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A new strategic approach for R&D project portfolio selection using efficiency-uncertainty maps

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Abstract

Purpose – New business practices and the globalization of markets force firms to take innovation as the fundamental pillar of their competitive strategy. Research and Development (R&D) plays a vital role in innovation. As technology advances and product life cycles become shorter, firms rely on R&D as a strategy to invigorate innovation. R&D project portfolio selection is a complex and challenging task. Despite the management's efforts to implement the best project portfolio selection practices, many projects continue to fail or miss their target. The problem is that selecting R&D projects requires a deep understanding of strategic vision and technical capabilities. However, many decision-makers lack technological insight or strategic vision. This article aims to provide a method to capitalize on the expertise of R&D professionals to assist managers in making informed and effective decisions. It also provides a framework for aligning the portfolio of R&D projects with the organizational vision and mission.

Design/methodology/approach – This article proposes a new strategic approach for R&D project portfolio selection using efficiency-uncertainty maps.

Findings – The proposed strategy plane helps decision-makers align R&D project portfolios with their strategies to combine a strategic view and numerical analysis in this research. The proposed strategy plane consists of four areas: Exploitation Zone, Challenge Zone, Desperation Zone and Discretion Zone. Mapping the project into this strategic plane would help decision-makers align their project portfolio according to the corporate perspectives.

Originality/value – The new approach combines the efficiency and uncertainty dimensions in portfolio selection into an integrated framework that: (i) provides a complete representation of the stochastic decision-making processes, (ii) models the endogenous uncertainty inherent in the project selection process and (iii) proposes a computationally practical and visually unique solution procedure for classifying desirable and undesirable R&D projects.

Keywords Project management, Risk management, Research and development, Efficiency, Uncertainty, Strategy map

Paper type Research paper

1. Introduction

In today's turbulent and competitive world, innovation helps the growth and survival of organizations (Masa'deh *et al.*, 2018). One of the key factors in forming this growth and

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survival is technology (Mumford, 2000). Hence, technological innovation has become one of the most popular and effective approaches to creating competitive advantage and long-term survival in organizations (García-Lopera *et al.*, 2022). For this reason, innovation has become an integral part of organizations' strategies for growth and survival in the era of business turbulence and technological competition (Nanda *et al.*, 2019). Research and development (R&D) are one of the oldest and most effective drivers of technological innovation. Companies initiate R&D projects to create cutting-edge products, services and business models. However, R&D processes are complex, interdependent, responsive to sudden changes in the research environment and heavily reliant on expert judgment (Nath and Mrinalini, 2000).

The traditional approaches to a project management focus on planning and assume a successful project will result from good planning practices. The good planning assumption is contrary to the complex and interdependent nature of R&D projects. Hence, new project management techniques focus on managing uncertainties and risks in R&D projects. Agile project management practices have evolved to address the uncertainties and risks in R&D projects (Kalinowski *et al.*, 2020). The practices used in agile project management differ greatly from those used in traditional project management. In some aspects, many agile project management concepts are the antithesis of conventional project management, as the spirit of this method is based on performing activities in small steps and making corrections and changes in each step. The use of predetermined milestones as "gates" between phases is a common technique used in project management to overcome this problem. Gated processes in project management are also known as stage-gate processes. This method requires a project to meet specific criteria within each phase before proceeding (Daim *et al.*, 2013). An R&D project management method should move from a tunneling mechanism to a funneling process in which a risk-aware selection process is used to promote value-added projects for the firm.

Like any other project, R&D projects have a finite duration and resource availability; hence, project managers strive to exit their businesses as quickly as possible (Klastorin, 2009). As a result, project management approaches are more suitable when decision-makers are familiar with the techniques and procedures for selecting project portfolios. Doing the right projects is the key to an organization's success. The project portfolio must meet diversification requirements, have adequate cash flow and not exceed resource limitations to achieve its goals and carry out its strategy. Therefore, choosing the project portfolio for R&D is important in two ways. First, for implementing an R&D project – like any other project – there are limited resources, and the organization must optimize its portfolio of projects. Second, the inherent uncertainty of R&D projects requires that the project portfolio be assessed in stages so that failed projects or projects more likely to fail are removed and possibly replaced by newer projects.

For this reason, the R&D project portfolio management process must be aligned with the overall corporate vision and mission (Yamakawa *et al.*, 2018). R&D projects have ambiguities inherited from the nature of innovation (Jalonen, 2011). This makes the project assessment process a challenging task. Hence, one of the most critical challenges in R&D is evaluating and selecting strategically valuable projects and programs (Young *et al.*, 2020; Knight *et al.*, 2020). This strategic project prioritization and selection requires a deep understanding of technologies and processes within the R&D projects (Yamakawa *et al.*, 2018). An essential part of strategy implementation is choosing the projects that have the most effect on advancing the planned strategy (Musawir *et al.*, 2020). But when it comes to technological projects, managers traditionally do not have enough knowledge to make informed decisions. On the other hand, the advantage of technology-oriented organizations is that they have experts with technological insight who are aware of the potential benefits, risks, opportunities, convergence and synergies that arise from the various technologies (Lubar, 1992). Normally, these experts are not sufficiently familiar with the organization's strategy to decide whether to implement the proposed projects.

Senior managers have been implicitly or openly planning a strategy for their organization for years. However, regarding the strategic selection of R&D projects, we noticed a knowledge gap between managers and technical staff. While managers know the company's strategy, they have limited knowledge of the technology and the R&D processes. Similarly, the technical team is familiar with technology and R&D but may not understand corporate strategy. We attempt to fill this gap by considering a wide range of uncertainties in a model with a transparent solution. This study proposes an intuitive and understandable model for R&D managers and corporate leaders. The model proposed in this study embraces R&D project portfolio management uncertainties using expert opinions on the opportunities and threats associated with each project. The proposed framework (1) delivers a big picture of the stochastic decision-making process for R&D project portfolio management, (2) embraces the inherent uncertainties associated with innovation processes and (3) introduces a practical process for real-life R&D project portfolio management. We formulate the following questions to address the above challenges:

(1) How can we seamlessly integrate technical and managerial knowledge of R&D teams for project selection decisions?

(2) How can we align the project selection decisions with the corporate strategy?

The remainder of this paper is organized as follows. In Section 2, we justify and present our proposed model. In Section 3, empirical results are discussed and Section 4 includes the summary and conclusions of this research.

2. Literature review

2.1 Relevant literature on strategic selection of innovative projects

Danila (1989) presented a complete review of strengths and weaknesses associated with the most widely used methods for strategically selecting R&D projects. Sanchez (1989) examined the impact of project selection techniques on forming a company's technology strategy and categorized corporate strategy into four sets of technical, market, economic and planning processes. His study showed firms that use economic strategies have preprogrammed selection criteria with rigid selection techniques. Killen *et al.* (2008) proposed a benchmark and identified the best project portfolio management practices. They found project portfolio management practices similar in the service and manufacturing industries. Menke (2013) presented a benchmarking framework and studied the best project portfolio management practices in R&D organizations. This study showed benchmarking the project portfolio management practices against best practices can improve project portfolio management practices in organizations. Cooper and Edgett (1997) showed thriving companies follow three significant objectives: Aligning projects with strategy, balancing resources among projects and achieving the maximum portfolio value. These findings emphasize the significance of strategic alignment with innovation portfolios, but it is unclear how this alignment may be achieved. It is possible to manage innovative projects by applying diverse strategies (Nobeooka and Cusumano, 1997) and firms that openly express strategic focus areas in their innovation portfolios (Bart and Pujari, 2007; Salomo *et al.*, 2008; Talke *et al.*, 2011) or connect the ideation portfolio management process with innovation portfolio management (Heising, 2012; Kock *et al.*, 2014) have more fruitful results. Specific tools and methods, such as strategic buckets, have been proposed to align innovation portfolios and the respective strategic aims (Chao and Kavadias, 2008); however, empirical results suggest that firms that have moved from purely financial to strategic tools are more successful at innovation (Szwejczewski *et al.*, 2006).

All of the above studies have focused on different aspects of corporate strategy to manage innovation portfolios; however, they lack insights into implementing strategic aims in the decision-making process. The reason is that ambiguity is at the core of innovation, which usually translates into risk and uncertainty. As explained before, the literature contains a profusion of models, methods and techniques which guide R&D project selection; however, few show the connection of R&D project selection to a corporate strategy under uncertainty. Cheung *et al.* (2009) pioneered filling this gap for technology-based companies in the face of a confusing variety of choices. However, they just focused on knowledge-oriented vagueness. Wang *et al.* (2010) introduced a framework to align R&D project risk management with corporate strategy, ignoring the status of innovation at the heart of the corporate strategy. This approach persists in studies that connect R&D project selection to corporate strategy. For example, Herfert and Arbige (2008) revealed how they align R&D portfolios with corporate strategy by introducing an iterative process within a firm. However, to assess projects against corporate strategy, they offer business and portfolio management tools. Rhéaume and Gardoni (2015) presented a comprehensive study investigating the relationship between corporate strategy and management of innovative activities, including R&D projects. They also failed to show any guideline or framework to translate innovation strategies to R&D resource allocation.

When assessing R&D projects against corporate strategy, none of the mentioned research offers any semantic guide to decision-makers to decide if a single project lies in the innovative aspect of corporate strategy. Ansoff *et al.* (2019) tried to fill this gap by applying the "strategic posture" concept to manage R&D projects. They defined two strategic postures for R&D projects: "incremental" and "discontinuous." Although this classification seems intrinsic, it does not give a clear sense of a go/no-go verdict. That is why they applied this classification to decide on the project management style and not to select projects.

A literature review on multi-criteria decision-making research on R&D project selection in the last 50 years by de Souza (2021) and his colleagues shows that, although project portfolio selection is an essential strategic process for various companies, most of the researchers have missed "Corporate Strategy" criteria for decision making.

The fact is that when a manager attempts to start any innovative activity, it plays an entrepreneurial role within the firm. Hence, just like any other entrepreneur, they need to know about the risk and rewards of that activity. It is up to researchers and R&D managers to communicate with top managers like CEOs and board members and give them an understandable and credible position of each project within the innovative aspect of corporate strategy. On the other hand, top managers have to signal the creative orientation of corporate strategy down to the organization, especially to the R&D department, to broadcast coherency between corporate strategy and innovative activities within the firm. This research aims to offer a simple, coherent and credible common framework between researchers, corporate entrepreneurs and decision-makers to make R&D project selection easier considering corporate innovation strategy.

2.2 Relevant literature on endogenous uncertainty

Uncertainty directly impacts the innovation process in organizations (Gomes *et al.*, 2020). According to Rowe (1994), uncertainty can be addressed using four main classes metrical uncertainty, structural uncertainty, temporal uncertainty and translational uncertainty in explaining uncertain results. Jalonen (2011) recognized that technology, market, regulations/institutions, society/politics, acceptance/legitimacy of outcomes, management approaches, timing and consequences of outcomes generate uncertainty in the innovation process. Consequently, uncertainty could result from organizational challenges of managing innovation or from uncertain effects (e.g. organizational performance, market acceptance) generated by innovation. As for R&D project selection, an R&D manager is mostly concerned about uncertainties within the realms of the R&D team, which certainly falls into the organizational challenges of managing innovation: technological, managerial and timing. Moreover, uncertainties are associated with the management of knowledge workers, resources and capabilities and the relationship management between the R&D teams and the rest of the firm (Souder and Moenaert, 1992; Osborne, 1996; Leifer *et al.*, 2001).

There is an intimate association between technology and innovation. Rogers (2003) argues that technology-based innovation primarily drives new ideas. The relationship between 'innovation' and 'technology' is so close that these two words are sometimes used as synonyms. According to Rogers (2003), technology generally includes technical tools and the knowledge to use them. These two aspects of technology can also cause uncertainty in the innovation process (Narvekar and Jain, 2006). Competition on a global scale needs well-timed actions and a swift pace of change. For instance, as the product life cycle shortens, the time to market becomes very critical to the product's success (Macdonald and Jinliang, 1994). Jalonen and Lönnqvist (2009) discuss the limitations of business events in knowledge management and present a model for predictive business by integrating the results from business event analysis with previous knowledge management research.

Time is a significant factor in the innovation process. Innovation is about new ideas, and its novelty depends on the context. A picture may seem novel at some time or someplace, while it may fail at other times or places. Regardless of the possible prejudice toward ideas, innovation researchers consistently admit the importance of timing in the success or failure of innovation (Macdonald and Jinliang, 1994; Schilling, 2002).

Risk management is the most critical area in R&D projects, and not managing the individual project risk factors will harm performance (Zwikael and Ahn, 2010). Hence, traditional tools used to manage risk in innovation projects are inadequate because the unknowns associated with innovation are unpredictable by their very nature (Koen *et al.*, 2010). Similarly, there is a lack of requisite metrics to make informed decisions in innovation projects. Hassanzadeh *et al.* (2014a) showed how uncertainty substantially affects portfolio decisions in real-world problems. The prime difference between risk and uncertainty is that the probability of potential risk outcomes is known or can be estimated. Whereas, that is not the case for uncertainty, especially in R&D projects.

2.3 Relevant literature on R&D project selection under uncertainty

Gaining the maximum value of the portfolio through the use of resources is often complicated by varying criteria of selection, subjective and inaccurate evaluations and dependency between projects (Ravanshadnia *et al.*, 2010, 2011). Danila (1989) selects the portfolio as the investment choice from a list of proposed investments to maximize some of the goals without violating the constraints. Cooper *et al.* (1997a,b) divided portfolio selection problems into dynamic and static categories. Bard *et al.* (1988) showed that in a dynamic approach, we face projects in progress and projects that have not been started yet. Selecting a static portfolio involves assessing the portfolio of the proposed projects. A typical position means an organization with a limited financial source to allocate new investments. We focus on the static set selection problem (Basso and Peccati, 2001).

Several methods have been proposed for selecting optimal project portfolios. For example, Cooper *et al.* (1997a,b) employed a decision tree and proposed a model that could consider the likelihood of project success. Similarly, Henriksen and Traynor (1999) proposed an evaluation method that sets the relative value for each project based on the project's suitability and cost. Using fuzzy logic, Coffin and Taylor (1996) introduced a multi-criteria decision-making methodology for choosing and planning R&D investments.

Several researchers, such as Chen and Cheng (2009), Huang *et al.* (2008), and Lin and Hsieh (2004), Tiryaki and Ahlatcioglu (2005), have focused on the uncertainty of the project in selecting portfolios of projects. For example, Huang *et al.* (2008) used a fuzzy analytical hierarchy process (AHP) to select a portfolio of R&D that considered the uncertainty of the project. Tiryaki and Ahlatcioglu (2005) used fuzzy AHP to select stocks on the stock market. Chen and Cheng (2009) used the fuzzy MCDM method and portfolio mapping projects in uncertainty. Eilat *et al.* (2006) proposed a DEA-based approach for selecting R&D prototypes. In addition, Bardhan *et al.* (2004) used realistic justification options and estimated traditional cash flows to evaluate securities related to IT investments. Ghapanchi *et al.* (2012) attempted to present an analytical representation of fuzzy data and consider the uncertainties in the projects. A serious limitation of their methodology, specifically for R&D projects, was that only a pairwise project interaction was considered (Chien and Huynh, 2018). Baker and Solak (2013) initiated a series of research on portfolio optimization of R&D activities. They applied a multi-model approach to a novel stochastic programming model version of a dynamic integrated assessment model to solve a decision-making problem, finding an optimal R&D portfolio in the face of climate change. They also developed a general framework applicable to others.

Hassanzadeh *et al.* (2014b) developed a multi-purpose integer binary programming model for selecting a portfolio of R&D projects for competitive purposes when the problem factor is undesirable in both objective functions and constraints. They used robust optimization to deal with uncertainty. Abbassi *et al.* (2014) proposed a balanced set of criteria for assessing R&D projects. They proposed a non-linear 0–1 mathematical programming approach to create a portfolio of R&D projects by balancing the portfolio values and risks and considering the interdependencies and other research constraints. Finally, the cross-entropy algorithm was proposed to solve the proposed model. Although they gave sufficient consideration to the relationships between the projects, they ignored their random nature. While Ringuest *et al.* (2000) noticed for the first time the importance of conditional randomness in choosing R&D portfolios, Bistline (2016) established an R&D Portfolio Management Framework for responding to uncertain sources as well as providing numerical results for the R&D strategy of the energy industry. Also, some research has indirectly considered uncertainty in R&D activities, as Hsu and Hsueh (2009) indirectly included the timing aspect of project uncertainty in input slack modeling. Salimi and Rezaei (2018) ultimately considered uncertainty in their decision criterion.

Monte Carlo Simulation was employed to tackle uncertainty in R&D projects by Mavrotas and Makryvelios (2021). They represented a degree of certainty of the projects in the final portfolio, which could potentially be used for strategic decision-making. In the same year, Hamidi *et al.* (2021) presented a strategic decision-making tool to assist company managers in analyzing various investment scenarios and selecting a balanced portfolio.

The above studies have analyzed the selection of uncertain projects through different aspects. We can categorize these studies based on the innovation aspects that they have considered. These aspects include knowledge, translating strategy to level of risk tolerance, risk management, portfolio management guideline, innovation process, innovation type and the uncertainty approach (Peykani *et al.*, 2022). As implied from the above discussions, only Ansoff *et al.* (2019) could cover all aspects. Nevertheless, they did not issue a clear go/any go verdict for a given project. There is a significant gap in all previous studies, as they have examined innovative projects against corporate strategy. Still, none could bring the management and technical teams together to reach a better decision (Peykani *et al.*, 2022).

3. Methodology and data

3.1 Research philosophy

Managers making decisions on R&D projects usually have basic technical knowledge and a limited understanding of the subtleties and complexities of the R&D process. This study explores how managers can make better decisions about the implementation of projects based on the intuition and knowledge of the technical staff. We also explore how to choose projects aligned with corporate strategies. We analyzed the collected data numerically to answer these questions.

Two types of data are collected. The first category is the input sources. This data includes the project management team's estimate of each project's costs and workforce requirements. The second category is the data collected from technical experts and R&D professionals reflecting their intuition about the success and failure and the value created from implementing each project. For this purpose, the respondents are asked about the likelihood of the project's success. In addition, they are requested to assign a value for the success or failure of the project.

The analysis of the collected data has three stages. In the first stage, the stochastic value curve and the value at risk are calculated for each project based on the experts' opinions. In the second stage, the input sources are used as inputs, and the value at risk is considered a negative output in data envelopment analysis (DEA) to calculate an efficiency score for each project. Moreover, each project's average probability of success is calculated as a representative of its uncertainty. This process transforms intuition into data managers can use to make effective decisions. In the third stage, the efficiency and uncertainty of the projects are mapped on a two-dimensional strategy plane. This strategic map is then used along with the organizational strategic directions to decide on the implementation of each project.

3.2 Portfolio risk calculation

Managing uncertain environments requires specific risk measurements and management solutions and techniques. Apart from the application context, a trustworthy solution should openly comprise possible undesirable consequences, resulting in adverse effects or might lead to considerable deficiencies. The scientific community has devoted an increasing level of attention to the definition of suitable risk measures since the seminal influence of Markowitz (1952) in the field of financial optimization. In this study, to propose a practical solution for risk management, we utilize the Conditional Value at Risk (C-VaR), which, as confirmed by the results presented by Rocafellar and Uryasev (2000), allows a more accurate measure of tails of the density function. In addition, C-VaR is a "coherent" measure, as stated by Artzner *et al.* (1999), and enjoys nice computational properties.

Often a project portfolio depends on numerous variables. A large number of these types of risk measures are produced in each project. However, these risk measures do not provide R&D policymakers and managers with a measure of the total risk. Value at Risk (VaR) is an attempt to provide a single number that summarizes the total risk in a portfolio. VaR has become widely used by corporate treasurers, fund managers and financial institutions. When using the VaR measure, we are interested in making a statement of the following form: "*We are X percent certain that we will not lose more than V dollars in time T.*"

Variable V is the VaR of the portfolio with two parameters: X as the confidence level, and T is the time horizon. VaR is the value we lose in period T, and we are X percent confident that the loss would not exceed this limit. We can calculate VaR by the probability distribution function of gains or losses during the period T. Losses are negative gains, and gains are negative losses. In the case of gains, as seen in Figure 1, VaR is equivalent to minus the gain at the $(100-X)th$ percentile of the probability distribution function of gains. For example, when T is five days and $X = 97$, VaR is minus the third percentile of the distribution of gains in the portfolio's value over the next five days. Alternatively, it is the 97th percentile of the distribution of losses in the portfolio's value over the next five days.

A measure that can produce better incentives for traders than VaR is the expected shortfall. This is sometimes called C-VaR, conditional tail expectation, or expected tail loss. Whereas VaR asks the question, "*How bad can things get?*" expected shortfall or C-VaR asks, "*If things do get bad, what is the expected loss*?"

The expected shortfall, like VaR, is a function of T (the time horizon) and X (the confidence level). As shown in Figure 2, the expected loss during time T is conditional on the loss being greater than the Xth percentile of the loss distribution. For example, suppose that $X = 99$, T is ten days and the VaR is $64 million. The expected shortfall is the average amount lost over ten days, assuming that the loss is greater than $64 million.

The C-VaR has better properties than VaR as it encourages diversification and far better inclusion of risk factors in R&D project portfolios. Hence in this study, we apply C-VaR as an undesirable output.

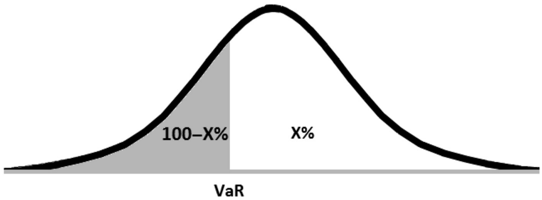
3.3 VaR and C-VaR calculation

The VaR demonstrates a normal distribution of past losses. VaR is widely used as a measure of risk in investment portfolios and represents the probability of an expected minimum over a period. VaR illustrates the extent of probable losses in "normal" market activities (Linsmeier and Pearson, 2000). When a portfolio manager claims that their portfolio has a one-year, $1 million VaR at the 99% confidence level, he means that if everything goes well, he is 99% sure that he would not lose more than $1 million in one year. Of course, the portfolio holder risks losing more than $1 million in that year with a 1% probability. The Monte Carlo simulation, historical returns and variance-covariance methods are the three approaches for calculating VaR (Stambaugh, 1996). Monte Carlo simulation generates random scenarios for possible gains and calculates VaR based on diverse scenarios. Correlations and variations of investments are used by the variance-covariance method to calculate the VaR of a portfolio.

Let us discuss how we calculate the VaR based on historical data. Assume that we have the information about future returns on a portfolio. This information indicates the VaR shows a loss limit that exceeds $(1-\alpha)\%$ of the cases. Therefore, the VaR is calculated for losses attuned for gains as follows. Losses are usually expressed in financial terms; however, we enumerate them in terms of gains (percentage). Let us assume V_t is the market value at time t and V_{t+h} is the market value at time $t+h$. We define loss (L) as:

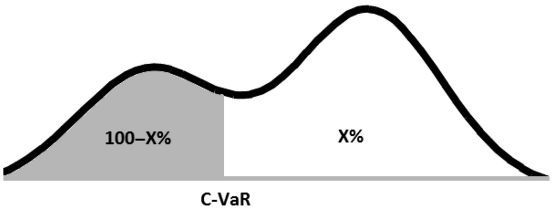
$$L = \frac{V_t - V_{t+h}}{V_t} = -rX \quad (1)$$

where $P(L > VaR_\alpha) = 1 - \alpha$.



Source(s): Hull, 2018

Figure 1.
Calculation of VaR from the probability distribution of the gain



Source(s): Hull, 2018

Figure 2.
Calculation of C-VaR from the probability distribution of the gain

The following non-convex integer program would exactly solve for VaR:

$$VaR = M_{\lfloor\lfloor(1-\alpha)s\rfloor:s\rfloor}(-rX) \tag{2}$$

where $\sum_{i=1}^{n} X_i = 1, X \geq 0$

The kth largest number between N numbers is indicated by $M_{\lfloor k:N\rfloor}$. If the portfolio gains have a normal probability distribution function, the VaR calculation requires a non-linear programming problem, as described below. Assume there are n stocks with a normal distribution $N(\mu, C)$ available for investment, where C is a symmetric and positive definite matrix. Some features of a normal distribution are useful for calculating VaR. Since $\xi \sim N(\mu, C)$ then $-X'\xi = \sum_{i=1}^{n} -X_i\xi_i \sim N(E(X), \sigma(X))$. Here $E(X) = -X'\mu$ and $\sigma(X) = \sqrt{X'CX}$. Then:

$$VaR = -(X'\mu) + \Phi^{-1}(1-\alpha)\sqrt{X'CX} \tag{3}$$

where $\sum_{i=1}^{n} X_i = 1, X \geq 0$.

Rockafellar and Ursayev (2002) established a new risk measure called C-VaR. VaR measures the minimum loss corresponding to the certain worst number of cases, but it does not quantify how bad these worst losses are. An investor may need to know the magnitude of these worst losses to discern whether there are possibilities of losing huge sums of money. C-VaR quantifies this magnitude and measures the expected loss corresponding to several worst cases, depending on the chosen confidence level. Using C-VaR makes the portfolio selection problem linear, and when we solve it, a minimum VaR is found since C-VaR ≥ VaR (Rockafellar and Ursayev, 2000). C-VaR is derived as follows:

Let $f(X, \xi)$ be the loss function of the portfolio. Usually, losses are in monetary terms, but we express losses in terms of returns (percentage). Given a confidence level, α, C-VaR is the expected value of all $(1-\alpha)\%$ losses and can be found using the following function:

$$CVaR(X, \eta) = \eta + (1-\alpha)^{-1} \int_{\xi \in R^n} [f(X, \zeta) - \eta]^{+} p(\zeta) d\zeta \tag{4}$$

where $\eta = VaR$, $\xi = random\ variable$, and $z^{+} = max\{z, 0\}$.

When scenarios of future returns are available, the C-VaR of a portfolio can be formulated discretely. Since r is the return matrix, rX is the portfolio of returns. Therefore the losses will be $-rX$. The problem tries to find the expected value of all the worst $(1-\alpha)\%$ losses. The following linear program would solve the problem:

$$\begin{aligned} &Minimize\ \eta + \frac{1}{s \times (1-\alpha)} \sum_{i=1}^{s} (y_i) \\ &subject\ to\ y_i \geq \sum_{j=1}^{n} [(-r_{ij}X_j) - \eta] \end{aligned} \tag{5}$$

where $y_i \geq 0\,;\ i = 1, 2, \ldots, s\,;\ \sum_{i=1}^{n} X_i = 1$ and $X \geq 0$.

If a loss scenario is greater than $VaR(\eta)$ then the y variable will take on the exact difference between the loss scenario and $VaR(\eta)$. If a loss scenario is less than VaR, then the y variable will take on the value zero. Since the distribution of y_i represents the tail distribution of losses exceeding VaR, the mean can be found by computing the weighted sum divided by $(1-\alpha)$. Then C-VaR is added to VaR, which the objective function calculates as required.

3.4 Fuzzy versus stochastic approach

While stochastic programming has been traditionally used for optimization techniques under uncertainty, many researchers have used a fuzzy approach to deal with uncertainty in R&D project portfolio selection. The differences between fuzzy mathematical programming and stochastic programming should be clarified, and the comparative advantages of each approach in different situations. The following describes two differences between stochastic and fuzzy mathematical programming approaches (Inuiguchi and Jaroslav, 2000):

(1) Stochastic programming problems can be solved easily once the random variable follows a normal distribution. However, stochastic programming is a complex problem to solve in cases of unspecific distributions. On the other hand, fuzzy programming problems are used to solve problems where a unimodal distribution binds the random variable. Fuzzy programming problems are easier to solve than stochastic programming problems.

(2) When random variables are independent, the optimum solution of fuzzy programming delivers only a small number of non-zero variables. In contrast, stochastic programming provides many non-zero decision values in the optimum solution.

Loch (2000) argues companies shall develop a tailored project portfolio and a consistent combination of processes to meet their strategic innovation needs. Hence, we emphasize that various solutions can be obtained, reflecting the decision maker's intention. From an R&D manager's perspective, he is looking for a practical tool to help him decide which project to include in his portfolio. Suppose the R&D team is mature enough to gain the assistance of experienced engineers and R&D veterans. In that case, the R&D manager has a huge potential to enhance the decision process by giving questionnaires to experienced engineers and R&D veterans and using the collected data for decision-making. This approach aligns with Carbonell and Escudero's (2016) approach. They examined the direct effect of decentralization in strategy-making on new product development (NPD) and a moderating effect of decentralization on the relationship between portfolio planning and program success. Their findings indicated that NPD portfolio planning positively influences NPD program success. Hence, taking opinions from experts is a good example of decentralization in decision-making. Kettunen and Salo (2017) showed that estimation errors about the future value of projects, combined with the fact that only some of the projects can be selected, have major implications for estimating the risk of the selected project portfolio. Hence, we take estimation errors of the future value of projects into account as a part of uncertainty consideration in the project selection process.

3.5 Proposed model

Modeling innovative activities into decision-making units with distinct input-outputs has gained merit in recent innovation efficiency research (Namazi and Mohammadi, 2018). R&D priority-setting involves systematically estimating costs and benefits (Janzwood, 2021). Hence, to model the process of an R&D project, we consider required human resources in terms of person-hour and fixed costs such as equipment, software licenses and laboratory costs. Current R&D costs are considered project inputs, and the outputs are considered project inputs risk and created value (Peykani *et al.*, 2022). In this model, the assumption is that, due to the nature of R&D, the output of a project is a value that results from the outcomes of innovative activities. Items such as a production-ready prototype and deposition of knowledge and technology in the organization boost created value, and items such as discredit and lost opportunity are considered counter-value. For example, if the project succeeds, the output may be a combination of a patent and a product to be marketed or, in the event of project failure, the value of knowledge applicable for other activities and projects, taking into account the counter-value of failure discredit, deduced from the organization (Peykani *et al.*, 2022). The model is shown in Figure 3.

This model presumes inputs as constants and values as stochastic output. In other words, required resource estimates are taken as deterministic numbers, while considering the uncertainties in the R&D activities, the created value has a distribution function. As described further, financial engineering and risk management topics motivate project risk calculation.

3.6 Stochastic value

When a decision-maker attempts to include a project within a portfolio of projects, they certainly think about the risks and uncertainties that may impact the project's expected outcomes. Knowledge is a key outcome of R&D projects (Martínez-Sánchez *et al.*, 2020). Hence, there is a major difference between R&D projects and other projects. According to research by Geng *et al.* (2018), knowledge is the central perspective of R&D project selection. Other views include economics, technology, operation, strategy, customer, partner and resources. Knowledge contribution of R&D projects can be categorized into three criteria (Peykani *et al.*, 2022):

(1) Individual learning (Nonaka and Takeuchi, 1996),

(2) Organizational level learning (Argote and Ingram, 2000; Botha *et al.*, 2014; Arenius *et al.*, 2002)

(3) Organizational culture change (Marsick and Watkins, 2003).

These categories of knowledge are projected contributions to the whole organization, and despite other project perspectives, they remain a positive contribution to the organization even if the project fails. This influence could be much stronger in the case of the project's successes. That means R&D projects still bring value to organizations when they fail (Weekly, 2021). Hence, we should consider this "failure value" in the project selection scenario (Peykani *et al.*, 2022).

As already mentioned, this model assumes that an R&D project can be valuable even in the event of failure, as the accumulated knowledge is the least the project brings to the organization.

Generally, the value of a project in case of failure is much less than its value if the project succeeds. Hence, for the calculation of created value, the following three parameters are specified:

(1) Projection of project success rate,

(2) Prediction of created value if successful, and

(3) The estimated value created in case of project failure is a percentage of the predicted value created in case of success.

Therefore, the created value is calculated as:

$$V = p \times V_s + (1 - p) V_f \times V_s \tag{6}$$

In this formula, V is the total created value, p is the probability of success, V_s is the value created in the event of success and V_f is the percentage of the value created in the event of

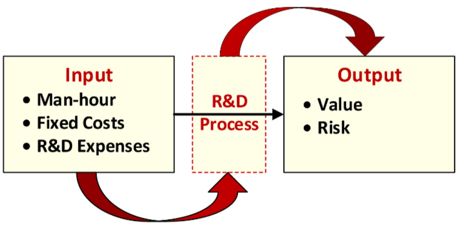


Figure 3.
R&D project process model

failure. The model assigns the binomial distribution for success, the normal distribution function for value created in the event of success, and the percentage of value in failure.

3.7 Data envelopment analysis with undesirable output

In real-life production systems, harmful or unwanted outputs may be generated as byproducts along with the desired products. Undesirable outputs include environmentally harmful wastes or contaminants, defective products, wasted time or resources or pollution. Ignoring undesirable outputs in efficiency measurement may result in a biased valuation of performance, flawed calculations and/or false decisions. The key solution is to consider the asymmetry between the desirable and undesirable outputs. In other words, one should seek to increment the desired outputs and decrement the undesirable outputs concurrently to achieve maximum efficiency. In our case, the risk is an undesirable output that should be minimized.

Aparicio *et al.* (2015) proposed different approaches for considering undesirable and desirable outputs in efficiency measurement. In this case, decreasing the undesirable outputs and increasing the desirable outputs relative to the same amount of input are used to describe the Malmquist-Luenberger productivity measure and avoid the contradictions of the initial research by Chung *et al.* (1997). Model (7) is used to calculate the efficiency of (x_o, y_o^d, y_o^u), as the input/output vector of the decision-making unit observations, and the output vector $g_y = (y^d, y^u) \neq O_{m+s}$, as the predetermined output target:

$$\begin{aligned} & \max_{\beta,\lambda} \beta \\ & \textit{Subject to} \\ & X\lambda \leq x_o \\ & Y^d\lambda \geq Y_o^d + \beta y_o^d \\ & max\{y_i^u\} \geq y_o^u - \beta y_o^u \\ & \lambda \geq 0 \end{aligned} \tag{7}$$

X, Y^d, and Y^u contain the inputs, outputs and undesirable outputs variables, respectively. Here, n is the number of decision-making units (projects), and m, s, and r are the number of inputs, outputs and undesirable outputs. The optimal solution corresponds to β_{CRS}^* and if $\beta_{CRS}^* = 0$ with the observation is directional efficient. Otherwise $\beta_{CRS}^* \geq 0$ signals inefficiency.

3.8 Data collection

To collect data for analysis, we consider R&D a widely accepted and well-established innovation process within various industries. This makes data analysis results easier for practitioners and researchers to digest. Sources of uncertainty in projects are diverse, making each project a unique experience (Hazir and Ulusoy, 2019). Hence, gathering probabilistic information about R&D projects is a challenge in itself. Involving experts with insightful knowledge of the possibility of events or values is a practical technique for generating input data for probabilistic decision models without historical data. This method is often called "expert judgment elicitation," obtaining probabilities from knowledgeable individuals (Hora, 2004). The application of expert elicitation in the stochastic evaluation of R&D projects has been the focus of academic research for the last decade (Bistline, 2016; Baker and Solak, 2013; Solak *et al.*, 2010; Baker and Solak, 2011). Expert judgment can be used when there are no sufficient historical data and consensus about the processes for translating historical data into predictions (Hora, 2007). However, eliciting and aggregating expert opinions is a challenging problem (Predd *et al.*, 2008; Roelofs and Roelofs, 2012). Hence, we used a Delphi process for expert elicitation to acquire probabilistic information in this research. Thirty-three projects were selected from an R&D department, and ten experts with more than ten years of R&D and product management experience were chosen to provide feedback on those projects.

Project managers provided estimates on person-hours, fixed costs and R&D costs. Hence the mentioned parameters are assumed as fixed inputs. Experts are asked to give their opinion based on their experience and understanding of the level of complexity, technology, required knowledge, future risks and market needs of each project about the probability of the success of projects, the expected value in the event of success and expected value in the event of failure of the project.

Mosleh and Apostolakis (1986) argue while experts have a reasonable bias, errors are symmetrically distributed about the bias and the assumption of a normal distribution is justified since the distributions of our variables are known. The stochastic approach is used to gain more accuracy for the solutions.

4. Empirical results

Data was collected from experts in a large IT company with a long history of R&D in data communication. This R&D unit has been a national role model, winning several international innovation awards (Namazi, 2016). Consequently, this unit was regarded as a representative at the national and international levels.

The unit employed 40 knowledge-based employees, including ten senior researchers and engineers who, in addition to technical knowledge, had a thorough understanding of the product market. All senior experts provided their opinions. These experts had postgraduate engineering backgrounds in electrical and computer fields with vocational training in project management. Each expert had more than ten years of experience designing telecommunication devices and managing R&D projects.

A review of the history of this R&D unit reveals that they update their platform once every four years. At the time of data collection, the R&D center was planning for the next five years, in which 33 projects were proposed for implementation. Hence, selecting projects and forming a project portfolio was the problem proposed for the R&D department. We selected all of the proposed projects for our evaluation. Project managers specified the required budget for running each project based on product requirements. In this budget, the equipment and facilities needed for the project were considered fixed costs, and consumables such as electronic components and milling were considered R&D costs. The human resources required for projects were also set in per-hour format in the budget.

According to previous experience designing and developing similar products, experts were asked to comment on the likelihood of success of each project and mark the value of this success for the organization on a Likert scale of 1–10. In addition, experts were asked to declare, if a project fails, how much of the knowledge gained during the project implementation would be useful to the organization. The failure value was set as a percentage of the success value. As stated in the last section, we employed the Delphi process for expert elicitation. Face-to-face meetings were adapted to implement Delphi. During this process, the range of the answers for the probability of success decreased so much that the whole group reached the same consensus, while there was still divergence in success and failure values. This ‘dialog’ contributes to generating innovative ideas and leads strategic conversations from the point of uncertainty instead of fixed plans as the basis of creativity and innovation (Barnett, 1996). The resulting data are presented in Table 1. In this table, “Man-Hour,” “Fixed Costs,” and “R&D Costs” are extracted from project charters, while “Probability of Success,” “Success Value,” and “Failure Value” are the results of the Delphi

Project	Man-hour	Fixed costs	R&D costs	Probability of success	Success value	Failure value (% of success value)
01	40,000	$300,000	$100,000	60%	9.9	35.0%
02	30,000	$200,000	$150,000	80%	8.3	26.4%
03	200	$2,000	$1,000	95%	5.9	24.4%
04	10,000	$25,000	$2,000	80%	7.1	18.0%
05	5,000	$1,000	$2,000	80%	6.3	18.6%
06	10,000	$5,000	$10,000	60%	4.7	15.7%
07	20,000	$4,000	$10,000	80%	9.3	17.1%
08	3,000	$50,000	$20,000	80%	5.1	15.7%
09	15,000	$2,000	$2,000	80%	7.6	13.6%
10	2,000	$2,000	$5,000	80%	3.6	10.7%
11	5,000	$2,000	$1,000	60%	4.0	08.0%
12	10,000	$25,000	$2,000	80%	5.1	11.7%
13	10,000	$5,000	$7,000	80%	7.0	10.0%
14	10,000	$4,000	$1,000	80%	5.3	11.4%
15	5,000	$1,000	$1,000	95%	5.4	17.1%
16	10,000	$2,000	$4,000	60%	4.6	08.6%
17	4,000	$1,000	$1,000	95%	8.7	10.1%
18	3,000	$500	$1,000	80%	4.0	08.1%
19	5,000	$10,000	$5,000	50%	4.6	04.6%
20	4,000	$5,000	$200	95%	4.3	10.7%
21	2,000	$50,000	$20,000	80%	3.3	05.1%
22	1,000	$2,000	$500	60%	5.1	03.3%
23	1,000	$1,000	$5,000	80%	3.3	03.3%
24	2,000	$1,000	$1,000	95%	3.4	06.6%
25	500	$200	$1,000	95%	3.7	03.9%
26	500	$500	$500	95%	3.3	02.7%
27	2,000	$50,000	$20,000	80%	2.6	03.9%
28	500	$200	$1,000	95%	2.7	02.6%
29	200	$100	$200	80%	1.7	01.6%
30	1,000	$1,000	$500	80%	3.0	03.3%
31	200	$2,000	$1,000	95%	3.4	05.9%
32	500	$200	$1,000	95%	2.1	01.6%
33	500	$200	$1,000	95%	2.9	03.3%

Table 1.
Data collected from the project managers and experts

process. The last two columns are averages of expert opinions, as consensus was achieved only for the probability of success.

These data were entered into the @Risk program for simulation. The value of the output using the stochastic output formulation, p and V_s and V_f , are simulated as follows:

(1) p (Probability of success) = Binomial distribution with one variable and a probability value

(2) V_s (Value created if successful) = Normal distribution function with the mean and variance of corresponding project data

(3) V_f (Percentage value created in case of failure) = Normal distribution function with the mean and variance of corresponding project data

The simulation was iterated one million times to achieve high accuracy for further calculations. The simulation of the stochastic distribution of value generated for one of the projects is shown in Figure 4.

In this figure, the horizontal axis is the created value, and the vertical axis is the stochastic distribution of the created value. As shown in this figure, the combination of the two

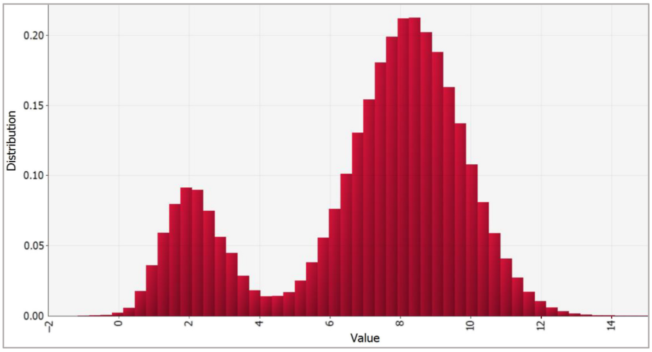


Figure 4.
Simulated output of Project 02

normal distributions of the value of success and failure in Formula 1 leads to the probability distribution in the form of two humps. Investigating the distribution of the probability of created value for all the projects shows that all of them have the same pattern. The major difference between the projects is in the width and ratio of the height of two bumps, the distance between them, as well as the average of the distribution function of the created value.

4.1 Project prioritization

Concerning that described in the previous sections and the comparison of Figures 1, 2 and 4, C-VaR seems to be a more appropriate option for the risk assessment of R&D projects. As the lower hump in Figure 4 indicates, t C-VaR embraces more risk factors than VaR and therefore is a better indication of project risk. C-VaR states how much we will lose if we fail. This loss is calculated relative to the average income, considering the probability distribution function of income instead of the probability distribution of gain or loss. The generated value output is the earnings average in financial engineering, C-VaR, which is equal to the average value created in the total probability distribution minus the mean of created value if the project fails.

In financial engineering, a typical percentage of risk is taken to account for the risk of a portfolio. For example, with a 95% confidence level, we will lose a maximum of $ 2 million in the next ten days (Definition of VaR), or a loss of $ 15 million (Definition of C-VaR) with a 95% confidence level in the next ten days if the situation is unfavorable. In financial engineering risk management, assuming a certain confidence level is particularly important for comparing potential losses between different portfolios. We calculate the C-VaR and VaR for the projects as two parameters for representing the risks associated with the projects. These calculations are made at four risk levels 5%, 10%, 20% and 30%. We calculate the project efficiencies using the above DEA approach, given the risks associated with the undesirable outputs. The result of the efficiency ranking is displayed in Table 2.

As shown in Table 2, five projects (Projects 03, 17, 20, 25 and 29) are ranked first at all risk levels. These five projects are in the efficient frontier at all risk levels. This implies that these projects are top priorities for a decision-maker to add to a project portfolio. Of course, the second round of DEA can be applied to these projects to gain a second-level ranking. However, our focus is on the differences or ranking between VaR and C-VaR approaches at different risk levels: At the 30% risk level, a large efficiency ranking is observed between the two approaches, namely VaR and C-VaR. For example, Projects 01, 02, 04 and 07 have more than ten levels of ranking difference, and Projects 09, 18, 24 and 28 have between 05 and 09 levels of change. Such differences can be observed in other risk levels; however, the breadth of change drops. At the 20% risk level, only Project 01 has more than ten change levels and

Table 2.
Efficiency rankings based on VaR and C-VaR at 5, 10, 20 and 30% risk levels

Project	VaR 5%	C-VaR 5%	VaR 10%	C-VaR 10%	VaR 20%	C-VaR 20%	VaR 30%	C-VaR 30%	σ VaR	σ C-VaR	Average Ranking
01	7	1	14	9	22	11	32	17	9.31	5.72	9.5
02	11	10	18	12	16	15	33	12	8.20	1.79	12.25
03	1	1	1	1	1	1	1	1	0.00	0.00	1
04	17	13	17	17	15	17	1	16	6.69	1.64	15.75
05	12	12	20	16	20	16	13	18	3.77	2.18	15.5
06	23	22	26	23	27	27	31	29	2.86	2.86	25.25
07	19	15	22	18	14	18	1	14	8.03	1.79	16.25
08	20	19	23	19	23	21	21	21	1.30	1.00	20
09	18	17	15	20	18	20	14	19	1.79	1.22	19
10	22	18	25	22	24	24	20	23	1.92	2.28	21.75
11	31	25	29	28	29	29	27	31	1.41	2.17	28.25
12	27	27	24	25	25	25	24	26	1.22	0.83	25.75
13	21	14	27	21	26	26	26	24	2.35	4.55	21.25
14	26	23	12	13	13	13	17	15	5.52	4.12	16
15	8	8	8	8	8	8	10	8	0.87	0.00	8
16	29	29	28	31	31	30	30	32	1.12	1.12	30.5
17	1	1	1	1	1	1	1	1	0.00	0.00	1
18	13	20	16	24	19	22	15	20	2.17	1.66	21.5
19	33	26	33	29	33	32	29	33	1.73	2.74	30
20	1	1	1	1	1	1	1	1	0.00	0.00	1
21	30	24	30	26	28	28	23	27	2.86	1.48	26.25
22	10	11	7	7	7	7	9	7	1.30	1.73	8
23	25	21	31	27	30	31	25	28	2.77	3.63	26.75
24	15	16	13	15	12	14	18	13	2.29	1.12	14.5
25	1	1	1	1	1	1	1	1	0.00	0.00	1
26	6	7	1	6	1	1	1	1	2.17	2.77	3.75
27	32	31	32	32	32	33	28	30	1.73	1.12	31.5
28	9	9	11	10	11	9	16	9	2.59	0.43	9.25
29	1	1	1	1	1	1	1	1	0.00	0.00	1
30	28	32	10	14	10	12	12	11	7.55	8.58	17.25
31	24	28	9	11	9	10	11	10	6.26	7.66	14.75
32	16	30	21	30	21	19	22	22	2.35	4.87	25.25
33	14	33	19	33	17	23	19	25	2.05	4.56	28.5
Average									*2.9*	*2.3*	*16.5*

Projects 05, 13 and 33 lie in the 5 to 9 change levels. At the 10% risk level, Projects 01, 02, 09, 13, 18, 26 and 32 have between 5 and 9 levels of change and one project ranking changes more than ten levels. At the 5% risk level, Projects 32 and 33 have more than ten change levels and Projects 01, 11, 13, 18, 19 and 21 lie in the 5 to 9 change levels.

Hence, most of the efficiency ranking differences between VaR and C-VaR risk calculations are observed at the highest risk level, that is 30%. Variances for efficiency rankings are calculated for each project and both approaches. σVaR represents the variance of the project ranking in different risk levels when using VaR to evaluate project risk, and σC-VaR is the same for C-VaR. Table 2 shows that C-VaR generally presents a more stable ranking score over different risk levels as the mean of σVaR is 2.9 while the mean of σC-VaR is 2.3. The typical shape of the distribution function of project values confirms the appropriate use of C-VaR vs. VaR as a project risk measure. In Table 2, we perceive that it could lead to dramatic effects on total project efficiency assessment in some cases. This is in line with Reyes Santos and Haimes (2004), finding that measuring risk via volatility can lead to inaccuracy.

As mentioned before, we calculated the project efficiencies according to different risk levels and discovered different efficiency rankings at different risk levels. That means project prioritization may change according to the risk level of the decision maker's choice. Although starting innovative practices requires courage, the decision-maker should always have some strategy while selecting projects. This is what happens in practice when companies decide on their innovative projects. That implies they do not just look at numbers but also consider how projects fit into their strategies. Hence, companies with effective product innovation programs rely on several tools to tune their R&D portfolios based on their strategy, including strategic buckets for resource allocation, fuzzy Analytical Network Process (ANP) and strategic relative alignment index (Chao and Kavadias, 2008; Santiago and Soares, 2020; Mohanty *et al.*, 2005; García-Melón *et al.*, 2015).

Most of these models filter the projects based on their correlation to corporate strategy and then attempt to rank projects to optimize the R&D portfolio. The problem with such approaches is that they may inhibit the decision-maker from having a general view of the strategic orientation of projects and may lead to ignoring certain projects. We consider a strategic approach to an R&D project selection by considering the standard deviation of the project rankings (σC-VaR) as a measure of project uncertainty. Let us consider the last two columns in Table 2. For example, the average ranking of project02 is 12.25, with a standard deviation of 1.79, suggesting a low degree of uncertain ranking between different risk levels. In contrast, project01 has an average ranking of 9.5, with a standard deviation of 5.72, suggesting a high degree of uncertain ranking between different risk levels.

4.2 Uncertainty-efficiency map

Companies use graphical structuring tools systematically to plot their portfolio of products, R&D projects and business units into various forms of quadrants according to their risks and returns. For example, BCG's growth-share matrix (Henderson, 1970) is used by companies to prune their businesses by classifying their products into quadrants of dogs, question marks, stars and cash cows, based on their potential for growth and profitability. Owen (1984) proposed a graphical risk-return matrix for classifying projects into four quadrants based on their probability of success and potential return. Portfolio managers use this risk-return matrix to build a balanced portfolio by grouping their projects into a "bread and butter" category (with a high probability of success and low potential return), "oysters" category (with a low probability of success and high potential value), "pearls" category (with a high probability of success and high potential return) and "white elephants" category (with a low probability of success and low potential return). Classifying R&D projects in these four quadrants helps the R&D managers balance their R&D portfolio since the bread and butter projects succeed regularly and oyster projects rarely succeed. In other words, bread-and-butter projects support today's business, while oyster projects provide for tomorrow's business.

Tavana (2002) proposed a strategic alternative assessment matrix called "Euclid" to plot strategic alternatives into four quadrants according to their mean Euclidean distance of *benefits* and *risks*. Euclid uses a probabilistic model where the ideal probability for a benefit is the highest probability among a set of subjective probabilities, and the ideal probability for risk is the lowest probability among the set. Tavana (2002) proposes two composite scores, the total Euclidean distance from the ideal benefit and the total Euclidean distance from the ideal risk are developed for each strategic alternative. The Euclidean distance of each probability from its respective ideal probability is calculated and squared in Euclid. The two composite scores are the sum of the Euclidean distances for each benefit and risk times its importance weights.

In the Euclid model, the horizontal dimension (x-axis) represents the benefits, the vertical dimension (y-axis) represents the risks and the origin represents the ideal alternative.

The mean Euclidean distance of benefits and risks divide the matrix into four quadrants: exploitation, challenge, discretion and desperation quadrants. The *exploitation* quadrant represents projects with high benefits and low risks, the *challenge* quadrant represents projects with high benefits and high risks, the *discretion* quadrant represents projects with low benefits and low risks and the *desperation* quadrant represents projects with low benefits and high risks. Figure 5 is inspired by the Euclid model proposed by Tavana (2002). We use the Euclid idea and concept to map all the projects into a strategy plane, as shown in Figure 5.

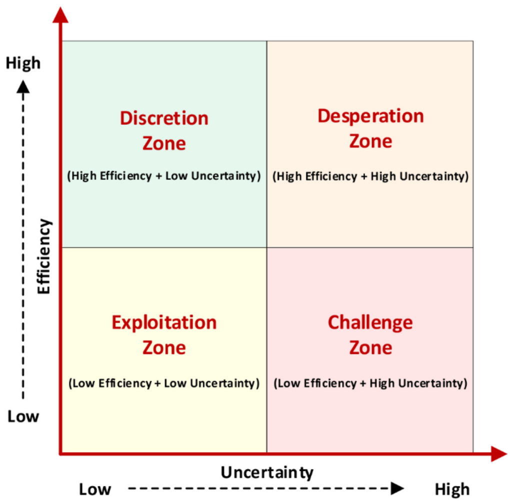
(1) **High-efficiency, high-uncertainty quadrant (Desperation Zone):** Projects are highly efficient and uncertain in this quadrant. Courageous decision-makers often undertake these risky but potentially rewarding projects.

(2) **Low-efficiency, high-uncertainty quadrant (Challenge Zone):** The projects in this quadrant are minimally efficient and highly uncertain. Risk-seeking decision-makers often undertake these highly risky projects.

(3) **High-efficiency, low-uncertainty quadrant (Discretion Zone):** Projects are highly efficient and minimally uncertain in this quadrant. Risk-averse decision-makers often choose these projects.

(4) **Low-efficiency, low-uncertainty quadrant (Exploitation Zone):** The projects in this quadrant are minimally efficient and minimally uncertain. Cautious decision-makers often undertake these safe projects.

It is important to note that while the concepts are similar, the two axes in the model proposed in this study are very different. While the horizontal dimension represents the benefits, the vertical dimension represents the risks and the origin represents the ideal alternative. In the model proposed in this study, we define the horizontal dimension as uncertainty and the vertical dimension as risks. Market uncertainties are the major difficulties in developing innovative products. Large uncertainty leads to high R&D risks and many failures in R&D projects (Wang and Yang, 2012). The R&D managers must incorporate flexibility in their

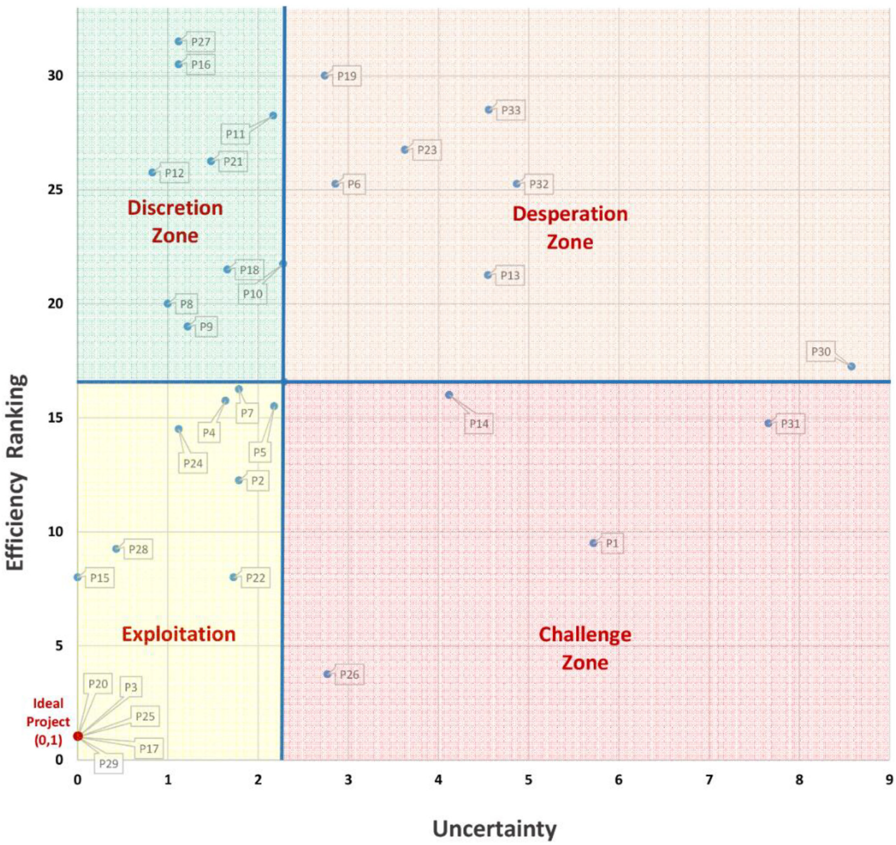


Source(s): Inspired by Tavana, 2002 and Peykani *et al.*, 2022

Figure 5.
Project selection strategy plane

decision-making process and take a blend of all four strategies when selecting project portfolios. Figure 6 illustrates the mapping of projects in Table 2 into the strategy map. In this figure, we put projects with an average ranking of more than 16.5 on the upper side of the efficiency axis and conversely, average rankings less than 16.5 lie on the lower side. On the other hand, projects with σC-VaR more than 2.3 rest on the right side of the uncertainty axis and projects with σC-VaR less than 2.3 sit on the left side.

As seen in Figure 6, the decision-maker can put five projects; namely, P3, P17, P20, P25 and P29, from the "Exploitation Zone" into his portfolio with peace of mind, as these projects have the number one ranking with zero uncertainty, or in other words, are always in the efficient frontier. However, innovation is about taking risks, so they have to go for the "Challenge Zone" and the "Desperation Zone" to gain a competitive advantage. Projects in the "Discretion Zone" shall be avoided unless experts reevaluate them. As stated before, the average uncertainty towards all of the projects is assigned as the center point of the horizontal axis, which is the vertical blue line in Figure 6. This means that in this map, uncertainty is relative between projects. One could slide the vertical blue line to the left or right to adjust the strategy plane according to their tolerance for uncertainty. Projects near borderlines are under question and need deeper expert elicitation.



Source(s): Inspired by Tavana, 2002 and Peykani *et al*., 2022

Figure 6. Efficiency-uncertainty project map

5. Conclusion

In this research, we focused on a practical solution to cope with the uncertainty of R&D projects during portfolio selection, as R&D managers and decision-makers always confront uncertainty when selecting the best portfolio. This ambiguity is deeper than generic project portfolio selection because contributions in terms of knowledge are vital in R&D projects (Peretz *et al.*, 2009). Hence, this specific nature of R&D activities makes project selection even more complicated since knowledge is a major contribution to the organization, even in the case of project failure. More specifically, whether a project succeeds or not, learning would happen at individual and organizational levels, impacting the organizational culture.

Failure in innovation may lead to innovation trauma, which inhibits generating new ideas due to severe disappointment from previous failures (Valikangas *et al.*, 2009). Obviously, in case of failure compared to success, knowledge contributions would be less, and other contributions like economic advantages could be unacceptable. Having the above framework in a lose-win scenario – the probability distribution function of the expected value for each project is simulated and motivated by financial risk assessment methodologies. C-VaR is selected as the major index for measuring the risk of a project. The use of C-VaR as a measure of R&D project risk is a major contribution to this research, as C-VaR is proved to be a better representative for a mix of different sources of risks considering the specific shapes of the probability distribution functions of R&D project outcomes.

In effect, a method has been developed to calculate the efficiency of R&D projects, which inherently have high-level uncertainties. Ordering the priority of the projects based on efficiency enables us to choose the portfolio of R&D projects with maximum efficiency and review the low-performing projects. This research assumes that the R&D team is mature enough to gain the assistance of experienced engineers and R&D veterans; hence the R&D manager has a vast potential to enhance the decision process by giving questionnaires to the experts and using the collected data for decision-making. Unlike most previous works, this research combines stochastic theory and the DEA approach to deal with uncertainty and deliver a solution consistent with the nature of R&D projects. A significant contribution of this research is to model the uncertainty of R&D projects using efficiency calculations. The above methodology has presented an R&D project risk assessment at project and portfolio levels.

At the project level, C-VaR is introduced as a measure of total project risk. Having this index calculated for all the projects, we can compare them from a risk perspective by having a risk score representing the total uncertainties that lead to risk. This is very important for R&D projects as uncertainty sources of such projects are diverse and hard to evaluate and enumerate. At the portfolio level, by addressing the measured risk as an undesirable output, projects are compared in the context of efficiency to deliver a balanced methodology for selecting projects based on expected value and risk.

This study explored how experts' technical knowledge may support decision-making for executing R&D projects. Accordingly, it was also looking for a way to align R&D projects with organizational strategies. The technical experts' intuition was used to determine the probability of success and the value of projects for two states of success and failure. For example, projects with a 50% probability of success are toss-up projects. Generally, there must be other motivations for implementing these projects. These reasons include the value obtained in case of failure and the costs associated with the project.

Apart from this, managers must have strategic reasons for choosing projects. The alignment of the projects with the organization's strategy plays a crucial role in its success and survival. Consequently, this research presented a conceptual map for managers to use when making decisions regarding the implementation of the project within the framework of the organization's strategic approach. For example, while a high-tech company takes an aggressive strategy towards the market, it most likely reflects the same approach to its R&D portfolio by selecting highly promising though risky projects. On the contrary, when a company has a conservative approach toward the market, it would presumably be unadventurous in selecting R&D projects. We proposed a strategy plane based on project efficiency and uncertainty to help decision-makers align R&D project portfolios with their strategies to combine a strategic view and numerical analysis in this research. The proposed strategy plane consists of four areas, namely "Exploitation Zone," "Challenge Zone," "Desperation Zone," and "Discretion Zone." Mapping the project into this strategic plan would help decision-makers align their project portfolio according to the corporate perspectives.

An organization's goals and strategic approach must be weighed against its technological and business features when deciding whether to implement or abandon projects. We summarize our findings as follows:

(1) R&D projects can be positioned strategically by considering efficiency and uncertainty simultaneously.

(2) When developing products/technologies, those involved can use intuition to help the decision-making process. However, organizational hierarchy usually buries these people. The quality of this partnership can be enhanced significantly through dialogue at all levels.

(3) Acceptable risk should be clearly defined to ensure that all decision-makers are on the same page.

This study uses expert knowledge to assess risk tolerance at specific stages of the R&D process consistent with organizational strategies. It also presents a guideline for managing an R&D portfolio by carefully considering risks associated with uncertainties. Contrary to previous research, this study offers a solution for strategic project selection while incorporating the intuition of technology development teams. However, this research focuses only on static decision gates of R&D processes, which is a limitation. In addition, this study did not examine the dynamic status of projects and the interdependencies among the projects. The success or failure of the projects may be interdependent, or there may involve some synergy among them similar to shared knowledge. Therefore, future research could consider the interdependencies among the projects in the evaluation process.

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