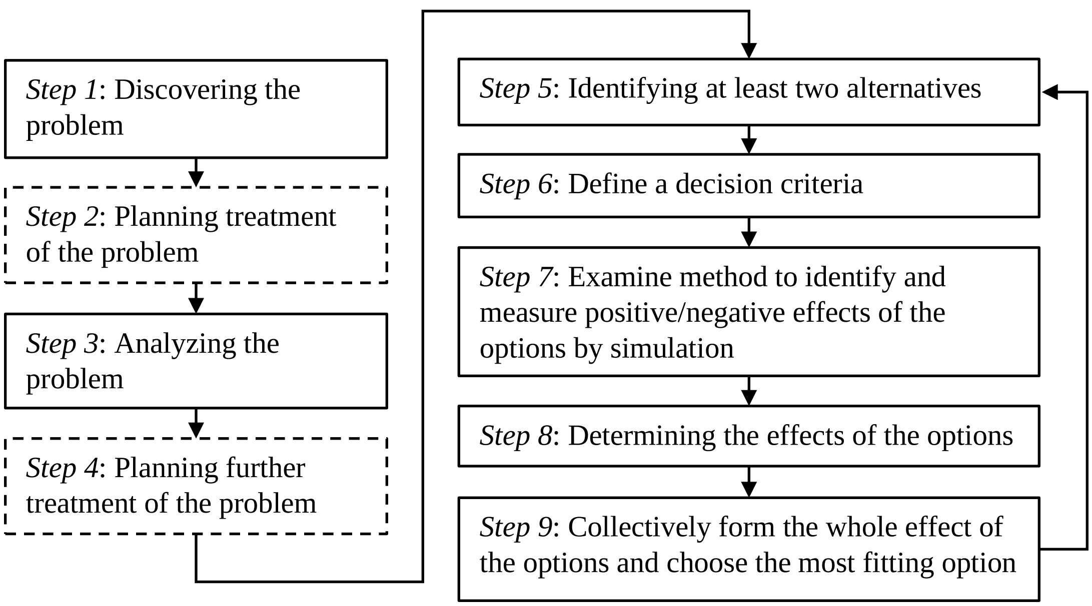


Figure 23: General procedure for decision-making [4]

The source of decision-making challenges arises from sorting through the methods which may contain a combination of multidimensional issues with qualitative and quantitative data to achieve the goal (Step 5). For example, dependently linked attributes require inputs from actors of different interests, who themselves may actually be unsure of the external environmental impact. The chosen method may be influenced by decision maxims, principles, documented procedures by expert experience in the field, lessons learned and experience in the field [4]. Coincidently, these issues in group decision-making transfer into an intelligent system as both are principally mathematical models. A group of persons with a special interest is required to design this model. Intelligent systems may accelerate to a further step and feed a solution into another decision-making environment or use it as data to actuate a process. Henceforth the discussion will simply refer to the development of a general model focusing on the variables leaning towards intelligent systems.

The decision-maker ranks the consequences and evaluates the impact of the choices and behaviors toward the new state. Emphasizing, a clear description of the objectives and responding attributes is necessary to succeed (Step 7). Hence beginning with the objectives (Step 8), it is convenient to have a reference from the initial state where one can easily identify the core transition to the new state (Step 9). There may be natural occurrences of objectives queueing not only profiling dominance but offering a sense of order and direction. Decision-makers must be careful not to lead the analysis astray. Focus is maintained by perusing relevant literature, providing an analytical approach that is consistent with the present practice. The objectives would assert certain attributes that aid in the clear understanding and measurements ranking the alternatives and ensuring the main goal is still achievable [5]. Failure to identify a suitable alternative sends the actor back to Step 5 to reiterate the steps.

3. Models

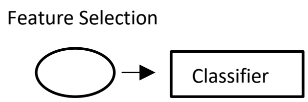
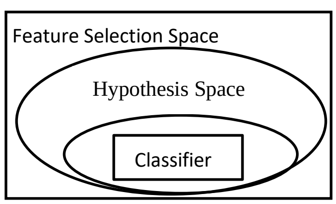
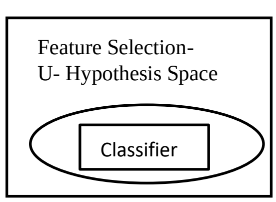
A model comprises the following development stages: Identify a clear objective and depict the expected results; Determine key variables and their relations; Construct the model that provides the expected result; Model analysis to verify, validate and if necessary calibrate and the last stage simulate. A model can be considered a mathematical expression closely emulating a physical system or process composed of variables or decision parameters; constants and adjustment parameters; input parameters, data; phase parameters; output parameters; noise and random parameters. It is generally represented as a functional relationship of the form:

$$\text{Dependent Variable} = f(\text{Independent Variables}, \text{Parameters}, \text{Forcing Functions}) \quad \text{according to [6]}$$

The Dependent Variable reflect the system behavior; Independent Variables are dimensions that determine the system behavior; Parameters reflect the system's properties or composition and Forcing Functions are the peripheral impacts acting upon the system. The model should represent an analytical selection that is quicker and affordable than replicating a full-scale environment for the decision-making process. It provides the flexibility to compute solutions under different combinations of variable values. In the order of increasing quality and amount of resources/effort required, models are categorized as satisficing, adaptivising and optimizing respectively. Some models give purpose providing solutions that predict behaviors or prescribe the order for actions. They can also be time-based where the solution is repeatable due to a static environment or is continuously altered due to dynamic conditions like interval variations and/or distance or to the natural responses from the environment. Also, there are solutions derived from deterministic models where the values are confirmed with no randomness. The extremes are solutions from probabilistic models where the values are random due to the nature of the statistical analysis. The variables in these models are either discrete or continuous based on the nature of the components in the environment. These represent the lower and greater extremes of the model characteristics that are hybridized to develop closer to a realistic solution [7].

The main goals of models are to diligently simulate an environment to determine a most accepted and plausible response based on both known and unknown interactions. The actor should easily interpret the model design and comprehend the operations and responses of the model. The ability to distinguish the association or correlation amongst the variables is essential for efficient model design. Tolerating that one may not be capable to represent all variables in a physical or psychologic system and an error is expected. Errors should be evaluated to determine the level of detachment from the actual environment. The components of the detachment involve an irreducible error, a squared bias, and a variance response [8]. Unfitting choice of independent variables contributes to unnecessary noise and false interactions carrying the dependent variable away from the real state. Acquiring and processing independent variables require resources and with a limited budget, one may require to reduce the number of variables by a strategic elimination process. Developers must set a limit on the scale of the model, as larger models tend to create a greater number of computational points resonating large quantities of combined cross interactions amongst the variables.

Table 25: Summary of feature selection techniques adapted from [9]

Method	Application	Advantage	Disadvantage
Filter	Evaluates fundamental properties 	*Univariate* Fast Scalable Independent of the classifier	Ignores feature dependencies Ignores interaction with the classifier
		Multivariate Models feature dependencies Independent of the classifier Better computational complexity than wrapper methods	Slower than univariate techniques Less scalable than univariate techniques Ignores interaction with the classifier
Wrapper	Evaluates the performance of a subset of features based on the resulting performance of the applied learning algorithm 	*Deterministic* Simple Interacts with the classifier Models feature dependencies Less computationally intensive than randomized methods	Risk of overfitting More prone than randomized algorithms to getting stuck in a local optimum (greedy search) Classifier dependent selection
		Randomized Less prone to local optima Interacts with the classifier Models feature dependencies	Computationally intensive Classifier dependent selection Higher risk of overfitting than deterministic algorithms
Embedded	Searches for a subset of features in the classifier construction that is highlighted in the combined space of feature subsets and hypotheses 	Interacts with the classifier Better computational complexity than wrapper methods Models feature dependencies	Classifier dependent selection

This phenomenon can be reduced, by separating the variables into two categories the first, predictive where the dependent and independent variable is highly correlated and the second, prescriptive where the independent variable reduces the expected error of the dependent variable [10]. The model is commonly simplified by reducing the number of independent variables while maintaining its initial policy [11].

4. Feature Selection

Since the 1970s, 'feature selection' in this case alternatively represented as 'variable selection' has been researched and developed for the common application of reducing models before it is implemented [12]. Managing the independent variables is necessary, where they are either individually or combined for the process through a filter, wrapper or embedded method. Some also pass the variables through a hybrid of the methods to maximize the strength of each method. Table 25 summarises the different methods describing the routine applied and sharing insights of each method.

Eventually, two distinct but sometimes confused teams evolved and have been responsible for the many available intelligent systems. One group focused on artificial intelligence by mimicking the human thought process including psychology, philosophy and cognitive sciences. The other group worked on computational intelligence which modeled natural intelligent systems, for example, a neural network was modeled based on the physical functions of the brain [13]. Developers are not only working to reduce the expected error and simplifying the model but also have to economize the process. The system contains rules in the form of constraints that are initiated at specific levels and environments. This can be controlled with reference data and rules that allow the system to observe, learn and store data patterns for the next step. They also evolve and adjust the model for the next pass omitting involvement of subject matter experts to review the model. Developers aim for the latter to avoid high expert costs [14].

Table 26: The types of variable learning sources adapted from [15]

Source	Relation	Data Form
Direct Sensory Experience	Observations from our sensory organs	Responses from sight, smell, taste, touch, and hearing
Authority	Perceived experiences	From the conversation, reading and the following media
Electromechanical Sensor	Physical measurements	Data gathering instrumentation
Reflection	Reorganized conjoined thoughts from observed knowledge	Belief system (current state) deduced, induced and reasoned
Mystic	Human internalizing	From dreams, Subconscious, hallucinations, superstitiously invoked

Artificial intelligent systems are also naturally inexorable affected by the one variable which will disagree with the cognitive portion in the model. This model can easily be defunct in another credible condition reducing a complex intelligent system back to basic modeling principles. Simplifying the environment contributes to a larger irreducible error which should fall within a previously agreed range [16]. Table 26 illustrates the types of learning sources relating to the type of source and form of data collected.

On the other hand, the solution also includes deontological and teleological evaluations measured by egoism, benevolence, and principle. Based on the type of actor, individuals displayed traits of self-absorption, affiliation, and personal morality; regional groups displayed professional interest, collective interest and organization rules/procedures and multicultural groups displayed traits of proficiency, communal obligation, and laws/professional rules. These were seen to be related by an individual's age, gender, education level, experience, and moral philosophy. Decision-making with actors having greater that one person could be impacted by influences of a code of ethics, ethical climate, organizational size and industry type [17].

5. Influences on Independent Variables

The factors of innovation impact the choice of the independent variables, see Table 27. All projects are constrained to the availability of resources. It is critical that value is received for the effort of any project.

Table 27: Factors influencing the variables adapted from [18]

Factors	Sub-Factors
Resources	Motivation Funding access Time Competence Insurance /Risk
Customer influence	Procedure Quick onsite solution Health and Safety
Networks	Experts and industry Research organizations and universities
Regulations	Performance-based standards State regulations Industry standards

Unavailability of equipment or modes of acquiring variable data limits the model and the actor must measure the risk of compromise. The team must also understand the customer's (internal and external) specific needs to get the correct results. External customers may request unrealistic milestones and add to the work stress. The development of the system requires knowledge and it is best practice to pursue a network of experts for guidance. Then possibly the most important factor is to ensure that variables use valid data and comply with the standards and laws of the respective discipline [18].

6. Bias

According to the Merriam-Webster Dictionary, the word 'bias' can be defined in many forms. Such examples are, 'An inclination of temperament or outlook'; 'An instance of such prejudice'; 'Bent, Tendency'; 'Deviation of the expected value of a statistical estimate from the quantity it estimates' or 'Systematic error introduced into sampling or testing by selecting or encouraging one outcome or answer over others'. These apply to many situations with a common connotation describing the deviation from a true reference. Presently, most forms of decision making involve a high degree of human input. Humans are involved from the start during the model design, collection of data, within the data entry and during the revision of the model.

The actions to avoid the effects of the weak judgment in decision-making should be initially guided by the actor's awareness of the environment. This requires experience via repeated feedback and expert deliveries having strategic continuous evaluations avoiding preferential and psychological bias, see Table 28. The involvement of external participants can reduce the bias because of the involvement of parties that are not beneficiaries of the decision. It is recommended to develop a model including the correlation of the attributes for a better solution. Also, actors are better at selecting variables and coding algorithms to compute reliable solutions without bias rather than using sole intuition. Identifying the deficiencies and forming adjustments require the actor's intuition which carries the importance of being aware of the environment [19]. It seems that rational thinking resists the effectiveness of reaching the goal and decision-makers intuitively choose attributes that may be far from relevant.

Table 28: Foundations of Bias [19]

Category	Source	Cause
Rational decision making	Experience; Presence of conversion costs and/or uncertainty.	Learning; Comparison to similar situations; Identical options.
Cognitive misperceptions	Failure; Fear of re-entering bad experience; Anchoring.	Endowment effect-Snowball effect of negative memories; Losses are highly weighted; The premeditated setting of an acceptable range that is not optimal.
Psychological	Misperceived sunk costs; Regret avoidance; Non/optimal Consistency; Regret Avoidance; Self-perception.	Commitment; Disagreeable experience; Change undesirable; Views of others; Internal rationalization; Imposed; To be in control.

The deflection from true values is inevitable as human involvement tends to gravitate out of proportion to an alternate choice as the option without seeking other opportunities. This chosen option is likely to be the most recently experienced with an acceptable performance because of the natural disinclination to change the norm especially if the option is new and unknown. Most prefer to be static and omit the new venture to avoid future anticipated anxieties. Experts use the term status quo bias referring to this type of natural behavior [20]. The strength of the actor and a large number of options also impact the degree of bias. Status quo bias is not a calculated error, it is the product of combined unconscious behaviors performed without retrospective favor. Defining a policy, clearly describing the environment and its constraints with strong evidence lowers the ambiguity and conceivably permits unemotional participation. Setting an open environment creates an infinite amount of human interactions throughout the decision-making process increases the chance of a status quo bias. One can observe responses produced from simple convenience, habit, a popular choice, policy, fear of being different or rational thinking [21].

7. Discussion

Successes toward innovative change are heavily dependent on the access to resources and also depend on customer influences, conditions, availability of networks and regulations. The innovations involving new products, processes or equipment will own its problem comprised of conflicts of mutual and/or unrelated standards [18]. The conflicts of decision-making according to Polič, can be stressful and require behavioral management in a dynamic environment to ensure the objectives are met within its agreed constraints. Essentially the control of rational and intuitive decision-making environments can ease management concerns of actors during the process.

Table 29 summarises some of the stresses and offers some modes of action to reduce and manage the effects [22].

Table 29: Stresses of Decision-Making [22]

Source of Stress	Cause	Action
Variety of data sources	Environments contain multiple interactions Challenge of sorting and collect data Large data sets require software adding another level of unknowns within the software	A clear understanding of objectives Acquire correct tools/resources Willing and competent participation
Partial and contradicting data	Wrong data acquisition method	Change the approach method
Continuously changing environment	System change Increase or decrease level understanding	Continuous review
Management of actors	Human Factors	Set clear, accurate and precise information. Team environment
Adverse working environment	Low level of comfort	Provide all needs
Failure is not an option	Fear of disappointment Job loss	Be aware of the result repercussions
Work overload and Time not managed	Lack of understanding tasks	Team involvement to decide the project flow deadline
Information overload	Too many details	Break up into small tasks

Threatening environment	Internal and external influences	Know the environment and prepare for all outcomes

According to White, one should apply intelligent systems to automated systems where the environment already exists as venturing into systems with a high degree of understanding may be good practice. Unknown systems can be applied experimentally to determine cause and effect situations.

An intelligent system solves complex decisions and pushes the computational limits to greater capabilities. It solves complex problems with large datasets at improved rates and possesses a high chance of eliminating human intervention with the rise of evolving systems. This situation has its obvious benefits but actors should understand the risks, especially when the system runs automatically and contains algorithms that initiate and carry out calibrations or changes in its supervised data profiles. One mimicking human behavior should be able to forecast the expected error through a comprehensive understanding of the inputs, choices, weights, and consequences of the results [23]. To some extent the reversed principles behind the three laws of robotics by Isaac Asimov may now have to be considered as evolving intelligent systems become popular. The corresponding response for first law- ‘A robot may not injure a human being or, through inaction, allow a human being to come to harm’ response ‘A human should not produce a model that is unacceptable to industry standards’; second law- ‘A robot must obey orders given it by human beings except where such orders would conflict with the First Law’ response ‘Evolving systems should be designed to maintain the objectives of the initial model’ and third law ‘A robot must protect its own existence as long as such protection does not conflict with the First or Second Law’ response ‘Human intervention should maintain the first and second corresponding response’. The literature shows that conflicts will appear, produced by human behavior both with a purpose as discussed above and organically processed internally.

Developing decision-making models should comprise a complex management system operated with persons trained in the discipline of the subject analyzed and psychology. One should be cautious, as the decision-making technology advances in the realm of evolving in its own ecosystem. Care should be taken to provide continuous monitoring of the systems by a manageable ethical team highly competent, cross-functional and willing to learn.

The paper partially veered to the hard-core components of decision-making which has its own but relative environment and isolated challenges. Many researchers are now focusing on the cause and effects of soft environments, for example, the deliberation on the behavioral cognitive responses of people. In the future, it would be interesting to compare the impact of the management of hard and soft disciplines of decision-making.

8. Conclusions

This paper appraised the variables of decision-making systems of the simple decision-making process and intelligent systems. The components and purpose of models were explored to introduce the selection, influences, and bias on variables. It was evident that an expected model error will always be present. Particularly, when involving multiple persons at either the development or data gathering stage of the model. The dynamic human cognition combined with the formations from the conscious and unconscious biased circuit within the mind contributed to the error. The advent of evolving intelligent systems surely guarantees the full attention of actors to ensure an ethical result.

Many disciplines replicate systems to achieve an agreed solution through the design of models. Acknowledging the unfortunate possibility of the conscious and/or unconscious bias is critical to achieving a higher acceptance level or reduced error margin. The paper promotes the awareness of bias and increases the quality of the model. A model error can be reduced with the analytical selection of variables and an actual understanding of the stimuli within its environment. Finally, it was discovered that systems of this nature can evolve continuously formed naturally (in the case of intelligent systems where the supervised data may be automatically updated) or through a change of the system objectives (the actor requires a new solution). It is encouraged to periodically monitor the model with an ethically competent team to ensure objectives are met under a controlled and assented environment.

Future research work encompasses the derivation of the highly influential components that characterize the bias of variables in model development. This attempts to identify the contributing characteristics of bias and determination of the relative weighted effect toward the identified bias. The results of this work will reduce the model error drawing the model closer to a true solution.

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