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ADAPTIVE DECISION-MAKING MODELS FOR PROJECT PORTFOLIO MANAGEMENT

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THE AIM OF THE STUDY was to substantiate a distribution-based adaptive approach to decision-making in project portfolio management under conditions of a dynamic external environment. The study focuses on overcoming the limitations of traditional portfolio evaluation methods that rely on average performance indicators and deterministic planning, which are insufficient in conditions of uncertainty and non-stationary project outcomes.

RESEARCH METHODS. The following research methods were used in the article: general scientific methods of analysis and synthesis; methods of studying economic and managerial processes, including comparison and structuring; distribution analysis of project outcomes; confidence interval analysis; and methods of adaptive decision-making based on iterative data updates. A graphical method was applied to illustrate differences in project outcome distributions and their impact on portfolio-level decisions.

RESULTS. The article proves that the distributional characteristics of project outcomes are of fundamental importance for effective project portfolio management in dynamic environments. It is shown that projects with similar average performance may differ significantly in terms of variability, dispersion, and strategic potential. The study systematises projects according to their distribution profiles and demonstrates that low-variance projects contribute to short-term stability, while high-variance projects increase strategic optionality and long-term portfolio resilience. The proposed adaptive approach enables continuous reassessment of project attractiveness based on evolving empirical distributions and reduces the anchoring effect in managerial decision-making. The results confirm that incorporating distribution-based logic into portfolio management improves responsiveness to environmental changes and supports more balanced resource allocation.

KEYWORDS: adaptive management; decision uncertainty; distribution analysis; project portfolio management; risk dispersion; strategic flexibility; dynamic environment.

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АДАПТИВНІ МОДЕЛІ ПРИЙНЯТТЯ РІШЕНЬ ДЛЯ УПРАВЛІННЯ ПОРТФЕЛЕМ ПРОЕКТІВ

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МЕТА ДОСЛІДЖЕННЯ полягала в обґрунтуванні адаптивного підходу до прийняття рішень в управлінні портфелями проєктів на основі аналізу розподілів результатів в умовах динамічного зовнішнього середовища. Дослідження спрямоване на подолання обмежень традиційних методів оцінювання портфелів, які базуються на середніх показниках ефективності та детермінованому плануванні й не враховують невизначеність та нестаціонарність результатів проєктів.

МЕТОДИ ДОСЛІДЖЕННЯ. У статті використано загальнонаукові методи аналізу та синтезу; методи дослідження економічних і управлінських процесів, зокрема метод порівняння, структурування та групування; аналіз розподілів результатів проєктів; аналіз довірчих інтервалів; а також методи адаптивного прийняття рішень на основі ітеративного оновлення даних. Для наочного представлення впливу характеристик розподілів на портфельні рішення застосовано графічний метод.

РЕЗУЛЬТАТИ. Доведено, що характеристики розподілів результатів проєктів мають визначальне значення для ефективного управління портфелями проєктів в умовах динамічного середовища. Показано, що проєкти з подібними середніми значеннями можуть істотно відрізнятися за рівнем варіативності, дисперсії та стратегічного потенціалу. Систематизовано проєкти за типами розподілів і встановлено, що проєкти з низькою варіативністю забезпечують короткострокову стабільність портфеля, тоді як проєкти з високою варіативністю підвищують стратегічну гнучкість і довгострокову стійкість портфеля. Запропонований адаптивний підхід забезпечує безперервний перегляд привабливості проєктів з урахуванням оновлених емпіричних розподілів і зменшує ефект «прив’язки» в управлінських рішеннях. Підтверджено, що впровадження логіки аналізу розподілів підвищує здатність портфеля адаптуватися до змін зовнішнього середовища та сприяє більш збалансованому розподілу ресурсів.

КЛЮЧОВІ СЛОВА: адаптивне управління; аналіз розподілів; динамічне середовище; невизначеність рішень; портфель проєктів; стратегічна гнучкість; управління ризиками.

Introduction. In the context of rapid changes in the external business environment, increasing uncertainty, and growing complexity of organisational activities, effective project portfolio management is becoming one of the key factors in ensuring long-term sustainability and strategic resilience of organisations. Globalisation, digital transformation, geopolitical instability, and market volatility significantly affect project performance and challenge traditional approaches to planning and resource allocation. These conditions require organisations to adopt adaptive decision-making mechanisms capable of responding to continuous environmental changes.

Despite the growing relevance of adaptability, many organisations still manage project portfolios using static evaluation models focused on predefined indicators, average performance values, and deterministic forecasts. Such approaches prioritise short-term efficiency and operational control while underestimating uncertainty, variability, and the non-stationary nature of project outcomes. As a result, portfolio decisions often fail to reflect the real dynamics of project performance, limiting the organisation's ability to exploit emerging opportunities and mitigate risks. The main problem lies in the perception of variability as a negative factor rather than as a potential source of strategic value at the portfolio level.

The issue of adaptive and strategic project portfolio management has been addressed from different perspectives. R.G. Cooper, S.J. Edgett and E.J. Kleinschmidt (2001) emphasised the importance of strategic alignment and systematic portfolio review for achieving organisational objectives. N.P. Archer and F. Ghasemzadeh (1999) proposed multi-criteria portfolio selection models, highlighting the complexity of balancing competing project priorities. However, these approaches largely rely on static assessments and do not explicitly account for the distributional nature of project outcomes.

Later studies focused on uncertainty and flexibility in portfolio decisions. C.H. Loch, A. DeMeyer, and M.T. Pich (2006) argued that managerial control in uncertain projects should shift from rigid planning to adaptive learning. Similarly, H. Sanchez and B. Robert (2010) demonstrated that portfolio flexibility enhances organisational responsiveness in turbulent environments. M. Martinsuo and P. Lehtonen (2007) highlighted the role of continuous portfolio adjustment in coping with environmental uncertainty, stressing that fixed evaluation criteria reduce portfolio effectiveness under dynamic conditions.

More recent research has incorporated concepts of dynamic capabilities and data-driven decision-making. D.J. Teece (2014) emphasised that the ability to sense, seize, and reconfigure resources is critical for organisational survival in volatile environments. C.P. Killen, R.A. Hunt and E.J. Kleinschmidt (2008) analysed adaptive portfolio management practices and concluded that learningoriented approaches outperform rigid optimisation models. Nevertheless, these studies still predominantly focus on expected values and qualitative assessments rather than on empirical performance distributions.

The importance of uncertainty and variability has been further explored in studies on risk-aware portfolio management. Y. Petit (2012) noted that risk aggregation at the portfolio level may obscure critical differences between projects with similar average performance. J. Geraldi, H. Maylor and T. Williams (2011) demonstrated that complexity and uncertainty require managers to consider multiple dimensions of project behaviour. In parallel, B.S. Blichfeldt and P. Eskerod (2008) showed that ignoring variability leads to systematic biases in project prioritisation.

In recent years, algorithmic and distribution-based approaches have gained attention. J. Luedtke, S. Ahmed and G. Nemhauser (2010) investigated decision-making under uncertainty using confidence bounds, while W.B. Powell (2019) highlighted the role of learning-based algorithms in sequential decision problems. These studies provide a methodological foundation for integrating distributional logic into portfolio management but remain insufficiently adapted to project-oriented organisational contexts.

In view of the above, it can be argued that project portfolio management requires a shift toward distribution-based adaptive decision-making that explicitly accounts for variability, dispersion, and uncertainty of project outcomes. The integration of empirical distributions into portfolio evaluation allows organisations to balance stability and flexibility, reduce cognitive biases such as the anchoring effect, and enhance long-term portfolio resilience.

The study aimed to substantiate a distribution-based adaptive approach to project portfolio management under dynamic environmental conditions. The objectives of the study were to analyse existing approaches to portfolio decision-making; examine the role of outcome distributions in project evaluation; and identify mechanisms for integrating adaptive, distribution-aware logic into strategic portfolio management processes.

Materials and Methods. A comprehensive approach to analysing adaptive project portfolio management under conditions of a dynamic external environment was employed. To achieve the objectives of the study, systematic, comparative, and analytical methods were applied, which made it possible to examine existing portfolio decision-making approaches and assess their ability to account for uncertainty and variability of project outcomes. The methodological basis of the study was a systems approach, which considers a project portfolio as a multi-level management system influenced by internal organisational factors and external environmental conditions.

The systems approach involved analysing project portfolio management as an integrated process dependent on organisational structure, decision-making mechanisms, risk management practices, and information availability, as well as on external factors such as market volatility, technological change, and macroeconomic instability. This approach made it possible to identify interrelationships between portfolio structure, project performance variability, and the organisation's capacity to adapt to environmental changes.

A distribution-based analytical method was emphasised in the study. Project performance was analysed through empirical outcome distributions rather than through average indicators. This allowed the identification of differences between projects with similar expected values but different levels of dispersion, variance, and strategic potential. Confidence interval analysis was used to assess uncertainty associated with project outcomes and to support adaptive reassessment of project attractiveness over time.

Comparative analysis was applied to classify projects according to their distribution profiles, including low-variance, high-variance, and mixed-distribution projects. This classification enabled the evaluation of their respective roles within the portfolio in terms of stability, flexibility, and long-term value creation. A graphical method was used to visualise differences in project outcome distributions and to illustrate their implications for portfolio-level decisions.

The analysis covered a multi-period observation horizon, which made it possible to track changes in project performance distributions as new data became available. This temporal perspective allowed the study of non-stationary behaviour of project outcomes and the assessment of how adaptive decision-making mechanisms respond to evolving information. The study relied on empirical project performance data aggregated at the portfolio level and processed using iterative analytical procedures.

To formulate practical recommendations for adaptive project portfolio management, the study applied a generalisation of best practices in portfolio decision-making and adaptive management frameworks. The combination of system analysis, distribution-based evaluation, and comparative methods enabled the formulation of well-grounded conclusions regarding the effectiveness of adaptive, distribution-aware decision-making in project portfolio management. The applied methodology ensured a comprehensive assessment of portfolio dynamics and provided a basis for developing practical recommendations aimed at improving portfolio resilience and strategic flexibility in dynamic environments.

Results. The results of the study confirm that the application of a distribution-based approach fundamentally changes the logic of project portfolio evaluation under conditions of a dynamic external environment. The empirical analysis demonstrated that traditional portfolio assessment based on average indicators masks significant differences in project behaviour and leads to an incomplete understanding of their strategic contribution. The obtained results provide evidence that variability, dispersion, and the shape of outcome distributions are critical determinants of portfolio effectiveness.

In the context of rapidly changing economic conditions and increasingly globalised and competitive markets, organisations are facing growing pressure to continuously reassess their strategic priorities and management practices. The acceleration of technological development, intensification of competition, geopolitical instability, and volatility of demand have fundamentally transformed the environment in which organisations operate. These changes significantly increase uncertainty and reduce the effectiveness of traditional management models based on stability, predictability, and long-term planning.

Under such conditions, the ability of organisations to manage complex portfolios of projects becomes a key determinant of their sustainability and competitive position. Project portfolios increasingly serve as instruments for strategic transformation, innovation, and organisational adaptation. At the same time, the growing number of parallel initiatives, limited resources, and high uncertainty of outcomes complicate the process of selecting, prioritising, and coordinating projects. As a result, portfolio management is no longer limited to administrative control but becomes a dynamic process of continuous decision-making.

The growing complexity of the external environment leads to a situation in which project outcomes demonstrate significant variability over time. Market shifts, regulatory changes, technological disruptions, and external shocks directly affect project performance and may alter their expected results. In this context, managerial decisions based on fixed criteria and average performance indicators fail to reflect the real dynamics of project behaviour. Such an approach increases the risk of misallocation of resources and reduces the organisation’s ability to respond effectively to emerging opportunities and threats.

Increasingly, uncertainty should be viewed not only as a source of risk but also as a potential source of strategic advantage. Projects characterised by higher variability may generate outcomes that exceed initial expectations and create opportunities for disproportionate value creation. However, realising this potential requires analytical tools that allow managers to understand and evaluate uncertainty in a structured manner. Without such tools, organisations tend to favour stable but low-potential initiatives, thereby limiting long-term growth and adaptability.

Against this background, the analysis of project outcome distributions gains particular importance. A distribution-based perspective makes it possible to assess not only the expected level of project performance but also the range and structure of possible outcomes. This approach enables a more nuanced understanding of how individual projects contribute to portfolio performance and how combinations of projects influence overall portfolio dynamics. By focusing on empirical distributions, managers gain insight into the balance between stability and flexibility within the portfolio.

The results presented in this section reflect the application of a distribution-based analytical framework to project portfolio management under dynamic environmental conditions. They demonstrate how different types of project outcome distributions influence portfolio behaviour and highlight the limitations of traditional evaluation methods. The findings provide an empirical foundation for understanding adaptive portfolio decision-making and create a basis for further discussion of mechanisms that enhance organisational resilience and strategic flexibility in highly competitive and rapidly changing environments.

Against the background of the identified variability in project performance and the diversity of outcome distributions, the need arises for a formalised decision-making mechanism capable of integrating both expected results and uncertainty into a single evaluative framework. The results of the distributional analysis indicate that portfolio decisions cannot rely solely on central tendency measures, as they fail to capture the strategic value embedded in dispersion and the dynamic nature of project outcomes.

In order to address this limitation, the study applies an adaptive approach to project evaluation based on confidence bounds. The underlying logic of this approach is grounded in the assumption that managerial decisions should simultaneously consider two key dimensions of project behaviour: the observed level of performance and the degree of uncertainty associated with that performance. Such an approach allows decision-makers to balance the exploitation of projects with stable and predictable outcomes against the exploration of projects characterised by higher variability and potential upside.

The transition from descriptive distributional analysis to a formal decision rule is based on the use of dynamically updated empirical data. As project outcomes are observed over successive periods, their distributions are continuously refined, and the level of confidence in performance estimates changes accordingly. Projects with limited observation histories exhibit wider uncertainty ranges, while projects with accumulated performance data demonstrate more concentrated distributions. This dynamic creates a natural mechanism for prioritising projects not only by observed results but also by the reliability of those results.

Within this framework, the final decision criterion is constructed by combining the estimated performance of a project with an uncertainty adjustment factor derived from its distributional characteristics. The adjustment reflects the width of the confidence interval and decreases as additional information becomes available. As a result, projects with high uncertainty are not systematically penalised at early stages but are given the opportunity to demonstrate their potential through further observation and resource allocation.

The proposed approach enables continuous re-ranking of projects within the portfolio as new data emerges. At each decision point, projects are evaluated using updated empirical distributions, and their relative attractiveness is recalculated. This mechanism prevents premature exclusion of projects based on limited information and reduces the anchoring effect associated with static prioritisation models. Instead, portfolio composition evolves adaptively in response to actual performance dynamics.

The formulation of the final decision rule provides a formal link between distribution-based analysis and practical portfolio management. It transforms qualitative insights about variability and uncertainty into a quantitative mechanism that supports systematic and transparent decision-making. By integrating performance and uncertainty into a single evaluative measure, the proposed approach ensures that portfolio decisions remain responsive to environmental changes while maintaining strategic coherence.

The described logic forms the basis for the final evaluative formula. This formula operationalises adaptive portfolio decision-making by incorporating dynamically updated confidence bounds and serves as a practical tool for managing project portfolios in environments characterised by high uncertainty and continuous change, as shown in formula (1):

$$\mathrm{DCB}_i(t) = \hat{\mu}_i(t) + \sqrt{\frac{c_1 \ln t + c_2 \ln\ln(\max\{e, t\})}{\max\left\{1, \sum_{s \in T_i(t)} \lambda^{t-s}\right\}}} + k\hat{\sigma}_i(t) + d\Delta_i(t) + bB_i(t) - rR_i(t) - sS_i(t). \tag{1}$$

For a clearer understanding of the proposed adaptive decision-making mechanism, each component of the final evaluative formula is considered in detail and accompanied by explanatory comments.

The formula begins with the term $\hat{\mu}_i(t)$, which represents the estimated mean reward of option *i* at time *t*. This component corresponds to the classical formulation of performance estimation and reflects the observed average outcome based on available data. It serves as the baseline indicator of project performance within the portfolio.

The next component is a modified version of the exploration bonus, commonly referred to as the "confidence margin". Unlike the standard formulation, this term is designed to decrease progressively as the number of observations increases. The proposed modification combines the use of Kullback–Leibler divergence to improve estimation accuracy with a discounting mechanism that gradually reduces the weight of older observations. In addition, a maximum function is incorporated to prevent instability of the formula during early stages, when the number of observations is limited. This ensures robust behaviour of the decision rule in the initial phases of project evaluation.

The term $k\hat{\sigma}_i(t)$ represents an additional incentive to select option *i* under conditions of increased volatility in the outcome distribution. This component captures moments in which potential regime changes are detected. In such situations, the algorithm allocates additional resources to explore the project further in order to better understand emerging changes in its performance distribution. As a result, volatility is treated not solely as a risk factor but also as a signal for adaptive exploration.

Beyond volatility, the formula explicitly incorporates a trend component denoted as $d\Delta_i(t)$. This element allows the model to detect and account for systematic changes in project performance over time. By capturing directional shifts in outcomes, the trend term enhances the sensitivity of the decision-making process to emerging patterns that would remain undetected under the standard Upper Confidence Bound framework.

The components $bB_i(t)$, $rR_i(t)$, and $sS_i(t)$, introduced in the previous subsection, collectively form a strategic overlay for the algorithm. Together, they ensure that portfolio decisions are not based solely on local data-driven optimisation but also reflect broader portfolio-level constraints and strategic considerations. These elements incorporate organisational priorities, cultural factors, and environmental conditions into the decision rule, aligning algorithmic choices with the overall strategic context of the organisation.

The values of the corresponding coefficients are determined based on the specific managerial context and portfolio objectives. Their calibration allows the decision-making mechanism to be adapted to different organisational environments and strategic preferences. The subsequent step of the research involves the implementation of the proposed algorithmic logic in Python for practical application and further empirical testing.

To illustrate the practical implications of the proposed decision-making framework and to visualise the role of distributional characteristics in project evaluation, the analysis proceeds with a graphical representation of empirical project outcome distributions. Graphical analysis is particularly important in the context of distribution-based approaches, as it allows the identification of patterns that cannot be adequately captured through numerical indicators alone.

The first graphical illustration presents the empirical distributions of project outcomes observed over a comparable time horizon. These distributions were constructed based on sequential performance observations and reflect the variability, dispersion, and concentration of outcomes for different projects within the portfolio. The graphical representation enables a direct comparison between projects whose average performance indicators appear similar but whose distributional profiles differ substantially.

By examining the shape and spread of the distributions, it becomes possible to distinguish between projects charactrised by stable and predictable outcomes and those exhibiting higher uncertainty and dispersion. This visual comparison provides an initial empirical basis for understanding how projects contribute differently to portfolio stability and adaptability. The figure serves as a descriptive foundation for further analysis of project behaviour under uncertainty and supports the subsequent discussion of adaptive portfolio decision-making mechanisms.

Figure 1 presents the empirical distributions of outcomes for three projects observed over an identical time horizon. The graphical representation clearly demonstrates substantial differences in the shape, dispersion, and concentration of outcomes across projects, despite the absence of significant differences in their average performance indicators.

Source: author's construction.

Figure 1. **Distribution of data from three projects**

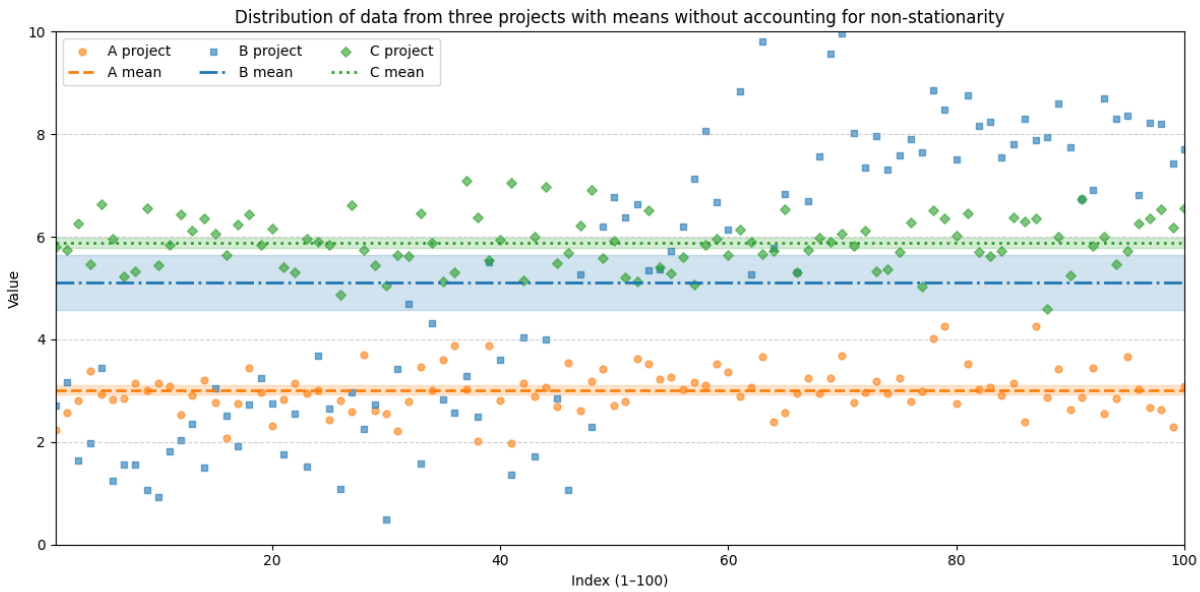
Project A is characterised by a narrow and highly concentrated distribution. Most observed outcomes are clustered within a limited range, indicating low variability and a high degree of predictability. Such a distribution reflects stable project behaviour and suggests a relatively low level of uncertainty. However, the limited spread of outcomes also indicates restricted potential for achieving values significantly above the central tendency.

Project B exhibits a markedly different distributional profile. The distribution is wide and dispersed, with outcomes spanning a broad range of values. This pattern reflects increased uncertainty and higher variability of project performance. At the same time, the presence of a long right tail indicates the possibility of extreme positive outcomes. This distributional structure highlights the strategic optionality associated with the project, which cannot be identified through average-based evaluation alone.

Project C demonstrates an intermediate distribution profile. Its outcomes are more dispersed than those of Project A but significantly more concentrated than those of Project B. The distribution is centred around higher values compared to Project A, while maintaining moderate variability. This structure suggests a balance between stability and flexibility, making such projects suitable for supporting portfolio performance while preserving adaptability.

The comparison of these distributions confirms that projects with similar expected performance may differ fundamentally in terms of uncertainty, risk exposure, and strategic contribution. The graphical analysis thus provides empirical evidence supporting the need for distribution-based evaluation in project portfolio management.

To further explore how different distributional characteristics influence portfolio behaviour under uncertainty, the analysis proceeds with the examination of projects exhibiting pronounced dispersion and dynamic changes in outcome variability over time. These characteristics are illustrated in the following graphical representation Figure 2.



Source: author's construction.

Figure 2. **Distribution of data from three projects with means without accounting for non-stationarity**

However, the situation changes fundamentally when new analytical perspectives are integrated into the model and the analysis is conducted within the conceptual framework of a VUCA environment, characterised by volatility, uncertainty, complexity, and ambiguity. Under such conditions, a static view of project performance becomes methodologically insufficient. Instead, a dynamic perspective is required, in which volatility is interpreted not as an anomaly or a threat but as an inherent property of complex systems evolving over time.

Within this dynamic paradigm, changes in project performance are no longer treated as random noise that can be smoothed or ignored. Each fluctuation is interpreted as part of an unfolding process, reflecting shifts in underlying conditions, learning effects, and structural transformation. From this perspective, increases in standard deviation acquire analytical significance. As previously noted through the interpretation logic similar to Bollinger envelopes, the expansion of variability serves as an early indicator of a transition to a new developmental phase rather than as a signal of deterioration.

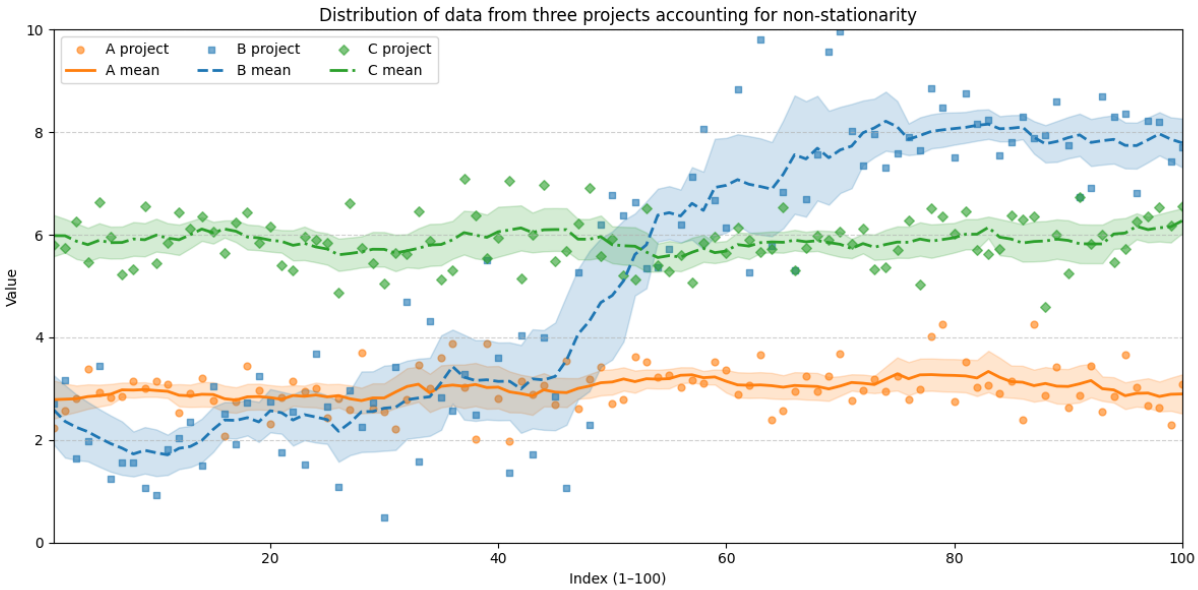
When these dynamics are examined in a time-series representation, a more nuanced picture of project behaviour emerges. At early stages of observation, Project B appears less attractive than Project A. Its estimated mean performance is lower, while its volatility is substantially higher. Under a static evaluation framework, this combination would suggest elevated risk and inferior efficiency, leading to early deprioritisation of the project within the portfolio.

However, dynamic analysis reveals a different trajectory. During the growth phase, Project B is characterised by increased variability and a widening confidence interval, reflecting uncertainty associated with early-stage development and limited information. At this stage, the project exhibits exploratory characteristics, where performance dispersion is a natural consequence of adaptation and learning. As additional observations accumulate and the underlying trend becomes more pronounced, the structure of the distribution begins to change. Standard deviation gradually decreases, confidence bounds narrow, and estimation error is reduced.

This transformation indicates that the initial instability of Project B does not represent persistent risk but rather a transitional phase leading toward a more stable and predictable performance regime. By the later stages of analysis, Project B demonstrates superior average performance relative to alternative projects, while its volatility declines to a level comparable with more stable options. As a result, the project that initially appeared as an outsider in static comparisons emerges as the most attractive alternative under a dynamic, distribution-aware evaluation.

These findings highlight the central objective of the proposed algorithmic approach. The task of the decision-making mechanism is not to eliminate projects that appear suboptimal at early stages but to continuously monitor their evolution and reassess their priority as new information becomes available. By maintaining exploration of less attractive alternatives and dynamically adjusting resource allocation, the algorithm is able to identify structural shifts in project behaviour and capture emerging value.

The integration of non-stationarity into the portfolio management process allows decisions to be aligned not only with current performance levels but also with developmental trends. This dynamic logic ensures that portfolio decisions reflect the evolving nature of complex systems rather than static snapshots of performance. The described evolution of Project B is graphically illustrated in the following Figure 3.



Source: author's construction.

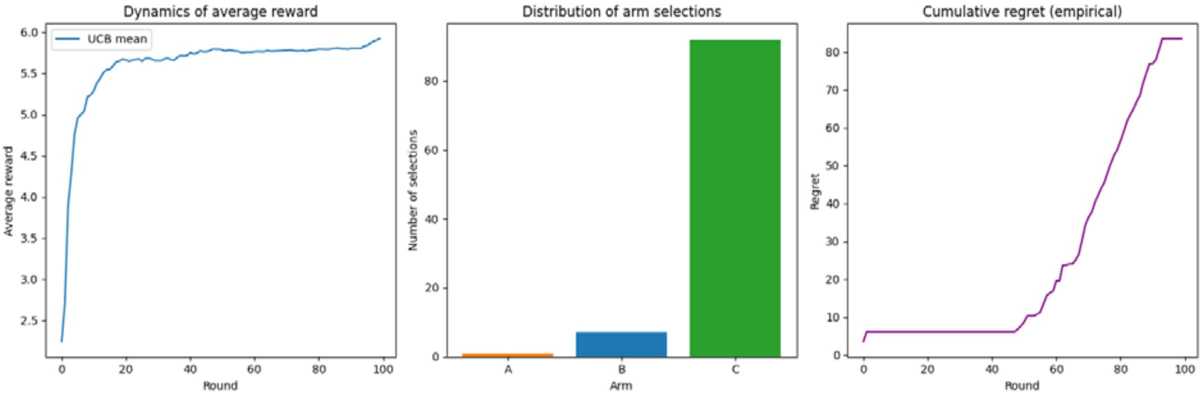
Figure 3. **Distribution of data from three projects accounting for non-stationarity**

To further assess the implications of dynamic, distribution-aware decision-making, it is necessary to compare the proposed adaptive approach with traditional selection mechanisms commonly used in sequential decision problems. One of the most widely applied methods in this context is the Upper Confidence Bound algorithm, which serves as a benchmark for balancing exploration and exploitation under uncertainty.

The classical UCB algorithm evaluates alternatives based on the combination of estimated average performance and an exploration bonus that decreases as the number of observations increases. While this approach provides a theoretically grounded mechanism for decision-making, it implicitly assumes stationarity of outcome distributions and treats uncertainty primarily as a temporary information deficit rather than as a structural characteristic of the system.

In the context of dynamic and non-stationary environments, such assumptions may limit the effectiveness of the traditional UCB framework. Specifically, the standard algorithm does not explicitly account for changes in volatility, regime shifts, or evolving trends in performance over time. As a result, alternatives that exhibit high variability during early stages may be prematurely deprioritised, despite their potential to evolve into superior options under changing conditions.

The following graphical representation illustrates the results of applying the traditional Upper Confidence Bound algorithm to the task of alternative selection under the same empirical conditions used in the previous analysis. The Figure 4 demonstrates how the classical UCB mechanism allocates selection frequencies over time and highlights its response to uncertainty and performance dynamics. This comparison provides a basis for evaluating the limitations of static confidence-bound approaches and sets the stage for subsequent analysis of the advantages offered by the proposed adaptive framework.



Source: author's construction.

Figure 4. **Performance results of the standard UCB model**

The modified model proposed by the author demonstrated significantly superior performance compared to the classical Upper Confidence Bound approach. The standard UCB algorithm treated the decision-making environment as stationary and therefore concentrated almost exclusively on Project C, which appeared to be the most efficient alternative based on average performance indicators. This behaviour reflects a structural limitation of the classical approach, which prioritises early leaders and assumes stability of outcome distributions over time.

In contrast, the proposed adaptive model was able to timely account for dynamic changes in the behaviour of Project B. In the modified framework, the dynamics of the estimated mean reward did not converge prematurely to a theoretical asymptote, as observed in the classical UCB. Instead, the average reward continued to grow over time, reflecting the algorithm's ability to adapt to evolving conditions and to incorporate newly emerging information into the decision-making process.

This improvement was achieved through several key methodological enhancements. First, a discounting or "forgetting" mechanism was integrated into the model, reducing the influence of outdated observations. This prevented historical results from exerting excessive impact on current decisions and increased the sensitivity of the algorithm to recent changes in the environment. As a result, the model remained responsive to shifts in project performance rather than being anchored to early observations.

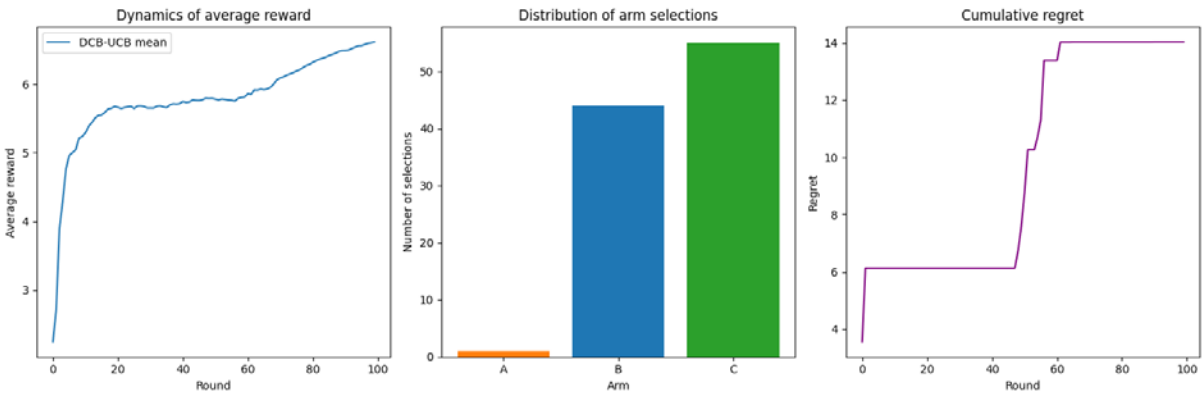
Second, an adjustment based on standard deviation was introduced. In periods of increasing variability, the algorithm interpreted rising dispersion as a signal to intensify exploration. This mechanism enabled the timely detection of latent changes in outcome distributions and prevented premature exploitation of alternatives whose apparent stability was temporary. Volatility was thus reinterpreted as an informative signal rather than as a purely negative risk factor.

Third, the inclusion of a drift or trend coefficient strengthened the algorithm's ability to detect directional changes in average performance. When mean values began to evolve consistently in a particular direction, the model increased attention to these alternatives, allowing emerging trends to be recognised at an early stage. This feature significantly enhanced the responsiveness of the decision-making process to non-stationary dynamics.

As a result of these enhancements, the model exhibited a characteristic "exploration surge" during phases of heightened uncertainty. Periods of increasing standard deviation and detectable drift triggered more active information gathering, which was subsequently followed by stabilisation as additional data were accumulated. Over time, estimation error decreased, confidence bounds narrowed, and the algorithm transitioned toward more precise evaluations focused on the most promising alternatives.

Importantly, the modified approach avoided excessive concentration on Project C and allowed Project B to fully reveal its potential during the second half of the observation period. This led to a more balanced allocation of attention across alternatives, reduced accumulated regret, and enabled further growth in average reward. The results demonstrate that the adaptive model not only improves short-term decision quality but also enhances long-term portfolio performance.

Overall, the findings confirm that the proposed algorithm is capable of operating effectively not only under stationary assumptions but also in dynamic, non-stationary environments. This property is critically important for strategic project portfolio management in contemporary conditions characterised by volatility, uncertainty, and continuous change. The final graphical representation Figure 5 illustrates the performance of the Dynamic Confidence Bound algorithm in the alternative selection task and summarises the advantages of the proposed approach.



Source: author's construction.

Figure 5. **Performance results of the Dynamic Confidence Bound model**

Discussion. The results obtained in this study provide important insights into the limitations of traditional project portfolio decision-making models and demonstrate the advantages of adaptive, distribution-based approaches under dynamic environmental conditions. The empirical findings confirm that static evaluation frameworks, which rely on average performance indicators and stationarity assumptions, are insufficient for managing portfolios in environments characterised by volatility, uncertainty, and continuous change.

One of the key observations emerging from the analysis is that classical selection mechanisms, such as the standard Upper Confidence Bound algorithm, tend to converge prematurely toward alternatives that appear optimal at early stages. This behaviour reflects an inherent bias toward exploitation under the assumption of stable outcome distributions. While such an approach may be effective in stationary settings, it becomes problematic when project performance evolves over time and exhibits regime shifts. The tendency to concentrate decision-making on early leaders limits the ability of the portfolio to adapt and increases long-term regret.

In contrast, the proposed Dynamic Confidence Bound approach demonstrates a fundamentally different decision logic. By explicitly incorporating distributional characteristics, volatility signals, and trend dynamics, the model remains sensitive to changes in project behaviour throughout the entire decision horizon. The results indicate that volatility, traditionally treated as a negative risk indicator, can be reinterpreted as an informative signal of structural change and developmental transition. This perspective aligns with contemporary views on managing complex adaptive systems, where instability often precedes transformation rather than failure.

The integration of discounting mechanisms further enhances the adaptability of the model. Reducing the influence of outdated observations allows the algorithm to remain aligned with current conditions and prevents historical performance from dominating present decisions. This feature is particularly relevant in project portfolio management, where external shocks, technological shifts, and organisational learning can rapidly alter project trajectories. The findings suggest that forgetting mechanisms are not a weakness but a necessary component of effective decision-making in non-stationary environments.

The inclusion of trend detection through drift components represents another important contribution of the proposed approach. By identifying directional changes in performance, the model is capable of recognising emerging opportunities at an early stage. This capability addresses a critical gap in traditional portfolio management, where changes in trends are often identified with delay due to reliance on aggregated indicators. As a result, the adaptive model supports proactive rather than reactive decision-making.

From a portfolio management perspective, the findings highlight the importance of maintaining a balanced exploration–exploitation strategy over time. The results show that early-stage uncertainty should not automatically disqualify alternatives, as projects that initially appear less attractive may evolve into high-performing options. This insight has direct managerial implications, suggesting that portfolio resilience depends not only on selecting stable projects but also on preserving diversity and optionality within the portfolio.

The discussion of results also underscores the relevance of the proposed approach in the context of VUCA environments. By embedding non-stationarity directly into the decision-making process, the Dynamic Confidence Bound framework aligns algorithmic logic with the realities of strategic management in complex and unpredictable settings. This alignment enhances the practical applicability of the model for organisations seeking to improve long-term portfolio performance under uncertainty.

Overall, the findings contribute to the growing body of research on adaptive project portfolio management by demonstrating how distribution-based and dynamic confidence mechanisms can improve decision quality. The proposed approach extends classical selection models and provides a methodological bridge between theoretical decision algorithms and real-world portfolio management challenges. These results create a foundation for future research and practical implementation of adaptive decision-support systems in project-oriented organisations.

Conclusions. This study substantiates the relevance of adaptive, distribution-based decision-making for project portfolio management under dynamic and non-stationary environmental conditions. The findings demonstrate that traditional portfolio selection models based on static assumptions and average performance indicators are insufficient for capturing the evolving nature of project behaviour in volatile environments.

The proposed Dynamic Confidence Bound approach extends classical decision-making frameworks by explicitly integrating uncertainty, volatility, and trend dynamics into the portfolio evaluation process. By treating variability as an informative signal rather than solely as a source of risk, the model enables continuous reassessment of project attractiveness and supports more flexible and resilient portfolio configurations.

The results confirm that adaptive mechanisms reduce premature convergence on early-performing alternatives, lower accumulated regret, and improve long-term portfolio performance. The inclusion of discounting, volatility-based exploration, and trend detection allows the decision-making process to remain aligned with current conditions and responsive to structural changes in project performance.

The practical value of the proposed approach lies in its applicability to real-world project portfolio management, where uncertainty and change are inherent characteristics rather than exceptions. The model provides a systematic framework for balancing stability and exploration, supporting strategic decision-making in complex environments.

Overall, the study contributes to the development of adaptive portfolio management methodologies and offers a robust foundation for further research and practical implementation of dynamic decision-support systems in project-oriented organisations.

REFERENCES:

Archer, N. P., & Ghasemzadeh, F. (1999). An integrated framework for project portfolio selection. *International Journal of Project Management*, No. 17(4), P. 207–216. DOI: https://doi.org/10.1016/S0263-7863(98)00032-5.

Auer, P., Cesa-Bianchi, N., & Fischer, P. (2002). Finite-time analysis of the multiarmed bandit problem. *Machine Learning*, No. 47 (2–3), P. 235–256. DOI: https://doi.org/10.1023/A:1013689704352.

Besson, L., & Kaufmann, E. (2018). The generalized likelihood ratio test meets klUCB. *Advances in Neural Information Processing Systems*, No. 31, P. 348–358. URL: https://papers.nips.cc.

Blichfeldt, B. S., & Eskerod, P. (2008). Project portfolio management – There's more to it than what management enacts. *International Journal of Project Management*, No. 26 (4), P. 357–365. DOI: https://doi.org/10.1016/j.ijproman.2007.06.004.

Bollinger, J. (2001). Bollinger on Bollinger Bands. McGraw-Hill.

Cooper, R. G., Edgett, S. J., & Kleinschmidt, E. J. (2001). Portfolio management for new product development. *R&D Management*, No. 31 (4), P. 361–380. DOI: https://doi.org/10.1111/1467-9310.00225.

Dachner, A. M., Ellingson, J. E., Noe, R. A., & Saxton, B. M. (2021). The future of employee development. *Human Resource Management Review*, No. 31 (2), Art. 100732. DOI: https://doi.org/10.1016/j.hrmr.2019.100732.

Edeji, O. C. (2024). Human capital investment and organizational performance. *Journal of Business Economics and Management*, No. 25 (1), P. 44–60. DOI: https://doi.org/10.3846/jbem.2024.18934.

Gartner. (2022). Adaptive decision-making models. URL: https://www.gartner.com.

Geraldi, J., Maylor, H., & Williams, T. (2011). Now, let's make it really complex. *International Journal of Operations & Production Management*, No. 31 (9), P. 966–990. DOI: https://doi.org/10.1108/01443571111165848.

Ghasemzadeh, F., & Archer, N. P. (2000). Project portfolio selection through decision support. *Decision Support Systems*, No. 29 (1), P. 73–88. DOI: https://doi.org/10.1016/S0167-9236(00)00065-8.

Hancco, J. F. A. (2022). Strategic HR development as a source of competitive advantage. *Management Science Letters*, No. 12 (3), P. 251–260. DOI: https://doi.org/10.5267/j.msl.2022.1.002.

Harvard Business Review (2020). Managing in a VUCA world. URL: https://hbr.org.

Kahneman, D. (2011). Thinking, Fast and Slow. Farrar, Straus and Giroux.

Killen, C. P., Hunt, R. A., & Kleinschmidt, E. J. (2008). Project portfolio management for product innovation. *R&D Management*, No. 38 (5), P. 525–538. DOI: https://doi.org/10.1111/j.1467-9310.2008.00530.x.

Kleinberg, R., Slivkins, A., & Upfal, E. (2010). Multi-armed bandits in metric spaces. *Proceedings of the 40th ACM Symposium on Theory of Computing*, P. 681–690. DOI: https://doi.org/10.1145/1806689.1806787.

Lattimore, T., & Szepesvári, C. (2020). Bandit Algorithms. Cambridge University Press. DOI: https://doi.org/10.1017/9781108571401.

Loch, C. H., DeMeyer, A., & Pich, M. T. (2006). Managing the Unknown. Wiley.

Luedtke, J., Ahmed, S., & Nemhauser, G. (2010). An integer programming approach for linear programs with probabilistic constraints. *Mathematical Programming*, No. 122 (2), P. 247–272. DOI: https://doi.org/10.1007/s10107-009-0273-1.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, No. 2 (1), P. 71–87. DOI: https://doi.org/10.1287/orsc.2.1.71.

Martinsuo, M., & Lehtonen, P. (2007). Role of single-project management in achieving portfolio management efficiency. *International Journal of Project Management*, No. 25 (1), P. 56–65. DOI: https://doi.org/10.1016/j.ijproman.2006.06.002.

McKinsey & Company (2021). Strategy under uncertainty. URL: https://www.mckinsey.com.

Mintzberg, H. (2009). Managing. Berrett-Koehler.

Nicolás-Agustín, Á., López-Zafra, E., & Ramos-Álvarez, M. (2022). Strategic evolution of HR leadership. *Journal of Business Research*, No. 144, P. 386–397. DOI: https://doi.org/10.1016/j.jbusres.2022.01.064.

OECD (2022). Managing uncertainty in complex systems. OECD Publishing.

Packendorff, J. (2014). The temporary organization revisited. *International Journal of Project Management*, No. 32 (7), P. 1295–1307. DOI: https://doi.org/10.1016/j.ijproman.2014.02.008.

Petit, Y. (2012). Project portfolios in dynamic environments. *International Journal of Project Management*, No. 30 (5), P. 539–553. DOI: https://doi.org/10.1016/j.ijproman.2011.12.002.

PMI (2021). The Standard for Portfolio Management. Project Management Institute.

PMI (2023). Pulse of the Profession. Project Management Institute.

Powell, W. B. (2019). A unified framework for stochastic optimization. Wiley.

Sanchez, H., & Robert, B. (2010). Measuring portfolio strategic performance. *International Journal of Project Management*, No. 28 (8), P. 768–782. DOI: https://doi.org/10.1016/j.ijproman.2010.04.006.

Shapira, Z. (2015). Risk Taking: A Managerial Perspective. Russell Sage Foundation.

Snowden, D. J., & Boone, M. E. (2007). A leader's framework for decision making. *Harvard Business Review*, No. 85 (11), P. 68–76.

Sutton, R. S., & Barto, A. G. (2018). Reinforcement Learning: An Introduction. MIT Press.

Taleb, N. N. (2012). Antifragile: Things That Gain from Disorder. Random House.

Teece, D. J. (2014). A dynamic capabilities-based entrepreneurial theory. *Journal of Management Studies*, No. 51 (8), P. 1271–1302. DOI: https://doi.org/10.1111/joms.12099.

Williams, T., Klakegg, O. J., Magnussen, O. M., & Glasspool, H. (2010). An investigation of governance frameworks. *International Journal of Project Management*, No. 28 (8), P. 782–793. DOI: https://doi.org/10.1016/j.ijproman.2010.06.006.

World Economic Forum (2020). The Global Risks Report. URL: https://www.weforum.org.

Xu, Y., & Mannor, S. (2012). Robustness and generalization in bandit problems. *Machine Learning*, No. 89 (3), P. 217–243. DOI: https://doi.org/10.1007/s10994-012-5298-1.

Zahra, S. A., Sapienza, H. J., & Davidsson, P. (2006). Entrepreneurship and dynamic capabilities. *Journal of Management Studies*, No. 43 (4), P. 917–955. DOI: https://doi.org/10.1111/j.1467-6486.2006.00616.x.

Zhang, C., & Zhang, Y. (2021). Non-stationary bandits and regime shifts. *IEEE Transactions on Neural Networks and Learning Systems*, No. 32 (11), P. 5021–5034. DOI: https://doi.org/10.1109/TNNLS.2020.3036218.

Zhou, Y., & Van Roy, B. (2021). Efficient reinforcement learning in non-stationary environments. *Journal of Machine Learning Research*, No. 22, P. 1–34. URL: https://www.jmlr.org.

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