Communications of the IIMA

Volume 20 | Issue 1 Article 2

2022

Business and/or Ethics? A Framework for Resolving Multicriteria Decision Dilemmas

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ABSTRACT

Corporate leadership is often in the unenviable position of balancing ethical choices and profit. Business decisions consider alternatives and make choices to further strategic business goals. Measures of business success are likely to be financial, including profit, revenue, sales, market share, cost of production, quality of products, innovative product development. Ethical decisions are choices among right and wrong outcomes or processes. Assessment of ethical choices may or may not be easily quantified, including consideration of positive and negative consequences, moral principles, and fair process. Inevitably, then, the inherent nature of business-ethics decisions will involve multiple decision criteria, including both business criteria and ethics criteria. These criteria may conflict, creating dilemmas that may be difficult to resolve. Sometimes ethical business decisions will be profitable, sometimes ethical business decisions will be more costly than less ethical alternatives and therefore be less profitable. Multicriteria analysis tools are designed for such decision dilemmas, yet responsibility inheres to the people who must choose. Conclusions are drawn for individual, corporate, and algorithmic decisions. Decision processes should answer these questions: Are units of measure comparable? Is the system open or closed? Is it deterministic or stochastic? Is there a risk to life? Who is responsible? Is the decision process transparent? Who cares about the outcome? What are their criteria for successful consequences? What ethical principles apply?

INTRODUCTION

Ethical business decisions are a challenge. Multiple stakeholders make various legitimate demands. Multiple demands may conflict or not even be comparable. Conflicting stakeholder demands together with demands of conscience create inevitable dilemmas at times. Organization structures can obfuscate responsibility.

Complex technology products embed responsibility in algorithms that appear in black-box form to users. In the uncertain time between idea and market, engineers designing a new product and managers strategizing its introduction to the market face questions of ethics along with business goals of efficiency and profitability. This paper traces the process of such business-ethics decisions. Drawing on ideas from engineering math, philosophy of ethics, and strategic management decision making, the paper begins with the concept of a business-ethics decision as a dilemma. Business-ethics decisions are multicriteria problems because of multiple demands made on the decision maker. Multicriteria decision methods are outlined, along with discussion of some applications of multicriteria analysis tools. Considering advantages and limitations of multicriteria models, a framework is recommended for resolving a multicriteria business-ethics decision dilemma. Consideration is extended to algorithmic and corporate decisions.

Business

A *business* is defined as an organization or enterprising entity engaged in commercial, industrial, or professional activities. The term *business* also refers to the organized efforts and activities of individuals to produce and sell goods and services for profit[1]. Rational business decisions rely on measures of success: profit, market share, cost, quality.

Ethics

Ethics is about right, as opposed to wrong, behavior. Ethics may be defined as the discipline dealing with what is good and bad and with moral duty and obligation[2]. Ethical decisions sustain right behavior and moral obligation based on outcome/consequences or process/principles, often there are multiple relevant measures.

Business Decisions

It is commonly assumed that business decisions are rational, meaning that the decision maker will consider alternatives and make choices to further strategic goals. With an eye to business strategy, the business decision maker will identify measures that assess strategic success. Those measures are likely to include one or more measures consistent with the definition of business above: profit, revenue,

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[1] https://www.investopedia.com/terms/b/business.asp retrieved 6/12/19.

[2] https://www.merriam-webster.com/dictionary/ethics retrieved 6/12/19.

sales, market share, cost of production, quality of products, innovative product development.

Development of relationships along the supply chain that will further any of these measures are also valuable. Stakeholder theory identifies investors, customers, employees, sometimes even outsiders in the firm's environment as potentially sharing in the consequences of business decisions, where a stakeholder is defined as anyone who influences or is influenced by a business' operations (Freeman, 1984, p.46). A strategic business decision maker needs to consider impacts of business decisions on all stakeholders impacted by that decision to further the firm's success.

The decision process involves generating alternatives that may lead to success measured by criteria of interest to stakeholders, analyzing the alternatives to predict which alternative is likely to lead to the greatest success using these measures, and then making a decision choice based on that analysis. The measures of success loom large in this process. Where there are multiple measures that conflict or create ambiguity in the choice process, priorities have to be set as a way of making the decision process operational.

Ethical Decisions

Ethical decision making aims at right (as opposed to wrong) choices by a focus on either the right outcome or the right process. Assessing ethically right outcomes looks at consequences of each alternative, the choice that creates the most good for the most people, or the impact of each alternative on the worst off. Assessing ethically right processes considers moral principles such as honesty, transparency, privacy, and fair process. Measures of ethical success can be qualitative, making comparison of alternatives difficult. There can easily be more than one measure of assessing rightness[3]. When multiple measurement criteria are not comparable, it is not clear what the best choice is. Ethical outcomes may even be inconsistent with ethical processes. To operationalize ethical decision making, priorities have to be set where a choice is between mutually exclusive alternatives.

Business-Ethics Decisions

Business-ethics involves decision making in business settings where assessment of success includes both business measures as well as ethics measures. Thus by the inherent nature of business-ethics decision making there will be multiple decision

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[3] See for example https://status.net/articles/ethical-decision-making-process-model-framework/ retrieved 6/12/19.

criteria. While decision scientists recognize ethics as a factor, there is no universal optimum or standard framework for solving these problems (Ormerod & Ulrich, 2013, p. 303). Complicating the matter further, some business-ethics criteria are qualitative while others are quantitative leading to ambiguity about how to measure what is best about the best choice. Even in the simplest case where there is one business measure and one ethics measure, there are three possible outcome scenarios: both measures indicate success, one measure indicates success while the other measure indicates failure, or both measures indicate failure. If there are more than two measures of success, in other words more than two decision criteria, there will be even more possible outcomes.

It is important to realize that a business-ethics decision becomes a dilemma when the best choice by a key ethics criterion is not best by other key measures. Such complex decision situations require more than just knowing what is right to operationalize the decision process. Such situations are dilemmas: rational choice alone cannot tell you what to do (Resnik, 1998, pp. 23-25). A thought-provoking application of such a multicriteria dilemma involves how to program an autonomous vehicle that may potentially be involved in an accident where there are options regarding who are the victims; all options are bad but one of them will happen. Thus it may be impossible to make a decision among various possible alternatives without overriding a moral principle (Aroskar, 1980).

DECISION PROCESS

The generic decision process arises either as part of the search for strategic opportunities (a positive trigger) or because a problem has presented itself (a negative trigger). As part of the decision process the decision maker sets objective(s), compares alternatives, and makes a choice among those alternatives. Analysis of the alternatives involves scoring each alternative’s contribution to the objective(s), and ranking the alternatives in order to facilitate a choice (Korhonen & Wallenius, 2020, p. 1). Where alternatives are mutually exclusive, one alternative will be acted upon and the others discarded. If not mutually exclusive, there could be a portfolio of alternatives where weights need to be chosen.

When the scoring mechanism includes only one measure of success, the optimal choice is clear. But the scoring mechanism, at times, may depend on multiple attributes. If alternative B has more of at least one attribute than alternative A and is not worse on any of the other attributes as illustrated in figure 1, the *principle of dominance* shows that alternative B is preferred (see for example Pattanaik & Xu, 2012).

Figure 1: B dominates A.		
Note: measure of 2 is preferred to measure of 1	**Alternative A**	**Alternative B**
Measure 1	1	2
Measure 2	2	2
Measure 3	1	1

But if alternative A has more of some attributes while alternative B has more of other attributes as illustrated in figure 2, there is a decision dilemma. The decision maker needs to rank the evaluative attributes in order to come to a conclusion as to whether alternative A or alternative B should be preferred (assuming they are mutually exclusive alternatives).

Figure 2: Ambiguous choice = Dilemma.		
Note: measure of 2 is preferred to measure of 1	**Alternative A**	**Alternative B**
Measure 1	1	2
Measure 2	2	1
Measure 3	1	1

DECISION DILEMMAS

It is the nature of a dilemma that one measure indicates success while the other measure indicates failure. When faced with mutually exclusive alternatives, the decision maker in reality must make a choice even though there is not a clear optimal alternative. Examples of such competing decision criteria include: increasing profit at the cost of environmental degradation, increasing market share at the cost of less total revenue, increasing product quality at the cost of less profit, speeding time to market at the risk of less quality testing. Keeney and Raiffa (1976, p.4) suggest that "there is no objectively correct solution" to such decision problems with multiple attributes and incommensurable units of measure. For mutually exclusive alternatives, the decision maker needs to rank the criteria in order to decide whether to implement alternative A or alternative B. For a portfolio of alternatives that can share resources, an optimal share has to be chosen. Since resources are finite, the optimal share involves setting weights and priorities. Such rankings, weights, and priorities, are not objective; the decision maker's values become part of the choice process. Therefore these choice processes select alternatives that are not objectively optimal—a different decision maker might make a different choice.

Incommensurability

If alternative A and alternative B cannot be measured by a common unit, A and B are incommensurate. The two choices may not have sufficient overlap to be expressed in terms of some shared value (Scharffs, 2000). It is then not possible to say that A is preferred, nor that B is preferred, nor that A and B are equivalent (Chang, 2002). It is impossible to measure tradeoffs between the two options without a common measure. If they are mutually exclusive alternatives, any choice is arbitrary, that is to say non-rational. A forced choice among mutually exclusive incommensurable alternatives will not optimize the values that are traded off.

The implication of incomparability is that there is no rational aggregating measure and no objective ethically justifiable weighting scheme for incorporating the incommensurate values into an aggregate measure. In turn, assignment of weights to incommensurable values creates problems for decision making (Boot, 2017). Choices that follow will not be impartial and ethically justified.

Some business-ethics decisions fall into the dominance category where one alternative is a clear winner and the most ethical decision is also the best money maker. But other business-ethics decisions are dilemmas with ambiguous optima. Trade-offs have to be evaluated, weights and rankings estimated, and difficult choices made. Figure 3 illustrates the decision dilemma where there are some business criteria and some ethics criteria.

Figure 3: Business-Ethics Dilemma.

Note: measure of 2 is preferred to measure of 1	**Alternative A**	**Alternative B**
Profit Measure 1	1	2
Ethics Measure 2	2	1
Measure 3	1	1

An individual decision maker may resolve incommensurable tradeoffs by using personal value system priorities. Organizational group decisions may resolve incommensurable tradeoffs through policy choices of a hierarchy of decision makers, where each individual resorts to personal value system priorities together with the dictates of decision makers higher in the organization hierarchy.

Algorithmic decisions likewise cannot optimize incommensurate tradeoffs. If programmed to make a non-rational choice, the algorithm is encoding some individual's personal value system priorities. Responsibility becomes blurred.

RESPONSIBILITY AND DECISION MAKING

For what is a decision maker responsible? "The central core of the concept of responsibility is that I can be asked the question 'Why did you do it?' and be obliged to give an answer" (Lucas, 1993, p. 5). Retrospective and prospective responsibilities can be distinguished, those responsibilities that respectively accrue after and before the event (Duff, 2004, p. 443).

Retrospective responsibility is answerability to someone for something that has already happened. There is considerable philosophical and legal literature on retrospective responsibility and consequent legal liability. The retrospective responsibility question is who is responsible for consequences (concern is with harmful consequences). There is general agreement that an agent who acted (or failed to act) with knowledge, or who should have known, is responsible for harm caused by the act or omission (Ginet, 2000). Action (or control) and awareness are key. Awareness is the "epistemic requirement" that moral agents are aware of the relevant factual and moral considerations or that they *should and could be aware* of them given the available evidence, the opportunity to adequately process it, and their cognitive capacities (Sher, 2009).

Responsible decision making is prospective, that is thoughts, plans and acts that are part of the decision process before an event. Responsibility inheres to the individual(s) who selected the decision criteria and set the priorities. Responsibility comprises awareness and action/control: awareness of the action, its moral significance, consequences, and alternatives (Rudy-Hiller, 2018). Has the decision maker selected the alternative(s)? If so, then he is aware of the action. Has the decision maker selected the criteria and the priorities? If so then he is aware of its moral significance. Has the decision process developed alternatives? If so, then the decision maker is aware of alternatives. Has the decision maker traced the alternative to its consequences? If so, then he is aware of consequences.

When there is one decision maker responsibility is clear. As noted above, the decision process includes setting objective(s), comparing alternatives, and making a choice among those alternatives by scoring each alternative's contribution to the objective(s), and ranking the alternatives in order to facilitate a choice. In the decision process each alternative is a potential action traced to its consequences. Setting objectives and ranking alternatives indicates awareness of moral significance. It follows that involvement in the decision process creates moral responsibility.

Where the decision is made in the course of work in a business organization it may be less clear who is responsible. Corporate decision processes and hierarchical organizations can serve to hide responsibility. But again, involvement in the decision process creates moral responsibility.

Where the choice mechanism is hidden in an algorithm it may not be clear at all who bears responsibility. Layers of obscurity create the perception of a responsibility gap (Matthias, 2004). But there have still been humans involved in the decision processes. “Responsibility and thus accountability for the consequences of choices related to design, development, implementation, and regulation must always land at the feet of the humans involved” (Van Wynsberghe & Sharkey, 2020, p. 282).

Corporate Decisions

A business organization has collective responsibility as does each of the individual members involved in a particular decision implemented by the business and its members as agents. Extent of responsibility is related to the agent’s power to commit the organization’s resources to an action. There has been considerable debate about the nature of organizational responsibility.[4] Velasquez (1983) takes the position that in spite of its organizational complexity, a corporation is ultimately a group of humans who are engaged among themselves in a variety of specific occupational and professional relationships which each believes to be in his or her self-interest. Corporate actions are the result of procedures and policies intentionally designed by members of the corporation to achieve specific goals. If harm is caused or wrongdoing occurs, moral responsibility is borne by individuals to the extent that each one participated in policy formulation, implementation, or oversight.

However, organizations are opaque. It is easy for individual responsibility to be lost in organizational complexity (Dan-Cohen, 1986). Leaders with organizational power may have a selfish interest in hiding their individual responsibility/liability in the corporation’s complexity.

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[4] Risser, D. T. (n.d.). *Collective Moral Responsibility*. Internet Encyclopedia of Philosophy. https://iep.utm.edu/collecti/ retrieved 8/12/21.

Algorithmic Decisions

Human-machine systems go back as far as the use of tools by people. Feedback loops and control systems also have a long history, including things like thermostats, and automatic trip switches. Relatively recent are the adaptive algorithms known as artificial intelligence (AI) and machine learning. The term “artificial intelligence” was coined by John McCarthy in a proposal for a conference at Dartmouth College that was held in 1956. Russell and Norvig observe that “computational rationality” would have been more accurate (2010, p. 17). Russell and Norvig define AI as “the study of agents that receive percepts from the environment and perform actions. Each such agent implements a function that maps percept sequences to actions” (p. viii). More concisely, Ryan defines AI as “artificial mimicry of tasks and functions that would otherwise require human intelligence” (2020, p. 2751). While it is artificial, it is not intelligent, other than in the machine context of adaptive autonomous application of perceived data to optimize a programmed goal. AI is simply *Algorithmic Imitation* of decision processes.

Adaptive autonomous agents with machine learning programming can have unintended negative consequences. Attempts to align such systems with human interests are inherently multicriteria. Application technologies depend on successful implementation of multicriteria methods but complexity creates serious limitations (Vamplew, Dazeley, Foale, Firmin, & Mummery, 2018).

Science fiction (and even Wikipedia[5]) merge myth and computer science under the same AI heading. Arguably, the term “artificial intelligence”, with its now considerable history in both science fiction as well as hard science, hampers the ability to be rational about ethically responsible algorithmic decision processes. Careless use of language can be misleading. Describing robot behavior as ethical decision making is “more likely to confuse than educate” (Miller, Wolf, & Grodzinsky, 2017, p. 392). “There are many situations in which robots can offer people something that would not otherwise be available” but the “responsible approach would be to…avoid a future in which robots are placed in positions and roles that require a moral understanding that they do not have” Sharkey (2020, p. 293). It is dangerous to distances human developers, owners, and users, from their responsibility for the technical systems that they have developed or deploy (Sharkey, 2020, p. 289).

[5] https://en.wikipedia.org/wiki/History_of_artificial_intelligence

Humans are responsible for the technology they develop and use. Usually many hands are involved in technological action, making transparency particularly critical. Black-box systems are morally problematic. Responsible human agents need to be aware of the action, its moral significance, its consequences (even possible unintended consequences), alternatives, and the instrument (Coeckelbergh, 2020). Jotterand and Bosco make a case for the moral imperative to keep the "Human in the Loop" in technological decision systems (2020).

For life and death algorithms, it is imperative that the coded priorities are transparent. It is relatively apparent self-driving cars fall into this category. However, recent social media criticism alleges that their algorithms can also fall into the life and death category because of behavior motivated by their content. It follows that their algorithms should also be transparent to reduce damage they may cause as well as to facilitate responsibility tracing.

Open versus Closed Systems

Modelling algorithms typically have some given data and some assumptions. The model should be tested against real data to judge its effectiveness. The usefulness of such tests depends on the nature of available real data, and particularly on whether the real system is open or closed. A closed system has no interactions with its environment ("Open and closed systems in social science," 2021) so the system will not change while the model is being tested and will be the same when the model is applied again. In contrast, an open system is defined as a "system in exchange of matter with its environment, presenting import and export, building-up and breaking-down of its material components" (Bertalanffy, 1988, p. 4).

In a closed system it would be possible, at least in theory, to analyze all possible alternatives and their impacts on all possible measureable criteria. In an open system, especially when dynamic and stochastic, it is not possible to analyze all possible impacts because new stimuli can be received at any time from the environment of the system, in whatever way that system's boundaries may be defined. The nature of the system will then be different. In transportation systems for example, a rail network might be considered a closed system while a road network would be an open system. Relative to one country's policies, the natural environment is an open system. For a hospital, patients come and go from an open system. One company's assets may be treated as a closed system, but financing and investment are in an open financial marketplace. Robots in social roles, such as on the battlefield or as caregivers, are in open systems; non-embodied computational systems are closed.

Randomness and dynamics of real life add complexity. We should not forget that software can fail to perform as expected (Charette, 2005).

MULTICRITERIA DECISION ANALYSIS METHODS

Multicriteria analysis methods have been developed to deal with decision problems having multiple attributes or objectives. The decision maker is being called upon to solve multiple objectives simultaneously. Yet because it is not possible to mathematically solve for a unique optimal solution when there are multiple goals, these situations are decision dilemmas. Preference is introduced either a priori through a weighting scheme, a posteriori after generating a subset of non-dominated Pareto efficient solution alternatives, or interactively in order to make a choice among feasible alternatives.

Koksalan, Wallenius, and Zionts (2011) give a nice chronological overview of multicriteria analysis methods from Benjamin Franklin in the 1700s through the beginning of modern multicriteria decision analysis in the 1960s to the early 2000s. Theoretical developments in multicriteria analysis are discussed along with some of the developments in mathematical methods on which multicriteria analysis depends. Since multicriteria analysis is complex, it has progressed alongside of development of computational power. They note some of the special purpose software as well as selected applications of multicriteria decision analysis.

Utility Functions

Since it is not possible to optimize multiple criteria simultaneously, all methods introduce a decision maker’s preference either explicitly or implicitly to arrive at a good solution. One approach is to use a weighting scheme to incorporate multiple criteria into a single composite objective function, such as a utility function, and then optimize that function. Keeney and Raiffa (1976) developed utility functions to combine various measures that are not naturally commensurate. Zionts and Wallenius (1976) suggest an interactive method for setting up a decision maker’s utility function. Maximizing the utility of engineering design can mean explicit consideration of which stakeholders’ criteria will be taken into consideration (Hulse, Hoyle, & Tumer, 2019). Setting up the utility functions in practice involves assumptions about measures that may be inconsistent and relies on subjective weights. In the absence of dominance, weights for multiple attributes are context-dependent (Pattanaik & Xu, 2012).

Goal Programming

Goal programming is a multicriteria decision tool that is driven by priorities assigned by a decision-maker to multiple goals. Considered an extension of linear programming, the term goal programming was first introduced by Charnes and Cooper (1961). Details of the model and some sample problems are given in Ignizio (1978). Given the goals and priorities, an objective is solved to minimize deviations from the goals. Weighted and lexicographic goal programming are common variations. Lexicographic goal programming solves for each goal in turn, in order of priority, subject to constraints. Deviations from the target values for each goal are assigned weights according to their relative importance to the decision maker and minimized as a sum in the weighted goal programming model.

An important feature of goal programming is that solved differences between goals show trade-offs between criteria. The priorities are subjective.

Several review papers cover development and extensions of goal programming with an overview of areas of application (see, for example, Tamiz, Jones, & Romero, 1998; Aouni & Kettani, 2001; Jones & Tamiz, 2002; Caballero, Gómez, & Ruiz, 2009). Applications of goal programming include examples in engineering (supply chain, logistics and transportation, manufacturing production planning, quality, reliability and maintenance engineering), management science (accounting—budgeting, cost allocation, corporate social reporting; finance—asset management, portfolio selection; marketing—sales operation, media planning; operations—inventory management, transportation; and natural resources (Colapinto, Jayaraman, & Marsiglio, 2017). Most of the applications include multiple business goals, including incommensurate criteria. Decision problems with multiple conflicting goals naturally lend themselves to solution by goal programming.

Analytic Hierarchy Process

The analytic hierarchy process incorporates decision maker preferences by using pair-wise comparison of criteria to develop ratios which in turn are used to determine weights. The decision process and alternatives are structured as a hierarchy with the weights guiding tradeoffs among multiple criteria. The weights are scaled to produce a consistent aggregate. Yet there is still some subjectivity in choosing weights; any lack of consistency is reported by an "inconsistency ratio" (Saaty, 1980). Later Saaty (1996, 1999) extended the analytic hierarchy process by structuring the decision process as a network rather than a hierarchy, known as analytic network process.

Hosseni and Brenner (1992) suggested using the analytic hierarchy process as a way to implement the stakeholder theory of the firm, where different stakeholders may have preferences for various decision criteria. Millet (1998) suggested that the analytic hierarchy process could theoretically be used to incorporate ethical criteria into business decisions. Stein and Ahmad (2009) suggest that analytic hierarchy models could be used for after-action review to rank order ethical reasoning cases. Weights created by the analytic hierarchy process might be used together with other analysis techniques.

Interactive Methods

Multicriteria Decision Analysis always includes the decision maker in some way, because of the impossibility of generally optimizing more than one criterion simultaneously. Interactive methods incorporate the decision maker into the process of the solution method explicitly. Interactive multi-objective optimization methods search for a preferred efficient solution, which is an alternative that cannot improve one criterion without impairing another criterion. Interactive methods proceed through several iterations. At each iteration a set of solutions is presented to the decision maker, who then makes choices that are used to further refine the solution set. Iterations continue until the decision maker is satisfied with a solution.

One of the earliest examples introduced preference of the decision maker into a mathematical programming algorithm in a man-machine interactive mathematical programming approach to multi-criterion optimization (Geoffrion, Dyer, & Feinberg, 1972). Kasımoğlu (2016) summarizes various interactive methods for multi-objective decision making solutions to continuous problems. Various interactive methods have been developed to match various mathematical assumptions (see chapter 2 in Branke, Deb, Miettinen & Słowinski, 2008). Since the decision maker is more involved in the interactive process than with either a priori or a posteriori indication of decision maker preferences, potentially the decision maker will be more aware of the array of solution alternatives.

Evolutionary Algorithms

Multi-Objective Evolutionary Algorithms solve for a set of solutions, and iteratively improve the set. As each iteration produces a set of solutions, the trade-offs between multiple criteria are made explicit. The goal is to see a set of solutions that shows the Pareto-optimal front. Eventually a decision maker chooses a solution from the set. While not an optimization, an evolutionary algorithm allows a decision maker to focus on a region of the Pareto front where the trade-offs indicate a productive compromise solution (Deb pp. 59-96 in Branke, Deb, Miettinen, & Słowinski, 2008). Interactive approaches to evolutionary algorithms involve the decision maker in the process of steering the search for each set of solutions (Jaszkiewicz1 & Branke, pp. 179-193 in Branke, Deb, Miettinen, & Słowinski, 2008).

APPLICATIONS OF MULTICRITERIA ANALYSIS

Quantitative multicriteria analysis has been applied in a variety of areas where multiple attributes are important. A review paper categorized applications into 15 fields: energy, environment and sustainability, supply chain management, material, quality management, Geographic Information Systems (GIS), construction and project management, safety and risk management, manufacturing systems, technology management, operation research and soft computing, strategic management, knowledge management, production management, tourism management and other fields (Mardani, Jusoh, Nor, Khalifah, Zakwan, & Valipour, 2015, p. 518). A few of them will be described to illustrate the array of applications, although this list is not exhaustive.

Energy and Environment

Bottoms and Bartlett (1975) used goal programming to aid land management sustainability decisions in a Colorado State Forest. Goals included economic as well as resource usage goals (budget, profit, recreation user days, cow-calf months of grazing, steer months of grazing, elk months of grazing, deer months of grazing, lodgepole pine, spruce-fir, sediment). Multiple runs with different orders of priorities for the goals showed trade-offs between the goal measures.

Energy, environment, and sustainability is a multifaceted concept that lends itself to consideration as a multicriteria decision. Both economic measures and environmental measures are important, and characteristically incommensurable. In the energy industry, Linares and Romero (2000) considered multiple criteria, including total cost, CO_2 emissions, SO_2 emissions, NO_x emissions, and radioactive waste, in a decision planning exercise for the production of electricity in Spain. A matrix of explicitly computed tradeoffs was created by optimizing each criterion separately. Then the analytic hierarchy process followed by goal programming was used to determine weights to generate compromise solutions. The chosen compromise solution was then subjective.

To model earthquake risk for disaster preparedness, 26 selected geographical features and population characteristics relevant to earthquake response planning for the City of Vancouver were identified. The analytic hierarchy process was used to create weights and combine weighted variables to produce multicriteria scores. The scores could then be used to aid decisions regarding resource allocation for post-disaster emergency response scenarios (Walker, Schuurman, Swanlund, & Clague, 2020).

Health Care

In the health care industry, multiple health attributes as well as economic criteria are important to an array of decisions. A review of articles reporting healthcare decision criteria identifies 58 criteria classified into 9 categories (Guindo, Wagner, Baltussen, Rindress, van Til, Kind, & Goetghebeur, 2012).

One approach incorporates multiple criteria into a single measure. The Health Utilities Index (HUI) is a multi-attribute scoring of incommensurate health conditions summarized into a utility function. The Health Utilities Index HUI2 classification system, for example, includes 7 attributes – Sensation, Mobility, Emotion, Cognition, Self-Care, Pain, and Fertility – each with 3 to 5 levels (Horsman, Furlong, Feeny, & Torrance, 2003, p. 5); those scores are then used to calculate a summary score of health-related quality of life (HRQL). Multi-attribute scales of overall HRQL are defined such that the score for dead = 0.00 and the score for perfect health = 1.00 (Horsman, Furlong, Feeny, & Torrance, 2003, p. 7). The overall HRQL can then be used in cost-utility and cost-effectiveness analyses.

A review of the use of multicriteria analysis to address trade-offs between costs and benefits of health interventions found multicriteria analysis used for investment in medical devices, drugs, and medical service programs such as screening and treatment. Most commonly used criteria included health outcomes, disease impact, and implementation of the intervention; economic criteria included cost-effectiveness criteria, and total costs/budget impact of an intervention. The number of criteria ranged from 3 to 15. Most of these health studies looked to create a composite weighted score to be used in subsequent decision analysis. Methods ranged from expert opinion based scores to analytic hierarchy process (Wahlster, Goetghebeur, Kriza, Niederländer, & Kolominsky-Rabas, 2015).

A hypothetical case study to evaluate healthcare management decisions demonstrates a comparison of various multicriteria analysis techniques. The problem is for a health advisory committee to choose the best medical device considering criteria of cost, feasibility of adoption into the health system, consistency with expected societal and ethical values, and clinical impact (Diaby & Goeree, 2014).

Business and Finance

Return and risk are two criteria of classic importance in financial decisions such as choice of an optimal portfolio. Even these two create difficulty for using a single-measure optimization model, and the list of measures of importance to financial decision makers is easily expanded beyond these two. Early applications of multicriteria analysis to investment decisions considered multiple financial goals. Lee and Lerro (1973) used a goal programming model to create a portfolio where goals were expected return, risk, current income, and a measure of tolerance for variation from expected market conditions.

Reviews mention similar financial applications of various multicriteria methods to financial analysis classified into a number of application areas (Zopounidis, & Doumpos, 2002; Steuer, & Na, 2003; Aouni, Colapinto, & La Torre, 2014). Criteria are typically multiple, incommensurate financial measures.

Socially responsible investment is a finance application that involves consideration of multiple decision criteria, some of which are financial and some of which are environmental or ethical. García, González-Bueno, Oliver, and Riley (2019) modeled a socially responsible portfolio of 10 assets from companies included in the Dow Jones Industrial Average. Three objectives were used—return, downside risk, and Bloomberg's environmental, social and governance (ESG) score. They used a fuzzy multi-objective evolutionary algorithm to solve for the Pareto front of non-dominated solutions and then sorted them by expected risk-adjusted returns to choose one portfolio.

RESOLVING BUSINESS-ETHICS DILEMMAS

Ethical business decisions are always made in a multicriteria context because there are at least two measures of interest—a business measure and an ethics measure. More broadly, stakeholder management commonly includes a moral dimension (Wall & Greiling, 2011, p.106). Sometimes the most profitable alternative is at least as ethical as others; put another way, sometimes the alternative which is most ethical is at least as profitable as other alternatives. That is, there is dominance. However, where there are multiple decision criteria, dominance is not guaranteed. Sometimes the most profitable alternative is less ethical and sometimes the most ethical alternative is less profitable. Including many business stakeholders, and also acknowledging ambiguity in how to measure what is ethical, the optimal alternative is by no means clear. However understanding the nature of multicriteria analysis can inform these types of decisions.

Resolving a Multicriteria Decision Dilemma

Resolving a decision dilemma must start with articulating the dilemma itself. This means identifying the multiple stakeholders and criteria by which each stakeholder measures success. For ethical issues criteria that loom large include principles, consequences, and fair/transparent process. Questions to structure a framework for resolution of a business-ethics dilemma include:

- Who are the stakeholders?
- What are the criteria of each stakeholder for successful consequences?
- What ethical principles apply?

Within this multicriteria decision framework alternatives can be developed and analyzed. Multicriteria analysis tools can help analyze the trade-offs among criteria with different measures. It should be acknowledged that priorities in multicriteria analysis are set subjectively. Maintaining transparent responsibility throughout the decision process is critical.

Algorithmic and Corporate Decision Dilemmas

The rational part of decision making can be programmed. But for a multicriteria decision, there may be a dilemma where some part of the decision process is non-rational. Can the subjective behavioral part of decision making be programmed? Technically, you can program algorithmic choices. But consider the inherent limitations of multicriteria analysis: weights can be arbitrary, priorities may change, and context can make a difference. Responsible management connects choices with consequences (Rudy-Hiller, 2018). Fully automated algorithms create distance between the priority setter and consequences of those priority choices. Distancing the decision maker from the consequences of those choices is an ethics problem. Use of algorithms can make it seem as though no one is responsible, yet clearly this is not true. The array of alternatives being considered, decision criteria, weights, priorities are all business-ethics responsibilities.

In an imperfect world (the real world we live in) separation from responsibility can be dangerous. Consequently, transparent human-machine systems are more responsible than fully automated systems. Transparency in corporate decisions is important for the same reason.

Responsible algorithmic decision systems should address the following questions:

- Are units of measure comparable? Can they be aggregated?
- Is the system open or closed?
- Is it deterministic or stochastic?

- Is there a risk to life?
- Who (plural) is responsible?
- Is the decision process transparent?
- What part of the process is subjective?

In addition the ethical dilemma questions articulated earlier need to be addressed:

- Who cares about the outcome (the stakeholders)?
- What are the multiple criteria for assessing successful consequences?
- What ethical principles apply?

Priorities and weights are subjective and should be human choices that are transparent and traceable. Multicriteria situations depend on some personal input to complete the process of making a decision. With these priorities and/or weights, multicriteria decision processes can then be completed by:

- Analyze/score/rank alternatives (use appropriate multicriteria methods)
- Choose alternative to implement

The framework for resolving a business-ethics dilemma responsibly is summarized in figure 4.

Figure 4: Business-Ethics Dilemma Decision Framework.

Decision process:	**System risk factors:**
• Who are the stakeholders? • What are the multiple criteria for assessing successful consequences? • What ethical principles apply? • Analyze/score/rank alternatives (use appropriate multicriteria methods) • Choose alternative to implement	• Are units of measure comparable? Can they be aggregated? • Is the system open or closed? • Is it deterministic or stochastic? • Is there a risk to life? • Who (plural) is responsible? • Is the decision process transparent? What part of the process is subjective?

CONCLUSION

To be realistic about the actual possibility of making ethical decisions in business, one must recognize that expecting all ethical business decisions to be always be more profitable than less ethical alternatives is as unrealistic as expecting business and ethics to never be in sync. This conclusion derives from the observation that making ethical business decisions is essentially a multicriteria enterprise. Sometimes ethical business decisions will be profitable, sometimes ethical business decisions will be more costly than less ethical alternatives and therefore be less profitable.

Multicriteria analysis is appropriate for business-ethics decisions because ethical business decisions always include at least two measures of success, a business objective and an ethics objective. There may sometimes be more than two measures. Models and algorithms can be very helpful. But resolving trade-offs among multiple and incommensurate objectives relies on human decision makers to be part of the decision process, either explicitly or implicitly. Responsible business-ethics decision should be transparent about this process. The process should not be veiled by corporate hierarchy or algorithms. Particular care should be taken in open systems where the data on which decisions are based is constantly changing.

Inevitably business-ethics decisions will sometimes be dilemmas. The best choice may not be best for all stakeholders. Responsible multicriteria decision processes are a moral imperative to resolve business-ethics dilemmas.

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