Article

Managing Uncertainty in AI-Enabled Decision Making and Achieving Sustainability

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Abstract: Artificial intelligence (AI) has been applied to various decision-making tasks. However, scholars have yet to comprehend how computers can integrate decision making with uncertainty management. Obtaining such comprehension would enable scholars to deliver sustainable AI decision-making applications that adapt to the changing world. This research examines uncertainties in AI-enabled decision-making applications and some approaches for managing various types of uncertainty. By referring to studies on uncertainty in decision making, this research describes three dimensions of uncertainty, namely informational, environmental and intentional. To understand how to manage uncertainty in AI-enabled decision-making applications, the authors conduct a literature review using content analysis with practical approaches. According to the analysis results, a mechanism related to those practical approaches is proposed for managing diverse types of uncertainty in AI-enabled decision making.

Keywords: artificial intelligence; AI-enabled decision making; uncertainty

1. Introduction

Various artificial intelligence (AI) technologies have been rapidly developed and implemented for an array of crucial decision-making tasks. Stakeholders hold high expectations that AI can deliver excellent decisions. AI-enabled decision-making applications have enabled civilizations to enhance humans' quality of life. As an example, the autonomous vehicle is a novel AI application that provides humans with convenient transport services by autonomously analyzing road conditions and making driving decisions. The autonomous driving technology is expected to provide benefits such as improved life convenience, time efficiency, reduction in congestion, and efficient use of traffic resources. However, since the testing of autonomous vehicles on public roads was first permitted, numerous accidents and problems have occurred. Even if equipped with the most advanced camera and sensing technologies for object recognition, autonomous vehicles still cannot perfectly anticipate every trajectory of surrounding objects and accurately identify animals in the road if they do not have descriptive data in their databases [1]. When an autonomous vehicle encounters an unfamiliar situation (such as heavy rain, flooding, or mud puddles), the uncertainty of the road situation increases, and so does the risk to passengers. Furthermore, autonomous vehicles may cause safety risks if their algorithmic decision-making mechanism cannot address ethical challenges [2]. The aforementioned scenarios indicate that AI applications cannot anticipate every situation and inevitably must deal with various uncertainties in the decision-making process. The uncertainty challenge is critical to AI-enabled decision-making applications; AI technologies must grapple with uncertainty to adapt to the changing world in the long term [3] and ensure the sustainability of AI-enabled decision-making applications.

Decision making is a process that enables people to gather intelligence, design alternatives, and make decisions to achieve a purpose [4,5]. Decisions are diverse in terms of scope, context,

frequency, and influence. A wide decision scope results in a high degree of decision influence. Frequent and sophisticated situational changes lead to numerous uncertainties in decision making. Decision making heavily relies on information and knowledge; however, the collection of information and diffusion of knowledge require considerable investments of resources (e.g., time, stamina, and attention). The acquisition, storage, and application of information often exceed the limits of the human brain and burden their decision-making capabilities. With the assistance of advanced computing, programming, and networking technologies, people can efficiently process data and foster technology adoption.

In the past, computers were mainly decision supporters that offered functions for collecting, storing, and calculating data by using one or more given formulas. Advances in AI have gradually expanded the role of computers in decision making; a modern computer can serve as a decision maker, performing functions such as identifying models (to generate a formula), judging, and making decisions. Industries are applying those information communication technologies to enable decision making in various industries, such as retail, recruitment, manufacturing, and transportation. For example, an unmanned store does not require the presence of personnel to monitor and handle inventory; an autonomous vehicle does not require a driver to detect and react to road conditions. Smart factories (functioning in the Industry 4.0 paradigm) employ machines to operate and manage production lines. Human resource (HR) departments utilize computers to evaluate and interview candidates. AI applications can perceive their surroundings and execute actions based on those perceptions [6]. However, computers have both advantages and drawbacks; thus, the more crucial the decision is, the more prudent the user must be when applying such applications.

AI-enabled decision-making applications rely on computers to collect available information, build modeling algorithms, and extrapolate rules to make decisions. However, the uncertainty challenge that exists in the decision-making process has not been comprehensively addressed. This research plans to examine two pending questions:

(1)   What are the sources of uncertainty in AI-enabled decision making?
(2)   How can uncertainty be managed in AI-enabled decision making?

To understand uncertainty in AI-enabled decision making and address the related research gap, a literature review was conducted and three sources of uncertainty (i.e., informational, environmental, and intentional uncertainty) were identified and used as three dimensions for an analytical framework of uncertainty. Furthermore, this paper examines the functions and possible limitations of AI technologies. We conducted a content analysis of the published AI literature to answer research questions. Departing from technical and computer engineering perspectives, this research investigated the development of AI-enabled decision making from a social science perspective, focusing particularly on realistic procedures for managing uncertainty. A mechanism model is proposed along with practical approaches for regulating the development of AI-enabled decision-making applications, mitigating irreversible consequences, and achieving sustainability. Considering that this model has been generalized from empirical data, this research is an exploratory research that aims to identify principles supporting the capability of computers to make decisions and overcome the uncertainty problems. Discussions and conclusions are provided in the final section of this paper.

2. Uncertainty in AI-Enabled Decision Making

Decision making is challenging and heavily relies on information and knowledge. Information is messages that imply the state of the world, whereas knowledge is interpretative frames used to understand messages and construct an inferential understanding of the world. With the advancement of computers, current AI can efficiently process information and make decisions for people. This section scrutinizes uncertainty in decision making and the functions and possible limitations of AI technologies.

2.1. Uncertainty in Decision Making

Uncertainty is ubiquitous in realistic settings and generates a major obstacle to effective decision making. Lipshitz and Strauss [7] pointed out that uncertainty has three features: subjectivity; inclusiveness; and conceptualization as hesitancy, indecisiveness, or procrastination. The definition of uncertainty has been widely discussed and is easily confounded by similar concepts [7–13], such as risk and complexity. Uncertainty is distinct from risk. Risk can be evaluated through statistical methods, but uncertainty cannot because it involves the inherent inability to recognize relevant influential variables and their functional relationships. Uncertainty is distinct from complexity. Complexity occurs in any system with numerous parts that interact in a complicated manner [14]. If a decision task is formidable and intricate, extensive computing capability may be helpful; but if the decision task is uncertain, then human analysts are far from comprehending that task; those human analysts may even be totally unable to make a proper decision regarding that task.

Uncertainty is difficult to concretely assess, accurately predict, and avoid. Lipshitz and Strauss [7] proposed three sources of uncertainty: incomplete information, inadequate understanding, and undifferentiated alternatives. As AI applications can apply to individual decisions, three sources with three dimensions are used as the analytical framework in this research to clarify the diversity of uncertainty. Herein, the three dimensions of uncertainty are informational, environmental, and intentional uncertainty [7–10,15].

Informational uncertainty. Typically, a higher degree of uncertainty corresponds to a greater need for complete information processing [11]. Incomplete information is the most frequently cited source of uncertainty [10]. Two situations require the use of information. The first involves inductive reasoning. When everything about a situation is unfamiliar, sufficient information (i.e., observations) is required to construct and verify possible assumptions. The second situation is when the assumptive formula is ready and information (i.e., an independent variable) is required to generate results.

The most uncertain part of information acquisition is the quality of information with respect to factors such as information diversity [16], information quantity, information representability, and information sources [17]. Some informational problems are related to the characterization of data as objective or subjective and as primary or secondary. Although Zack [13] contended that computers can reduce uncertainty by collecting information, ascertaining whether the information available is adequate and sufficient is not always possible [7,15].

Environmental uncertainty. Every decision task exists in a specific environment in the real world [18,19], which contains various anticipated and indeterminate contingencies [20]. Furthermore, the real world is a complex system with a fundamental mismatch between causal relationships and other phenomena. When decision makers are unable to understand the whole situation and manage environmental factors [8], they may be confused by the contradictory meaning conveyed by obtained messages. Some contradictory messages result from a fragmented rather than holistic perspective of the world. Consequently, inadequate understanding can prevent the achievement of a smooth decision-making process [7].

In addition, scholars in computer science have pointed out that causal explanations are ubiquitous in AI training [21], which tends to increase contextual uncertainty. Rust [22] further noted that "the biggest constraint on progress is not limited computer power, but instead the difficulty of learning the underlying structure of the decision problem." When humans inadequately understand the contextual structure of decision problems, it is dangerous for those humans to allow AIs to take charge of unclear or even harmful processes and structures [23] because those AIs may calculate an optimal solution for the wrong problem or target.

Intentional uncertainty. After alternatives have been generated in the decision-making process, the decision maker relies on criteria to make a final decision. Even when decisions are concrete and objective, the generation of criteria is still variable. In other words, even when a community has a standard decision-making process, humans inevitably make final decisions according to heuristics [12,24], prospections [25], or preferences. March [9] argued that rational choices encompass guesses regarding uncertain future preferences in addition to guesses regarding uncertain future

consequences. The preference problem reflects a nonlinear weighting of decisions, and most aspects are computationally expensive with rational functions [26].

Regarding decision tasks involving a moral challenge, Nissan-Rozen [27] argued that making comparisons between the values and judgments of different moral reasoning processes is impossible. Regarding decision-making tasks involving the fairness challenge, Lee et al. [28] argued that understanding distinct human requirements constitutes a critical step because multiple stakeholders have conflicting expectations. Individual decisions such as driving and purchasing decisions are more likely to involve a preference problem or even a dilemma problem [29] because of those incomparable and conflicting expectations. Furthermore, another type of intentional problem is undifferentiated alternatives, which reflects the lack of a significant preference. Undifferentiated alternatives may cause uncertainty [7] because the likelihood of future events is unclear [10].

In summary, three sources of uncertainty in the decision-making process are information completeness, environmental context, and individual intentions. Environmental uncertainty originates from the unpredictability of the environment, whereas intentional uncertainty originates from individuals' specific preferences and diverse needs. Informational uncertainty can be managed with relative simplicity by clarifying the causal relationships between variables and acquiring information that is as complete as possible. However, unanticipated occurrences may always occur in the real world, meaning that the management of informational uncertainty remains difficult. The classification of three uncertainty sources has been widely used in many studies [7,8,10,15] and was applied in the current research to reexamine decision-making tasks in AI applications.

2.2. How Does AI Learn to Make Decisions?

Computers are skilled at processing information, although this processing is generally passive. In addition to the growth of big data analysis and increased availability of computational power, advancements in machine learning technologies have led to considerable progress in AI [6]. AI is defined as "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks [30]." By employing AI, computers can actively learn from available information. Herein, we discuss three learning paradigms, each of which provides a specific function for AI in learning to make decisions.

Supervised learning. A computer learns to recognize labels (or "features") by using training data (i.e., a set of samples composed of labeled data) and develops a function that relates the features to the objective. After a computer has been trained, the validation function is applied to predict other example sets. Examples of supervised learning technologies are classification [31], decision trees, and support vector machines. Supervised learning can be used in areas such as recommendation systems and systems designed to check for email spam; for example, consumers label their favorite products and provide them to a recommendation system to predict other products that they may like [32]. Supervised learning is data-driven bottom-up processing. The quality of labeled data is key to the predictability of supervised learning [33]. Thus, developers must ensure that the labels have no faults or impurities. Furthermore, the number of labeled data should be neither too small nor too large.

Unsupervised learning. No training data (or labeled data) are available in advance. The input data must be grouped into patterns or classified with certain observations; this approach enables the computer to learn how to recognize patterns and similarities in the data. Unsupervised learning is a top–down approach [34] used to discover the structural form of data [35]. Examples of unsupervised learning are clustering, use of artificial neural networks, and dimensionality reduction. Unsupervised learning is a generative model used to identify new dimensions and subgroups based on environmental data, which enables unsupervised learning to be particularly effective for specific functions such as anomaly detection [36,37]. However, its detection capability mainly relies on extrapolating relations but not exactly causal relations. Causal relations may be blurred and require further examination by humans; therefore, applying AI for complex decision tasks is dangerous [38].

Reinforcement learning. The learning mechanism of the human brain involves the constant adjustment of behavior in response to encouragement and punishment for adaptation to the environment. Reinforcement learning is a consecutive decision-making process that involves repeatedly making a decision, interacting with the environment, obtaining a return (or "reward"), and modifying the decision until the expected value of the overall return function is maximized (or "optimized"). As it does not require the labeling of input–output pairs in advance or the explicit correction of suboptimal actions, reinforcement learning is a powerful exploitation mechanism for an autonomous agent that focuses on real-time planning to perform trial-and-error processes in the environment [39]. Examples of reinforcement learning include temporal difference learning, dynamic programming [22], and Q-learning [40]. Reinforcement learning involves the use of Bayes' theorem to calculate conditional probabilities. Critics have noted that even a simple problem requires heavy calculation, and the normative framework for processing information is too unified [26].

Although AI efficiently collects as much information as possible to make decisions, most AI-enabled successes are limited to relatively narrow domains such as board games, in which machine learning technologies have achieved outstanding performance [22]. AI technology still has at least two unsolved limitations. **The first limitation concerns sample selection and model fitting.** Sample selection is key to model building in machine learning. The sample may be only labels or historical data. Developers must ensure that the labels do not have faults or impurities. Even though the fault tolerance and noise immunity of models can be evaluated using some measurements [41] and even though erroneous input can be handled using some methods [42], additional problems persist. Using historical data to make decisions is highly risky [38] because the real world constantly changes and contingencies may occur at any time. During turbulent times in particular, predictions based on historical data are easily distorted. Another concern regarding the use of historical data is that the sampling data may be a biased indicator [21]. In addition to data representability, the quantity of sampling data is another problem. An insufficient amount of data cannot be used for an effective algorithm [21,43], whereas an excessive amount can lead to the problem of dimensionality. Moreover, even when the amount of data is barely sufficient, a model can still exhibit an "overfitting" problem, in which the model has too close of a fit to the training data but insufficient fit to independent (nontraining) data [44]. Particularly when sophisticated models and rules are difficult to fully understand, misunderstanding between computers and humans may cause potential crises.

The second limitation concerns the criteria setting. Machine learning still requires a criterion set, label set, or reward set. It is unclear whether the criterion is produced by individuals' preferences. Most computers not only assume the environment is homogeneous but also assume every individual has the same preferences and intentions. However, individuality is a highly valued trait. All humans have their own will and unique life meaning. By contrast, computers are produced from a single standard criterion, and a lack of diversity can lead to worldwide disasters. Particularly when some criteria are controversial, a compulsory code to unify rules is improper.

From the aforementioned examination of AI technology, the limitation of data sampling can be considered to correspond to environmental uncertainty because variations in the environment lead to difficulty in sampling and modeling. Furthermore, the limitation of criteria setting can correspond to intentional uncertainty. It can be speculated that the two types of uncertainty in AI-enabled decision-making applications are influential but recalcitrant. Russell and Norvig [45] pointed out that "acting rationally" is one approach to AI. Furthermore, a rational AI is "*one that acts so as to achieve the best outcome or, when there is uncertainty, the best expected outcome* [45]." Coping with various uncertainties that may result from particular limitations is clearly the key to AI development.

3. Materials and Methods

This section addresses the research question of how uncertainty can be managed in AI-enabled decision making. Most AI applications are still in the initial development stage; examples include unmanned stores and autonomous vehicles. Obtaining first-hand information on how AI applications

manage uncertainty is difficult at this stage. Instead of examining first-hand materials, this research examined case study content and project reviews in the literature. This methodology involves content analysis of multiple cases reported in the literature [4,46,47].

Businesses often confront emerging technology implementation projects and possess first-hand experience in the skills required to implement AI. For decades, organizations have tried to use AI to facilitate operations or to evaluate performance [48]. From this, researchers have turned their implementation experiences into case studies and published them. Refering to Eisenhardt [49], we collected cases by analyzing those publications. We began our review by searching journals in the Web of Science by using the following keywords: "artificial intelligence," "decision making," and "uncertainty" within five years. Then, we filtered papers by two criteria: (1) the paper presents challenges, principles, or empirical approaches of using AI to make decisions and (2) the paper has a clear link to the uncertainty problem. We then excluded papers focused on unrelated topics such as psychology or heuristics. Furthermore, instead of purely technical papers, this research included papers that discussed managerial and technical tasks. According to the processes mentioned above, we searched for, collected, filtered, and selected nine papers for further analysis (see Figure 1).
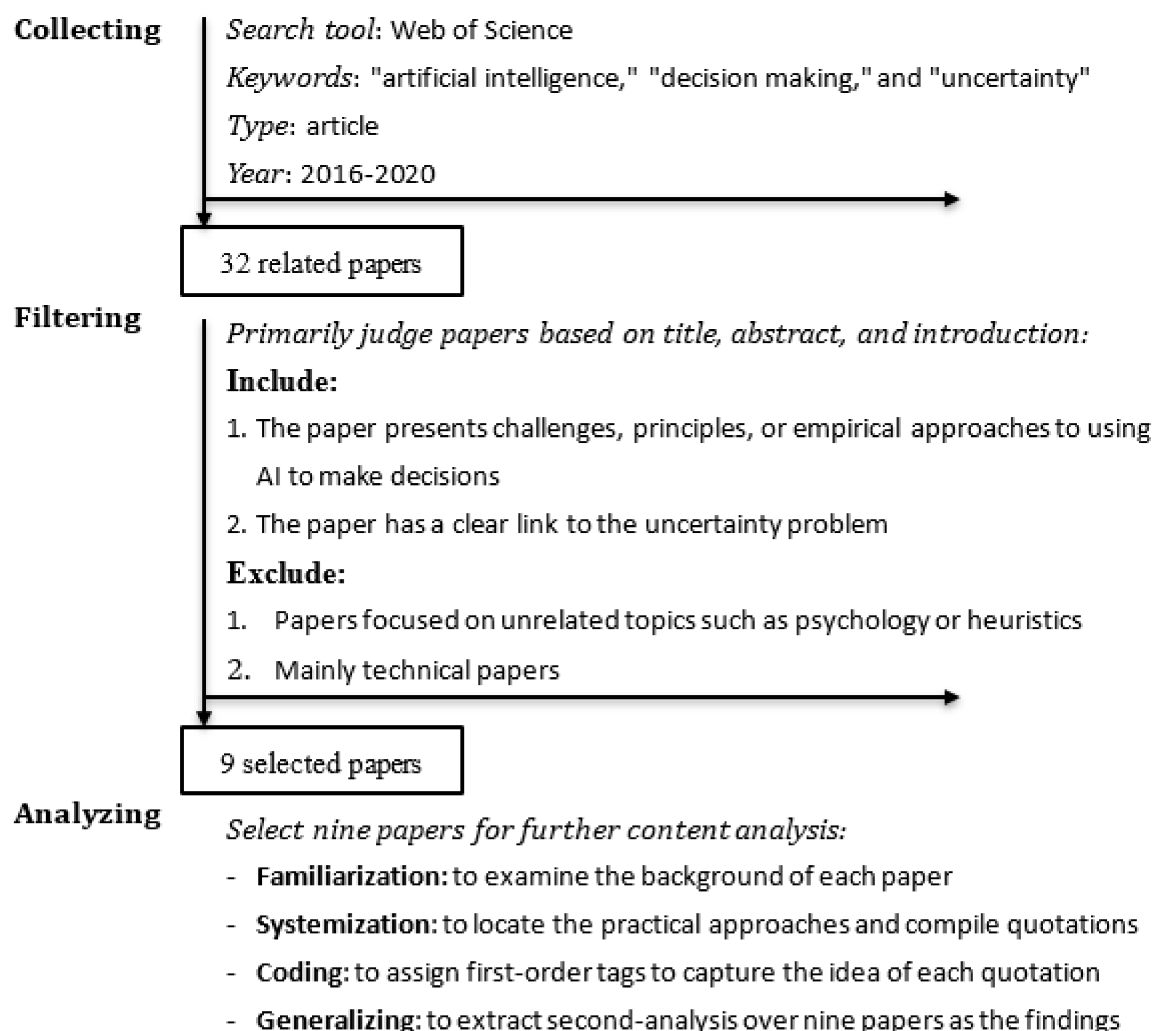
Collecting

Search tool: Web of Science

Keywords: "artificial intelligence," "decision making," and "uncertainty"

Type: article

Year: 2016-2020

> 32 related papers

Filtering

Primarily judge papers based on title, abstract, and introduction:

Include:

1. The paper presents challenges, principles, or empirical approaches to using AI to make decisions

2. The paper has a clear link to the uncertainty problem

Exclude:

1. Papers focused on unrelated topics such as psychology or heuristics

2. Mainly technical papers

> 9 selected papers

Analyzing

Select nine papers for further content analysis:

- **Familiarization:** to examine the background of each paper

- **Systemization:** to locate the practical approaches and compile quotations

- **Coding:** to assign first-order tags to capture the idea of each quotation

- **Generalizing:** to extract second-analysis over nine papers as the findings

Figure 1. Flow chart of research process.

Here we briefly describe the content and background of the nine papers.

- Bogosian [50] examined how machines cope with moral uncertainty. By characterizing moral uncertainty as a voting problem, the author proposed a computational framework to resolve the morality problem in AI machines.
- Costea et al. [31] proposed a two-stage methodology to classify nonbanking financial institutions based on their financial performance. They clarified how to identify and reallocate uncertain observations.
- Love-Koh et al. [51] discussed precision medicine that enables health care interventions to be tailored to groups of patients based on their disease susceptibility, diagnostic or prognostic information, or treatment responses. The complex and uncertain treatment pathways associated with patient stratification and fast-paced technology are critical topics for this development.
- Lu et al. [40] proposed a dynamic pricing demand response algorithm for energy management in a hierarchical electricity market that considers service provider's (SP) profit and customers' (CUs') costs. Reinforcement learning was used to illustrate the hierarchical decision-making framework in which the dynamic pricing problem was formulated as a discrete finite Markov decision process, and Q-learning was adopted to solve this decision-making problem. Through reinforcement learning, the SP was able to adaptively decide a retail electricity price during its online learning process, in which the uncertainty of CUs' load demand profiles and the flexibility of wholesale electricity prices were addressed.
- Willcock et al. [52] examined two ecosystem cases and discussed how data-driven modeling (DDM) can be made more accessible to decision makers who demonstrate the capacity and willingness to engage with uncertain information. Uncertainty estimates, produced as part of the DDM process, enable decision makers to determine what level of uncertainty is acceptable to them and how to use their expertise to make decisions in potentially contentious situations. They concluded that DDM helps to produce interdisciplinary models and holistic solutions to complex socioecological problems.
- Overgoor et al. [6] examined three marketing cases and discussed how AI can be used to provide support for marketing decisions. Based on the established Cross-Industry Standard Process for Data Mining framework, they created a process for managers to follow when executing marketing AI projects.
- Rust [22] examined three firm cases and discussed developments in dynamic programming. He argued that the fuzziness of real-world decision problems and the difficulty in mathematical modeling are key obstacles to a wider application of dynamic programming in real-world settings. He reviewed the developments in dynamic programming and contrasted its revolutionary effects on economics, operations research, engineering, and AI with the comparative paucity of its real-world applications to improve the decision making of individuals and firms. Finally, he concluded that dynamic programming has notable potential for improving decision making.
- Tambe et al. [21] identified challenges in using data science techniques for HR tasks. These challenges included the complexity of HR phenomena, constraints imposed by small data sets, accountability questions associated with fairness and other ethical and legal constraints, and possible adverse employee reactions to management decisions. On the basis of three principles (i.e., causal reasoning, randomization and experiments, and employee contribution), they proposed practical responses to these challenges that are economically efficient and socially appropriate for using data science to manage employees.
- Lima-Junior and Carpinetti [53] proposed an approach to supporting supply chain performance evaluations by combining supply chain operations reference metrics with an adaptive network-based fuzzy inference system (ANFIS). A random subsampling cross-validation method was applied to select the most appropriate topological parameters for each ANFIS model.

Table 1 presents descriptions of each paper, including its decision task, case quantity, and main learning paradigms. The nine papers helped us to examine 14 real cases and generalize their practical approaches.

Table 1. Basic descriptions of nine papers.

Author [Citation]	Decision Task	Case Amount	Main Learning Paradigms
Bogosian [50]	Moral philosophy	1	Supervised learning/Classification, Algorithm
Costea et al. [31]	Institutions performance classification	1	Supervised learning/Cluster algorithm, Neural network
Love-Koh et al. [51]	Precision medicine	1	Reinforcement learning/Markov modeling
Lu et al. [40]	Dynamic pricing problem	1	Reinforcement learning/Markov modeling, Q-learning
Willcock et al. [52]	Ecosystem services	2	Supervised learning/Bayesian networks
Overgoor et al. [6]	Marketing decisions	3	Supervised learning/Neural networks, Support vector regression, etc.
Rust [22]	Firm decisions	3	Reinforcement learning/Dynamic programming
Tambe et al. [21]	Human resource tasks	1	Supervised learning/Logistic regression
Lima-Junior Carpinetti [53]	Supply chains performance evaluation	1	Supervised learning/Neural network

4. Data Analysis

After collecting and selecting papers, we engaged in the iterative process of analyzing and synthesizing the uncertainty problems and solutions from the selected papers. Qualitative content analysis can be performed through data collection, data condensation, data display, and verification of correlations [54].

First, we familiarized ourselves with the research material by reading the nine papers after collecting data. Most papers presented a set of procedures for constructing an AI-enabled decision-making mechanism as well as the implementation principles and relevant difficulties. We carefully checked whether each paper addressed uncertainty problems in their AI-enabled decision-making procedure. Second, we systematized practical approaches to managing uncertainty problems. The process of data condensation (i.e., the coding of data) revealed ideas regarding what should be included in the data display. The approaches mentioned in each paper were compiled, and by using quoted text (Table 2) from the selected papers, we determined how the three uncertainties were addressed and managed. We then applied a technique of second-order tag, which involved assigning tags after a primary code to detail and enrich the entry. Given our focus on the three dimensions of the uncertainty framework, we performed "first-order analysis" to capture the ideas of each papers' illustration of how each AI-enabled decision-making procedure handles various uncertainties and "second-order analysis" to extract the findings. Finally, to increase reliability, the first round of analytical results was independently reviewed and verified with the other research team members. Table 2 shows the final version of the analytical results.

Table 2. Approaches to managing uncertainties in collected data.

Illustrative Quotations	Findings	Dimensions
"This provides normalized choiceworthiness rankings and is the only possible way of equalizing the value of voting for each value system, performs the role of giving each theory equal say. [50] *(p. 597)"* *" . . . the selection of input variables for each performance dimension is based on scientific rigor . . .* [31] *(p. 113)"* *" . . . statistical methods (and accompanying technical guidance) would be required to identify causality while controlling for the risks of selection bias and confounding in observational data.* [51] *(p. 1445)"* *"Inputs to the algorithm include the CUs' energy demand and the wholesale electricity prices . . . . Upon receiving these parameters, the SP then initializes . . .* [40] *(p. 225)"* *" . . . it is clear that ES scientists must contribute to and make use of large datasets to participate in the information age, particularly where data are standardised and made machine-readable.* [52] *(p. 172)"* *" . . . making sure that all of the data look similar in structure. . . . normalizing the data to enable easy comparison between different types of data. . . . formatting the data appropriately.* [6] *(p. 164)"* *" . . . top management has to make data sharing a priority in the short run and invest in data standardization and platform integration in the long run.* [21] *(p. 23)"* *"Organization of the set of samples: Normalization of the input and output values.* [53] *(p. 9)"*	Establishing norms (8)	**Managing informational uncertainty**

Table 2. *Cont.*

Illustrative Quotations	Findings	Dimensions
"The data are collected with the help of the personel of the supervisory authority. [31] *(p. 113)"* *" ... any reduction in sample sizes could be compensated for in time through the use of large, linked observational datasets.* [51] *(p. 1446)"* *"In this MDP model, the reward and energy consumption depend only on the energy demand and retail price at the corresponding time slot ...* [40] *(p. 223)"* *" ... , as with many statistical methods, DDM requires adequate data availability* [52] *(p. 167)"* *" ... it is important to explore the data. ... it is also useful to verify data quality. This involves checking to make sure that there is not any missing data or that the data actually make sense.* [6] *(p. 164)"* *" ... such algorithms may be applicable to problems where there is sufficient prior information to identify the structure of the DM's decision problem.* [22] *(p. 841)"* *"Typically, this information has to be extracted from multiple databases, converted to a common format, and joined together before analysis can take place.* [21] *(p. 19)"* *" ... these data should be obtained based on estimation or historical data extracted from traditional organizational systems.* [53] *(p. 8)"*	Collecting available information (8)	
" ... , while complete data on potential credence judges' moral views and other characteristics to use for this project may currently be lacking, this does not present a great barrier for creating morally uncertain artificial agents, since the credence function can be used broadly and need not be computed separately and repeatedly for too many scenarios. [50] *(p. 602)"* *"Based on the new membership degrees identify which uncertain observations became certain observations and reallocate them into the clusters. ... The solution of proposed procedure to (re)allocate the observations into performance clusters consists of the set of the final clusters' centers.* [31] *(p. 123)"* *"Value of information analysis, a technique for quantifying the value of reducing decision uncertainty, was also identified as key technique that could be beneficial to decision-making.* [51] *(p. 1446)"* *"A lack of uncertainty information and the inability to run models in data-poor environments and/or under conditions where underlying processes are poorly understood ... However, DDM can help to address these current shortcomings in ES modelling.* [52] *(p. 171)"* *"when data are incomplete, one can test for the causality of specific factors in other ways, ...* [21] *(p. 32)"* *"The use of fuzzy sets and decision rules enables neuro-fuzzy systems to deal with impreciseness of input data and domain knowledge ...* [53] *(p. 5)"*	Extrapolating potential information (6)	
" ... is expected to steadily improve. Similarly, health apps and AI-based algorithms are regularly updated and upgraded ... [51] *(p. 1447)"* *" ... to assign a Q-value to each state-action pair at time slot t, and update it at each iteration, in a way that reinforces good behavior.* [40] *(p. 225)"* *" ... the continual refinement of the previous models, so that even as the models themselves answer more and more questions, they are also answering them better and better over time.* [6] *(p. 181)"* *" ... this approach ... can continuously monitor states and decisions made by the actor and iteratively improve their performance concurrent with actual decision making.* [22] *(p. 842)"* *"Those councils should debate the assumptions, data, and ethical dimensions of AI algorithms ...* [21] *(p. 36)"*	Endlessly exploring and updating (5)	**Managing environmental uncertainty**
" ... assigning credences to a system of maximizing expected choiceworthiness in machine intelligence on the basis of a broad survey of moral philosophers' beliefs. [50] *(p. 601)"* *"The choice of the financial ratios of each dimension ... were collected with the help of the experts within the Supervision Department ...* [31] *(p. 126)"* *"Value of information-type approaches can help to quantify the extent of this uncertainty and the value of reducing it, through techniques such as expert elicitation.* [51] *(p. 1446)"* *"Using ARIES, we instructed the machine learning algorithm to access explanatory variables, indicated by the same experts who provided the estimates used in training as the most likely predictors of biodiversity value.* [52] *(p. 168)"* *"Involving stakeholders of the organization ... is important and the modeler should spend enough time to understand the business questions.* [6] *(p. 181)"* *" ... if RL is to be successful, it must have a capability to either (a) aggregate experience learned from advising similar DMs or (b) conduct offline simulations to train itself to be more effective from the much smaller number of real-world opportunities to advise individuals or firms on actual decisions.* [22] *(p. 848)"* *" ... AI Councils that include widely respected representatives of all stakeholders. ... solicit employees' contribution and feedback.* [21] *(p. 35)"* *" ... based on the judgments of specialists, the proposed system is able to automatically tune the fuzzy input variables and the inference rules based on a supervised learning procedure.* [53] *(p. 16)"*	Soliciting advice (8)	
" ... as adding another action requires a fixed series of evaluations to be done by each moral theory and adding another moral theory requires it to perform a fixed series of evaluations to be performed on each action. [50] *(p. 598)"* *"If these computer simulations are sufficiently promising, the actor is more likely to follow the recommended decisions in practice, and further validations of the critic's recommendations can be carried out via controlled field experiments as well as before/after comparisons to validate whether the simulated gain in performance from the DP decision rule is borne out in reality.* [22] *(p. 842)"* *"The only way to avoid this problem is to on occasion turn off the algorithm, ... to see whether candidates that do not fit its criteria continue to perform worse or perhaps perform better.* [21] *(p. 29)"*	Improving the readiness (3)	

Table 2. *Cont.*

Illustrative Quotations	Findings	Dimensions
" … *explicitly placing pragmatic interests on the same level as moral theories … having a clear rule for maximizing expected choiceworthiness is a policy which can be committed to and accepted on principled ideological grounds.* [50] (p. 605)" "*After selecting the performance dimensions, we choose different indicators for each dimension, based on the analysis of the periodic financial statements of the NFIs.* [31] (p. 126)" " … *any priority-setting process would require a clear and transparent decision-making framework.* [52] (p. 1445)" " … *Often this involves taking a set of data and holding it out and identifying a metric of performance that will be used to assess the model.* [6] (p. 164)" " … *most of the successful applications of DP still rely critically on human insight and intervention to … choose the functional forms representing the DM's preferences and the laws of motion for the problem …* [22] (p. 841)" " … *explainability, in this case the extent to which employees actually understand the criteria used for data analytic–based decisions.* [21] (p. 33)" "*The use of the metrics suggested by Supply Chain Council (SSC, 2012) contributes to a better alignment, standardization, and integration of performance measures across different tiers of a supply chain.* [53] (p. 16)"	Establishing public criteria (7)	**Managing intentional uncertainty**
" … *computations of moral uncertainty represent a process by which agents can act in accordance with the diverse values of humanity* [50] (p. 595)" " … *discrete choice experiments could be used to value patient preferences for increased knowledge …* [52] (p. 1445)" "*The effects of CUs' private preferences in the electricity market are addressed, e.g., dissatisfaction cost function.* [40] (p. 222)" " … *which makes human judgment an ever important part of AI. Judgment is necessary to determine the trade-offs of certain actions …* [6] (p. 161)" "*Thus other sources of information, possibly including direct elicitation of preferences and beliefs of the DM, may be necessary …* [22] (p. 841)" "*To preserve the integrity of decision making, human judgment should be exercised consistently …* [21] (p. 37)"	Allowing individual preferences (6)	
" … *to develop stochastic versions of these algorithms for solving DP problems that can converge asymptotically to optimal decision rules and value functions …* [22] (p. 843)" " … *acknowledging the random nature of some HR outcome and being explicit about it acknowledge the inherently stochastic nature of HR outcomes …* [21] (p. 37)" " … *suggests a sequence of steps to apply the random subsampling cross-validation method in order to select the candidate topologies that present the superior accuracy.* [53] (p. 9)"	Allowing random (3)	

5. Results

As exemplified in Table 2, approaches were extracted from collected papers addressing methods of managing various uncertainties. First, informational uncertainty can be managed by establishing norms, collecting available information, and extrapolating potential information. Among the collected papers, eight mentioned the relevant keywords or concept of establishing norms, eight papers mentioned collecting available information, and six papers mentioned extrapolating potential information. Second, environmental uncertainty can be managed through continual exploration and updates, the solicitation of advice, and improved readiness. Among the collected papers, five mentioned the relevant keywords or concept of continually exploring and updating, eight mentioned soliciting advice, and three mentioned improving readiness. Third, intentional uncertainty can be managed by establishing public criteria, allowing individual preferences, and allowing randomness. Among the collected papers, seven mentioned the relevant keywords or concept of establishing public criteria, six mentioned allowing individual preferences, and three mentioned allowing randomness. As discussed in Section 2, the analysis results indicated that environmental uncertainty and intentional uncertainty are relatively rarely focused on. The present section examines those approaches and elaborates on their mechanism for managing uncertainties in AI-enabled decision making.

5.1. Managing Informational Uncertainty in AI-Enabled Decision Making

To manage informational uncertainty, the main approach is exploiting accessible information [55]. When the exploitative model applied for making predictions is insufficient, data are collected to construct (or train) the model. In addition, the model must be further verified with additional independent (nontraining) data. Applying information deeply exploits the content of these data and is the main strength of AI. Many activities can be used to apply information, including collecting,

formatting, recognizing, circulating, storing, retrieving, sharing, filtering, and tracking. According to research in the field of management [11], organizations typically implement standard operating procedures to constrain the variability of their internal environment. Similarly, an organization can establish operating norms to effectively acquire, distribute, and interpret information [11,56]. These norms can ensure that the organization focuses on specific decision tasks in a given environment scope. Establishing norms for archiving, accessing, and integrating various data sets from different departments and hierarchies is difficult but crucial to AI training. Another major challenge is data compatibility [21]. Some papers described pragmatically implementing data clearing and formatting steps to make data compatible [6,21,52], whereas most papers mentioned details of initialization, normalization, and standardization [6,21,40,50,52,53] based on scientific rigor or guidance [31,51].

Typically, AI need to exploit, request, and collect adequate information with historical data or multiple data sets [6,21,31,40,51–53]. However, common among AI applications is the challenge of "small data," in which the accessible data are far from adequate for devising a machine learning algorithm for a specific decision-making task [21]. When information is incomplete, a human decision maker must extrapolate possible rules from available information through statistical methods or assumption-based reasoning [57]. AI-enabled decision-making mechanisms must flexibly deal with the impreciseness of accessible data and domain knowledge [6,21,50,53] by applying techniques [52] or tools, such as fuzzy sets [31,53] and rough sets [58]. For example, Jang [59] proposed ANFIS for combining the abilities of fuzzy set theory with artificial neural networks to solve complex and uncertain problems [53]. Fuzzy sets [60] are useful for managing uncertainty, although formalizing a fuzzy rule base can be difficult. The artificial neural network is a powerful tool for developing self-learning and self-adaptive systems through the identification of characteristics of available examples; however, it cannot explain relationships between variables. As ANFIS applies fuzzy sets as the model architecture [59], not only can original rules be converted into fuzzy sets but experts' experience and knowledge can be converted into inference sets to make up for the lack of data descriptions.

5.2. Managing Environmental Uncertainty in AI-Enabled Decision Making

To manage environmental uncertainty, applying the tactics of acknowledging uncertainty is worthwhile [7]. First, we recognize the decision environment and its context as well as set the definitions and boundaries of decision problems. Various environments must be explored within the boundaries. In addition to the variability of a decision environment, explorations cannot always be completed. In other words, the only strategy for survival in a changeable environment is the continual exploration and gradual expansion of knowledge regarding the world. For the development of AI-enabled decision-making applications, a basic approach is regularly scanning the environment with an inquisitive attitude [6,21,48]. To adapt to environmental volatility, an AI-enabled decision-making mechanism must remain flexible and continually adjust and update its variables [6,40]. Although such flexibility may be inconsistent with productivity improvement and cost reduction, it is key to expandability and sustainability [61].

Experts have domain knowledge and experience and can provide decision makers with anchors and guidance regarding a wide range of explorative topics [62], particularly initial access to knowledge. When applying AI to develop a decision-making mechanism, soliciting advice from experts or specialists [31,50–53] is an essential step for acquiring environmental knowledge and enriching the scope of interpretable frames. In addition to experts, various sources can contribute useful facts for decision makers, such as consumers, employees, investors, business associates, and consultation organizations [6,21].

Regarding the unpredictability of the decision environment, a realistic approach to improving the readiness of the AI-enabled decision-making mechanism is to develop procedures for responding to any unanticipated or undesired situations. In particular, preset procedures must avoid irreversible consequences [7] and adapt to the changing environment in the long term [3]. An AI-enabled decision-making mechanism can weigh potential gains and losses in advance [50], establish a buffer

against unstable states, rearrange priorities after unpredictable contingencies [11,21], or establish a threshold for determining when to yield control rights to humans [21].

*5.3. Managing Intentional Uncertainty in AI-Enabled Decision Making*

The key to managing intentional uncertainty in AI-enabled decision-making applications is to manage the priorities of different criteria for various stakeholders (or groups). Each criterion can be attributed to diverse stakeholder expectations of AI-enabled decision-making applications. To satisfy stakeholders and sustain the development of AI applications, the balance of meeting distinct expectations between different stakeholders is essential. Especially in some specific decision tasks, statistical models trained by computers require a transparent reasoning mechanism for selecting variables and characterizing their relationship to the decision problem. Interpretability is critical for convincing humans. One method for improving the interpretability of AI is to enhance the generalizability of algorithms; another is to allocate criteria selection to human workers. Decision making requires criteria for the evaluation of alternatives and decision making. These criteria must prioritize the public values [63], principles, criteria, or metrics [6,21,31,50,52,53] in advance. There have been useful methods to evaluate the multi-criteria decision making, such as the analytic hierarchy process.

Most decision-making processes prefer consistent and stable criteria. Some research has even regarded the variability of individual factors (e.g., differences in experience, attention, context, and the emotional state of decision makers) as being characteristic of human decision making [64], and variability may negatively affect decision making. However, a decision-making mechanism with only a single criterion may fail to meet numerous distinctive objectives or make decisions that meet humans' real needs. AI-enabled decision making must be aligned with individuals' preferences to enhance the predictability of AI decision-making results, thereby increasing human trust. Furthermore, for cases not influenced by individual preferences among the available options (referring the concept of "undifferentiated alternatives" in Lipshitz and Strauss [7]), the setting of random parameters in machine learning is another common approach [21,53]. Accordingly, AI applications manage intentional uncertainty by establishing criteria reflective of human values, considering individuals' preferences, and allowing randomness.

6. Discussion

This research aimed to clarify how AI can be used to assist organizations in decision-making tasks and even overcome uncertainty problems. From a review of the literature, we found that uncertainty in decision making may be related to the degree of information completeness, environmental context, and individual intentions. By examining recent AI developments, we found that these three factors of uncertainty are present even with the assistance of computers in decision-making tasks. According to these insights, we applied these three dimensions to the framework of uncertainty (i.e., informational, environmental, and intentional uncertainty) to form a unified concept of uncertainty. Considering that most AI applications are still in the initial development stage, we collected data by filtering managerial and academic publications. As data were collected from various research backgrounds, multiple cases helped to clarify the developing dynamics in this novel field and achieve some explorative findings that are generalizable to different contexts.

Figure 2 illustrates the final findings; it summarizes a decision-making mechanism for managing uncertainties in the AI-enabled decision-making deployment process. This mechanism involves three approaches for each type of uncertainty. Other studies in the AI field have only focused on technical approaches, whereas the present study also considers managerial approaches. Acknowledging the perspective of collaboration between humans and computers [65], this research particularly focuses on the pre- and post-implementation stages in designing an AI-enabled decision-making mechanism. Most development processes for AI applications require ongoing updates to sustain their adaptability to the changing world.
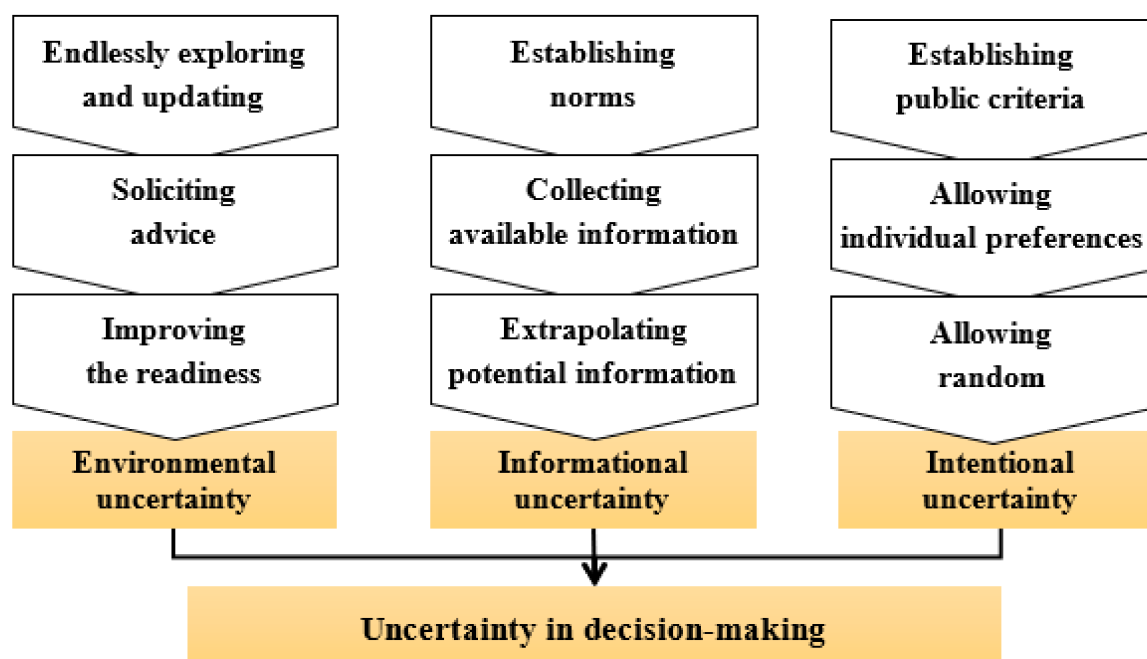
Figure 2. A management mechanism for AI-enabled decision making.

We collected analytical material from the relevant literature, and most of the analytical techniques applied were derived from Miles and Huberman [54] and Eisenhardt [49]. Eisenhardt [49] discussed two weaknesses in the methodology of multiple cases. First, with the intensive use of empirical evidence, analysis results may lack the simplicity of an overall perspective. Second, the analysis results may be too narrow and idiosyncratic. Although the decision tasks collected in the research material were distinct, it can still be worthwhile to examine the diverse cases and to generalize some findings for this exploratory research. Future research should accumulate more facts and evidence to verify our findings.

7. Conclusions

In this research, we reviewed studies on uncertainty in decision making. When a decision is made, uncertainty is the most common and difficult problem to solve. Uncertainty can delay decision making and mainly arises from three sources: informational, environmental, and intentional uncertainty. With the evolution of AI and improvements in computer science, the role of ICT in decision making has gradually transitioned from decision-support functions to decision making functions. Computers can learn to recognize labels, patterns, and similarities in data. Computers can provide an exploitation mechanism that repeatedly reacts to environmental conditions. However, given the limitations of AI, uncertainty still appears to be an imperative problem in AI-enabled decision making and warrants further examination.

This research makes several contributions. This was the first study to adopt the three dimensions of uncertainty to elucidate uncertainty problems in AI decision making and identify solutions. In the second chapter, we acknowledged the potential limitations of AI technologies by exploring their current development. With reference to related studies, we proposed a mechanism model with practical approaches for managing various uncertainties. As we explored and classified uncertainties in depth in the definition stage, the management mechanism proposed in the research was more complete.

This research adopted the social-science perspective and proposed a management mechanism to cope with uncertainty problems in the development of AI-enabled decision making. The advancement of computer science has made solutions to cope with uncertainty problems available. Current solutions for uncertainty problems mostly focus on technical approaches, such as fuzzy sets [66] and stochastic

optimization [67]. By contrast, this study applied the social-science perspective and developed a management mechanism that demonstrates how humans and computers cooperate. However, the management mechanism was not designed to replace current technical approaches but to complement them. In other words, this research focused on cooperation between humans (managerial) and computers (technical). The concept of human–computer cooperation is lacking in the development of AI applications. Most people still have unrealistic dreams for convenient services delivered by AI applications. Scholars have argued that such high convenience will be harmful in the long term [68]. The management mechanism proposed in this research is useful for guiding the development of AI applications to become more sustainable.

Finally, the management mechanism can be deployed in the pre- and post-implementation stages of AI application development. The execution of the management mechanism as well as its ongoing updates for AI-enabled decision-making applications may enhance the smoothness and accuracy of the overall decision-making process and its components. Although most people expect to enjoy the convenience of advanced technologies, AI is not omnipotent and should not be considered an almighty technology. Although some people believe that computers can learn by transforming acquired information into knowledge, AI still requires a management mechanism to maintain its decision-making process. Furthermore, the application of AI requires the investment of resources and assistance from (human) research and development teams, including for setting goals, defining problems, determining criteria, and calibrating the system to ensure satisfactory results. Hence, a maintenance mechanism instituted by human teams must be included during the measurement of the decision-making performance of AI applications.

Nonetheless, this research has some limitations. First, the approaches collected from academic literature may not be sufficient. With more mature applications appearing, future research needs to consider empirical cases further. The coding process is another limitation because the researcher's knowledge, experience, and mindset substantially impact the results (of coding) [69].

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