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An Intelligent Decision Support System Inspired by Newton's Laws of Motion

Nafe Moradkhani, Frederick Benaben, Benoit Montreuil, Matthieu Luras,
Clara Le Duff, and Julien Jeany

Abstract The purpose of this study is to present a novel perspective on decision technology based on classical physics rules, considering risks and opportunities as physical forces deviating systems as an object from their stable states. The forces are created by changing the internal and external characteristics of the system. The ultimate objective is to propose a multi-criteria performance framework within the geometrical space of the system Key Performance Indicators (KPIs) based on classical physics rules by mapping management concepts onto physical notations. The present study is tuned to a model of interaction between the inventory management module and the workforce supply chain to present the main work. In addition, the significance of the study as an intelligent decision system to manage the given model through Newton laws is investigated.

45.1 Introduction

Many of the current problems are unintentional outcomes of prior actions. Too often, initiatives designed to solve serious challenges fail, intensify the problem, or create

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new ones. A detailed examination of complex systems and their surroundings can shed light on the breadth of system disturbances and viable control solutions. The proposed study builds on a model of interaction between the inventory management module and the labor supply chain outlined in John Sterman’s book, “*Business Dynamics*” [1]. The Physics-of-Decision (POD) paradigm introduced in [2] is used to facilitate the intricacies of the inventory-workforce model by offering a multi-dimensional performance management framework. According to the original POD paradigm, risks and opportunities may be considered as physical forces applied to the system that can push or pull it in its performance space by varying the system’s KPIs. The chosen inventory-workforce model for this study is a part of a developed manufacturing supply chain model, which consists of (i) a stocks-and-flows structure for acquiring process inputs and (ii) management policies governing the various flows, is divided into three distinct but interconnected models: (i) material management, (ii) inventory management, and (iii) workforce management. Due to a constraint of space, the research presented in this paper focuses on the coupled inventory-workforce part. Figure 45.1 depicts a simple overview of the manufacturing supply chain model, with the highlighted blue portion of the model used in this study. The main goal of this study is to provide a decision support tool for complex management systems based on classical physics rules by mapping management concepts onto physical notations. Particularly, the focus is on the mobility of the researched system inside its performance space, where the motions are analyzed in a multidimensional space defined by the system’s KPIs rather than in 3D space. The following two objectives are addressed in further detail in this study by applying the POD theory to the inventory-workforce model.

1. The kinematic analysis examines the behavior of a system’s performance trajectory considering its inputs, states, and outputs in its multi-dimensional KPI space.
2. Newton’s motion laws are implemented in the system evaluation space by considering risks and opportunities as physical forces applied to the system’s performance trajectory.

The remainder of this paper is organized as follows. Section 45.2 focuses on current research activities related to the Physics of Decision subject and the inventory-

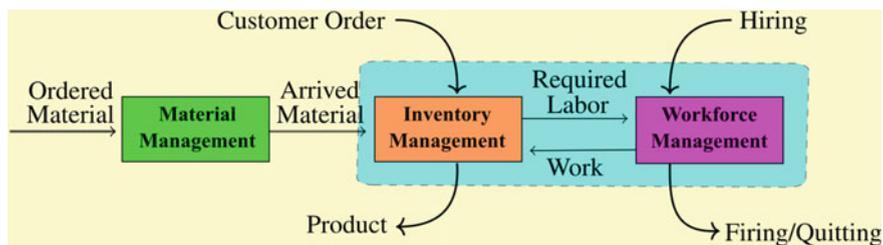


Fig. 45.1 Simple schematic of the manufacturing supply chain model

workforce model as a case study. Section 45.3 first tunes the inventory-workforce model to the Physics of Decision (POD) framework as an Intelligent Decision System (IDS) and then studies the physics motion rules on the tuned model to the POD framework by mapping the management concepts onto the physical notations. Finally, Sect. 45.4 provides conclusive remarks and proposes areas for further research.

45.2 Background and Related Works

The characterization of the system and the interaction between its parameters are at the heart of system diagnostics. Identification of such links and their influence on the system's performance is required for system control. System states describe the system's changing situations across time [3]. Different approaches to risk management have resulted from many domains and perspectives. For example, Failure Mode and Effects Analysis (FMEA) [4] and Cost-Benefit and Risk-Benefit Analyses (CBA and RBA) [5]. Such approaches are inherent in the POD framework, which has been examined in a variety of contexts, including crisis management [6], supply chain management [7], polling place management [8]. By leveraging these instances, the following section describes preliminaries and basic concepts of the POD framework.

45.2.1 Physics of Decision Foundations

The Physics of Decision is being used as a time-dependent approach to investigate systems by leveraging simulation modeling in the following three steps: characterization, identification, and control. The process of determining the system's inputs, their range of variation, and the system's outputs is known as the *characterization* step. Next, the *identification* step is used to define or estimate the map function between the system's inputs and outputs [7]. Finally, the *control* stage is concerned with the effective regulation of the movement of the investigated system as an “**object**” in a multi-dimensional space of its KPIs that is pushed and pulled by “**physical forces**” derived from its input variation.

The mathematical representation of this approach can be expressed as a function \mathbf{F} from an input space \mathcal{X} into an output space \mathcal{Y} . The function \mathbf{F} is defined implicitly by the specified input-output pairs in the *characterization* stage [2]. The method of representing time-dependent systems by vector differential or differential equations is well established in systems theory and applies to a fairly large class of systems [9]. For example, the differential equation

$$\begin{aligned} \frac{dx(t)}{dt} &\triangleq \dot{x}(t) = \Phi[x(t), u(t)], \quad t \in \mathbb{R}^+ \\ y(t) &= \Psi[x(t)]. \end{aligned} \tag{45.1}$$

Where $u(t) \triangleq [u_1(t), u_2(t), \dots, u_p(t)]^T$, $x(t) = [x_1(t), x_2(t), \dots, x_n(t)]^T$, and $y(t) = [y_1(t), y_2(t), \dots, y_m(t)]^T$ represent a p input, m output system of order n . While $u_i(t)$ represents the i -th input vector at time t , $x_i(t)$ represents the i -th state variable of inputs' vectors, $u_1(t), u_2(t), \dots, u_p(t)$, at time t , and $y_i(t)$ represents the i -th output vector at time t . Functions Φ and Ψ are static nonlinear maps defined as $\Phi : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}^n$ and $\Psi : \mathbb{R}^n \rightarrow \mathbb{R}^m$. The function Φ presents the states of the system inputs in space \mathcal{U} ; Since the number of inputs is considerably fewer than their possible states ($p \ll n$), the Φ would be a $n \times p \rightarrow n$ dimension function. The Ψ function is used to depict the relationship between inputs (vector $u(t)$) and outputs (vector $y(t)$) through *identification* stage. The vector $x(t)$ denotes the state of the system at time t and is determined by the state at time $t_0 < t$ and the input $u(t)$ defined over the interval $[t_0, t)$. The output $y(t)$ is determined by the state of the system at time t ($x(t)$). Equation (45.1) is referred to the input-state-output representation of the system [9]. This paper is concerned with dynamic systems which can be represented by differential equations corresponding to the differential equation given in (45.1). These take the form

$$\begin{aligned} x(k+1) &= \Phi[x(k), u(k)], \\ y(k) &= \Psi[x(k)]. \end{aligned} \tag{45.2}$$

where $u(\cdot), x(\cdot)$, and $y(\cdot)$ are discrete-time sequences. Figure 45.2 depicts the Physics of Decision framework as a time-dependent technique with the input-states-output vision. The most essential takeaway from the presented framework in Fig. 45.2 is to see the investigation system as an object in its multi-dimensional performance space \mathcal{Y} , which might be pushed and pulled by produced forces (F_1, F_2, \dots, F_p) resulting from its inputs variation (u_1, u_2, \dots, u_p) at any time t .

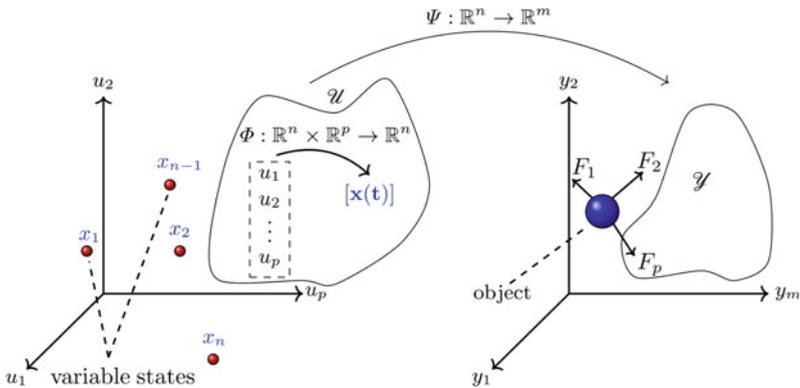


Fig. 45.2 Mathematical representation of the physics of decision approach

45.2.2 *System Dynamic Model of Inventory-Workforce Management*

The inventory-workforce model illustrates how production scheduling and employment regulations interact, potentially causing inconsistency in effectively responding to consumer demand. To avoid the “material management” section, this study assumes that the required material is always available or infinitely flexible for the “Production Start” flow in the inventory model, although, in reality, production is determined by material availability (see Fig. 45.3). Aside from that, the model makes some significant simplifying assumptions. Order backlog is ignored and customer orders are exogenous. The inventory-workforce model emphasizes labor’s importance as a production factor. When the workforce model and the inventory model are combined, production starts to adapt with a delay to the targeted start time. The inventory level with the connected workforce model decreases further after the demand shock (high order from customers) than the inventory model without it. The inventory model structure and the equations between its parameters, stocks, flows, and Causal Loop Diagrams (CLD) are thoroughly described in Chap. 18 of the “*Business Dynamics*” book [1]. Chapter 19 discusses the workforce model and its link to the inventory model. The behavior of the coupled model, including oscillations and their sources, is also explored [1]. This study avoids repeating how the models work and suffices with the structure of the models and the relationships between the parameters, stocks, and flows presented in Fig. 45.3. Dashed arrows represent the shared parameters of the two coupled models. Apart from a lack of space, the reason for skipping the inventory-workforce model explanation is that the goal of this research is to apply the POD paradigm to the time-dependent models (e.g. system dynamic models) rather than the models themselves to propose a decision-making tool to simplify the complexities of such models.

45.3 **Physics-Based Intelligent Decision System**

This section describes how to build an Intelligent Decision System (IDS) by mapping management concepts onto classical physics notations. In further depth, the proposed model is tuned to the POD framework, and then Newton laws are studied in relation to it.

The inventory-workforce model described in Sect. 45.2.2 is tuned to the POD framework presented in Sect. 45.2.1 as follows. The first stage, *characterization*, is carried out in this manner. The POD framework considers the parameters in Fig. 45.3 with just *output* arrows (this property is present in 16 parameters) as inputs in the space \mathcal{U} . Figure 45.3 depicts the model’s inputs with an asterisk symbol (*). The remaining components, such as flows (e.g., “Shipment Rate”), stocks (e.g., “Labor”), and hybrid variables (e.g., “Desired Vacancies”) are outputs in the space \mathcal{Y} . Input parameters are those that the simulation modeler is able to assign values and alter (*).

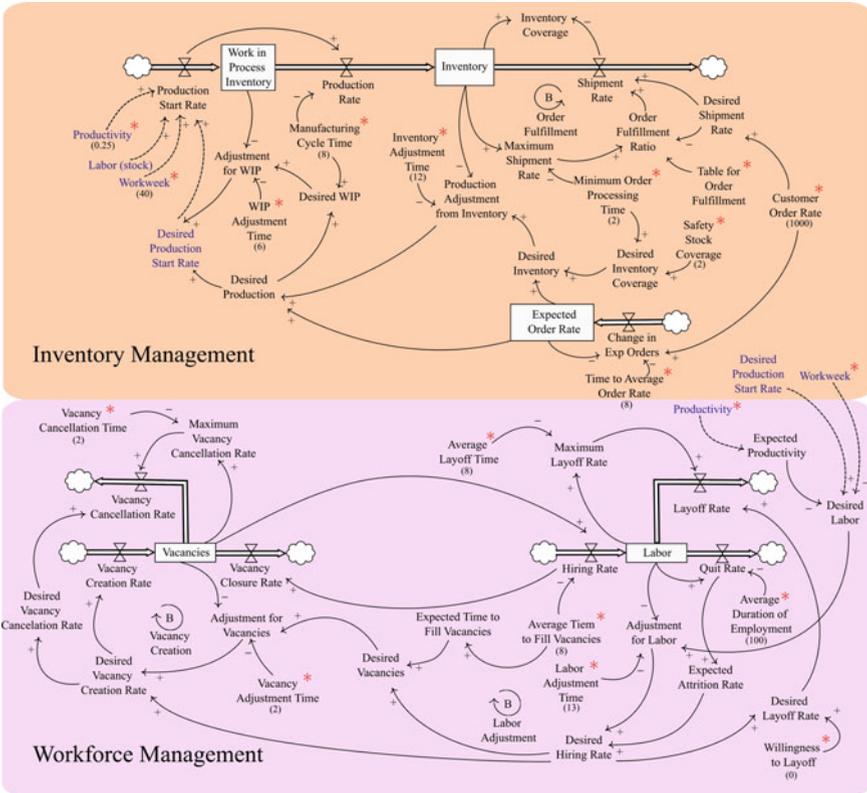


Fig. 45.3 System dynamic model of inventory-workforce management provided in [1]

Hybrid variables, on the other hand, can be utilized as input from a different point of view. The distinction between inputs and outputs is clearly based on the system management’s perspective; it is just a way to separate inputs from outputs inside the POD framework. After mapping management concepts onto physical notations, then the *identification* and *control* steps of the POD approach in the inventory-workforce model are explored.

45.3.1 Newton’s First Law Experiments and Results

Since managing a system necessitates achieving certain objectives, which are often defined by quantitative KPIs, this study follows suit (however qualitative indicators could be used in other contexts) [2]. The following explains how a KPI and its associated concepts are related to physics notations such as displacement, velocity, and acceleration.

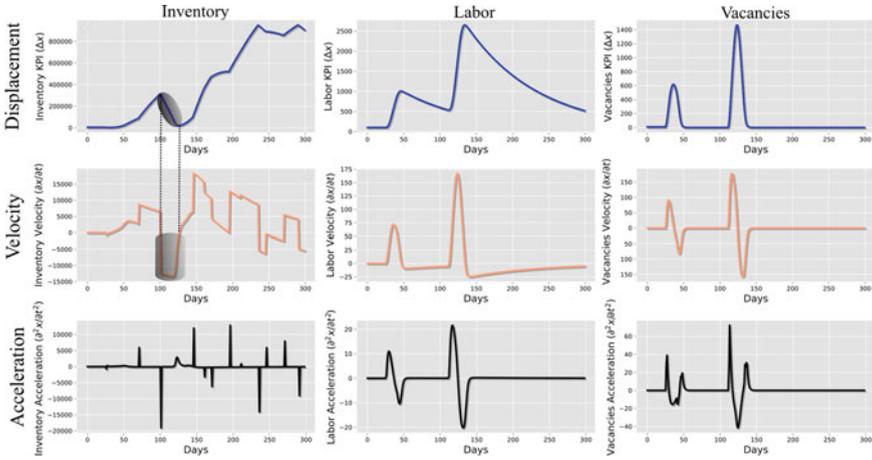


Fig. 45.4 The displacement, velocity, and acceleration for the selected KPIs

1. Displacement \Leftrightarrow Variation: The *displacement* (Δx) of the system on the associated axis to a KPI in the performance space \mathcal{Y} (e.g. y_i) is equivalent to the *variations* of that KPI,
2. Velocity \Leftrightarrow Growth: The derivative of a KPI ($\frac{\partial y_i}{\partial t}$) shows its positive/negative *growth*, which is equalized to the system's *velocity* ($\frac{\partial x}{\partial t}$) on the KPI's connected axis,
3. Acceleration \Leftrightarrow Fluctuation: The velocity derivation indicates the system's *acceleration* ($\frac{\partial v}{\partial t} = \frac{\partial^2 x}{\partial t^2}$) on the connected axis; The acceleration value may reflect how strongly or weakly a KPI fluctuates in a positive or negative direction on its connected axis, while its direction is always the same as the net force acting on the system produced by inputs' variation (*).

Since the “Customer Order” is exogenous, its variations create an external force to the system in the output space \mathcal{Y} . Figure 45.4 as an example depicts the displacement, velocity, and acceleration for the Inventory, Labor, and Vacancies KPIs (see Fig. 45.3) over 300 days while the plots are connected to the cyclic external force of the “Customer Order” change with the allocated values indicated in parentheses for the inputs in Fig. 45.3, with the recurrence period being $10 + 5 \times UDD^1(0, 4)$ days and the Order rate being $1000 \times UDD(0, 20)$ order. Each output y_i as a KPI has a stable-state in the performance space \mathcal{Y} that indicates its balanced level in response to the internal or external created forces. The interaction of the system inputs in space \mathcal{U} determines the balanced level for each output, which may change based on the system constraint for the input parameters (*). However, by appropriately assigning the inputs' values, the created forces may always be neutralized, demonstrating the presence of at least one stable-state at any time.

¹ Uniform Discrete Distribution.

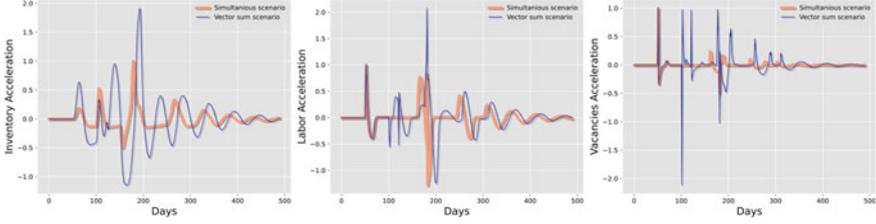


Fig. 45.5 The scaled to maximum acceleration of simultaneous and individual forces

The stable-state situation might occur in one of two ways: (i) There is *no interaction* in the system; (ii) The *total sum of the forces* entering the system is $\mathbf{0}$, indicating that the parameters have been adjusted and adapted to neutralize the applied force. An example of a stable-state of the system to neutralize created force of 1000 orders from customers is indicated in parentheses for the inputs' values in Fig. 45.3. This is an example of the system's second case of stable-state, which indicates that the input values are allocated in such a way that the "Customer Order" force is neutralized. In other words, the system does not move in output Space \mathcal{Y} , nor do the KPI values vary with time. The total produced internal vector forces of the inputs ($\vec{F}_{i1}, \vec{F}_{i2}, \dots, \vec{F}_{i16}$) neutralize the external force caused by the "Customer Order" (\vec{F}_e) by assigning well-combined input values (*). This instance supports Newton's first law, often known as the "law of inertia" (Eq. 45.3), which asserts that an object at rest will remain at rest, and an object in motion will continue to proceed straight and with constant velocity if and only if there is no net force acting on it [11].

$$F_{net} = F_e + \sum_{j=1}^{16} F_{ij} \xrightarrow{F_{net}=0} \vec{F}_e = \sum_{j=1}^{16} \vec{F}_{ij}, \quad (45.3)$$

$$F_{net} = 0 \Leftrightarrow \frac{\partial v}{\partial t} = 0.$$

If the "Customer Order" is always 1000 orders considering the allocated values to the inputs (*) in Fig. 45.3, the desired levels for Inventory, Labor, and Vacancies KPIs are 4000 products, 100 labor, and 8 available places, respectively. While in the presented example in Fig. 45.4 (the "Customer Order" is changing occasionally) the level of Inventory is less than the desired level (4000 products) starting on day 26, which is why the number of Labor and Vacancies and so on are altered and adjusted throughout the experiment.

The major takeaway of Newton's first law in the POD framework is the perpetual existence of the stable-states in the KPIs multidimensional space to neutralize the applied forces and put the system in a non-movement mode.

45.3.2 Newton's Second Law Experiments and Results

To begin, this section takes the neutralized “Customer Order” force for 1000 orders with the values assigned to the inputs in Fig. 45.3 as a baseline to examine the second Newton law for the potential internal forces of the input variations (*). Newton's second law describes a simple relationship between the acceleration of an object with its mass m , and the net force F_{net} acting on that object, $\vec{F}_{net} = m \vec{a}$. Given the calculated acceleration in Sect. 45.3.1, if the mass of the system remains constant, the net force is the vector sum of the total applied forces to the system (considered as an object). Considering the Newton's second law, $F_i = ma_i$, this takes the form of the following for the produced forces of the p inputs in Fig. 45.2:

$$F_{net} = \sum_{i=1}^p F_i \Leftrightarrow a_{net} = \sum_{i=1}^p a_i. \quad (45.4)$$

The following experiment is used to justify Eq. 45.4 to check whether the mass of the system is constant or not.

1. $F_1 \Rightarrow$ A force from inventory sector is created when the “Safety Stock Coverage” increased from 2 to 4 over a (day 50, day 70) timeframe,
2. $F_2 \Rightarrow$ A force from workforce sector is created when the “Productivity” increased from 25 to 40% over a (day 100, day 150) timeframe,
3. $F_3 \Rightarrow$ A force is from workforce sector created when the “Average Time to Fill Vacancies” increased from 8 to 10 over a (day 120, day 180) timeframe.

The results for this example on the KPIs' acceleration as the most challenging scenario are shown in Fig. 45.5 for the simultaneous and vector sum of the individual accelerations due to the applied forces. The F_1 , F_2 , and F_3 are applied in one experiment in the simultaneous scenario, whereas the F_1 , F_2 , and F_3 are applied in three separate experiments in the vector sum scenario and the results are added up together. The claim of the most challenging experiment is supported by the fact that the forces possess the following characteristics. (i) selected inputs come from both the inventory and workforce sectors; (ii) forces have a wholly indirect influence on the KPIs in question (Fig. 45.3), and (iii) to account for the simultaneous effect of the interacting forces, the applied forces are examined for relatively extended periods (not only a brief shock to the system). The presented results on Fig. 45.5 concludes Eq. 45.5, the sum of the accelerations stem from individually created forces is not equal to the created acceleration in the simultaneous scenario. Despite the fact that what the system's mass is; yet, this limitation has no bearing on the claims in Eq. 45.4, as well as Eq. 45.5.

$$a_{net} \neq \sum_{i=1}^p a_i \Leftrightarrow F_{net} \neq \sum_{i=1}^p F_i. \quad (45.5)$$

Comparison between the results of simultaneous and vector sum of the applied forces to the system proves that the mass of the system is time-dependent and varies over time (\dot{m}). In the vector sum case, generated fluctuations, primarily during the impact and release moments of the forces (50th, 70th, 100th, 120th, 150th, and 180th days), are principally due to the inefficiency of Newton's second law with the $F = ma$ form for mass-variable systems.

Variable-mass systems, like a rocket burning fuel and ejecting spent gases, are not closed and cannot be directly treated with the second law; the equation of motion for a body whose mass m varies with time by either ejecting or accreting mass is obtained by applying the second law to the entire, constant-mass system consisting of the body and its ejected or accreted mass. The second Newton law for such systems take the following form:

$$F + u \frac{dm}{dt} = m \frac{dv}{dt}. \quad (45.6)$$

where u is the exhaust velocity of the escaping or incoming mass relative to the body [10]. Given the system's acceleration on the Labor and Vacancies KPIs in Fig. 45.5, the initial force F_1 created a force over (day 50, day 70), and the simultaneous and vector sum scenarios of acceleration of the applied force are the same. This indicates that, in certain cases, Eq. 45.6 might be used to non-closed systems in the same way that it is applied to closed systems. In other words, in Eq. 45.6, the value of $u \frac{dm}{dt}$, which indicates momentum advection, is 0. Advection is the transfer of a material or quantity by the bulk motion of a fluid in physics [11]. In the other words, in this example, the produced force by F_1 moves the system by ejecting or accreting mass (Inventory KPI in Fig. 45.5) as fluid while it included some dissolved or suspended materials (Labor and Vacancies). Despite the lack of a definition for mass, this section acknowledges that the inventory-workforce model in the POD performance space is not a closed system and that the applied forces resulting from input variations eject or accrete mass to the considered system as an object in its performance space.

45.4 Conclusion and Perspectives

The goal of this work was to apply physical laws to multidimensional performance management as an intelligent decision technology. The inventory-workforce model's complexities are eased by correlating management concepts with physical notations. Kinematic analysis and Newton's laws were used to investigate the significance of the recommended approach. One major conclusion from this study is that the exact application of physical rules for variable-mass systems may enhance results. Furthermore, this vision opens the door to studying more concepts such as momentum, potential energy, gravity in order to simplify the system's complexities and determine stable states in order to avoid and take advantage of potential risks and opportunities.

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