IJM

International Journal of Management

Publishing Refereed Research Article, Survey Articles and Technical Notes.

ISSN Print: 0976-6502 / ISSN Online: 0976-6510

IAEME Publication

Chennai, India

editor@iaeme.com/ iaemedu@gmail.com

https://iaeme.com/Home/journal/IJM

International Journal of Management (IJM)
Volume 16, Issue 3, May-June 2025, pp. 172-186, Article ID: IJM_16_03_012
Available online at https://iaeme.com/Home/issue/IJM?Volume=16&Issue=3
ISSN Print: 0976-6502; ISSN Online: 0976-6510; Journal ID: 6251-7894
Impact Factor (2025): 13.89 (Based on Google Scholar Citation)
DOI: https://doi.org/10.34218/IJM_16_03_012

A DETERMINISTIC FORECASTING FRAMEWORK WITH CAUSAL SCENARIO ANALYSIS

Dharmateja Priyadarshi Uddandarao
Northeastern University, Boston, MA, USA.

Abstract

This paper presents a novel deterministic forecasting model for pre-dicting future business revenue over a certain horizon by incorporating causal "what-if" scenario analysis. Using monthly historical data on various business metrics, the framework builds a flexible, component-based forecast indepen-dent of any specific revenue model (e.g., applicable to subscription or ad-based businesses alike). The deterministic model captures causal relationships between business growth, goals, and revenue generation, allowing explicit simulation of interventions, such as feature launches, that boost business growth by a specified percentage. We detail the forecasting framework, causal modeling methodology, deterministic assumptions, and mathematical formulation of the model. An il- lustrative use cases demonstrate how different intervention timings and strengths produce adjusted revenue forecasts.

Keywords: Deterministic Forecasting, Causal Scenario Analysis, Intervention Model-ing, Scenario Planning, Performance Evaluation, Investment Analysis

Cite this Article: Dharmateja Priyadarshi Uddandarao. (2025). A Deterministic Forecasting Framework with Causal Scenario Analysis. *International Journal of Management (IJM)*, 16(3), 172-186.

1. INTRODUCTION

Forecasting business revenue is a cornerstone of strategic planning, particularly in volatile and highly competitive markets. Accurate revenue forecasts allow companies to make informed investment decisions, allocate resources efficiently, assess risks, and evaluate strategic opportunities. Traditional forecasting techniques often rely on statis- tical extrapolations of historical data or leverage advanced machine learning models that identify patterns and trends. While these approaches can be effective under cer- tain conditions, they may fall short in environments characterized by dynamic changes, strategic interventions, or the need for scenario-specific insights.

One significant limitation of conventional forecasting methods is their reactive na- ture. Statistical and machine learning models typically project the future based on past behaviors without accommodating hypothetical or planned future changes. These mod- els tend to produce a single output or a range defined by statistical confidence intervals, yet they may lack interpretability and flexibility in adjusting to business context shifts. For instance, launching a new product feature, changing pricing strategies, or initiating marketing campaigns can substantially influence user behavior and revenue generation. Relying solely on historical data to model such future actions can lead to inaccurate or misleading projections.

In contrast, deterministic forecasting offers a structured and transparent alternative. A deterministic model assumes fixed relationships between variables and produces a single forecast for each specific set of assumptions. By doing so, it simplifies the fore- casting process and enhances interpretability. The clarity of cause-and-effect relation- ships in deterministic models is particularly useful in corporate settings where decision- makers prefer precise and actionable insights. As Lenahan explains, deterministic fore- casting is especially powerful when the dynamics of the system are well understood and relatively stable [1] .

Building upon deterministic principles, causal scenario analysis introduces an ad- ditional layer of strategic depth. Causal forecasting explicitly models the relationships between explanatory variables (e.g., user growth, product usage) and outcome variables (e.g., revenue). It empowers analysts and business leaders to simulate the effects of planned interventions by modifying the underlying drivers of the forecast. This capa- bility is central to modern planning, where the goal is not merely to predict the future but to shape it by evaluating potential actions in advance [2,3].

Scenario planning as a discipline has long been employed in strategic management, particularly in environments of high uncertainty. Organizations ranging from multina- tional corporations to academic institutions like Monash University have implemented scenario models to test the impacts of various external and internal changes on op- erational and financial metrics [4,5] . The integration of deterministic forecasting with causal modeling elevates scenario planning by allowing for quantitative projections that trace outcomes directly back to specified inputs.

Moreover, deterministic models are particularly amenable to integration with busi- ness intelligence tools and spreadsheet-based simulations. Because these models use clearly defined equations and assumptions, they can be easily embedded into financial models, making them more accessible to decision-makers across finance, strategy, and operations functions. This usability factor is crucial for widespread adoption in organi- zations where data science capabilities may be limited.

Another advantage of deterministic causal forecasting lies in its flexibility to accom- modate diverse business models. Whether a company generates revenue from subscrip- tion fees, advertising, or usage-based pricing, the model described in this paper can be customized by adjusting its component structures. For example, subscription businesses can use ARPU (Average Revenue Per User) as a revenue driver, whereas advertising businesses might focus on monetization per session or per user action. This modularity enhances the generalizability of the model across different industry contexts.

Importantly, this paper fills a critical gap in the literature by providing a practical implementation of deterministic causal forecasting. Prior studies have examined the theoretical aspects of causal inference, deterministic simulations, and scenario planning separately, but few have combined them into a unified, applied framework tailored for business revenue forecasting [6,7]. Our contribution lies in formalizing this integration, demonstrating the mathematical formulation, and applying it to realistic use cases with varying intervention strategies.

The model's foundation in causal inference principles also aligns it with contem- porary academic advancements. For instance, Pearl's structural causal models and Hol- land's work on counterfactual reasoning provide theoretical underpinnings for under- standing the impact of interventions [3]. These concepts are now finding their way into applied business forecasting, where the emphasis is shifting from mere prediction to explanation and intervention planning.

Finally, the inclusion of scenario-specific parameters and timelines allows for sensi- tivity analysis and comparative evaluation. Business leaders can test multiple "what-if" scenarios—such as launching a new feature at different points in time—and observe the deterministic outcomes on revenue. This capacity to isolate the effects of timing and magnitude of interventions enables a more informed and proactive decision-making process.

In summary, this paper proposes a deterministic forecasting model enriched with causal scenario analysis to address the limitations of traditional forecasting approaches. The model supports flexible customization, clear interpretation, and direct application to strategic planning processes. By simulating the effects of interventions, it equips organizations with a forward-looking tool that blends rigor with practicality. The fol- lowing sections delve into the technical construction of the model, mathematical for- mulation, illustrative use cases, and implications for strategic decision-making.

2 Forecasting Framework and Causal Methodology Deterministic Modeling Approach

Forecasting Framework and Causal Methodology Deterministic Modeling Approach We use a deterministic modeling approach that yields a single forecast for a given set of inputs. There are no stochastic terms; all variables are driven by pre-defined equations. As noted by Lenahan, deterministic forecasting provides clarity when system dynamics are known [1].

Our forecasting model is rooted in a deterministic modeling philosophy, which as- sumes a fixed, rule-based relationship among input variables and outcomes. This ap- proach provides a point-estimate projection, where each input leads to a unique, non- random result. The primary advantage is transparency and control: for any given set of inputs, the forecasted trajectory is clear, reproducible, and explainable. Unlike stochas- tic models, which involve randomness and probability distributions, deterministic mod- els exclude uncertainty in their predictions, making them highly suitable for strategic planning, especially when the decision-making context favors clarity and interpretabil- ity over probabilistic risk.

At the core of deterministic forecasting is the notion of deterministic functions: given the current state of the system and a defined set of rules, the model will produce the same future state every time it is executed. This model assumes no random shocks; instead, each future value is calculated by applying a mathematical transformation to the current values. For example, if a user base grows by 2% each month, then this rate is applied as a fixed multiplier over time. This ensures repeatability and allows businesses to isolate the effects of specific assumptions.

This property is particularly beneficial when modeling the effects of interventions. For instance, if a new feature is launched in month 12, and it is expected to increase user growth by

0.6% monthly, the deterministic model will propagate this impact for- ward in a predictable manner. As a result, different scenarios can be simulated with precision by adjusting the input parameters. The resulting forecasts are not just likely outcomes—they are the exact consequences of the assumptions encoded in the model.

Component-Based Structure: The model is modular, forecasting key components separately before aggregating them. This aligns with financial modeling practices and allows independent adjustments to user growth, engagement, or monetization.

Variables include:

- **User Count U_t:** the number of active users or customers in month t. This could be monthly active users or active subscribers.
- **Usage** M_t– the total usage in month t (e.g. number of sessions, hours spent). This metric captures how intensively the user base is using the product.
- **Revenue** R_t– the total revenue in month t.

These variables are causally linked. User count influences total usage, as more users likely drive higher aggregate usage and both user count and usage drives revenue. By explicitly modeling these nodes, we can induce causal reasoning. For example, if an in- tervention increases user count, the model will promote that effect into increased usage and subsequently into revenue [8,9] . While stochastic models (e.g., ARIMA, Monte Carlo simulations, machine learning) account for uncertainty and variability, they often produce opaque results. Their black-box nature can be a hindrance in strategic discus- sions where understanding the "why" behind a forecast is crucial. In contrast, determin- istic models provide clarity and traceability.

Moreover, deterministic frameworks are computationally efficient and easy to im- plement in tools familiar to business stakeholders when they decide to test various plan- ning scenarios.

3 Mathematical Formulation of the Model

Mathematical Formulation of the Model

We now formalize the deterministic model. Let t index the months, with t=0 as last observed month (the starting point for forecasting), and we aim to forecast up to t = T (next 36 months, i.e. 3 years). At the core of the model are deterministic update equations for user count, usage, and revenue. One simple formulation is as follows

User count growth : We model the user base growth via a growth rate g(t) that may change over time (especially with interventions). The user count equation can be written as:

$$U_{t+1} = U_t \times (1 + g(t))$$

where g(t) is the fractional growth rate in month t. In absence of interventions, g(t) might be a slowly varying function estimated from historical data (e.g. average monthly growth) or a constant. For example, if users grew 25% YoY (year over year) historically, the equivalent monthly growth g_{base} 1.84% per month (since $(1 + 0.25)^{1/12} = 1 + 0.0184$) We can incorporate more complex user dynamics as needed. The key is that U_t is updated through a deterministic function of the previous state.

Usage Dynamics: The total usage Mt can be modeled in terms of user count. One way is to use an average usage per user, a_t , such that Mt = a_tx U_t . We may forecast at based on historical trends in user engagement. If each usage is relatively stable, at could be treated as constant or slowly increasing (if users become more engaged, at grows a few percent per year). In a subscription model, usage might not directly drive revenue, but it could correlate with retention. In an advertising-based model, usage is directly tied to revenue generation (more usage means more ads impressions). Our framework leaves the relationship flexible. We can model usage growth similarly to user growth (e.g. an engagement growth rate), or even make usage a function of user count with diminishing returns (to show that a new user might be less active on average). For simplicity, one deterministic formulation is:

$$a_{t+1} = a_t \times (1 + h),$$

where h is a monthly growth rate in per-user usage. Then $M_t = a_t U_t$. This ef- fectively captures usage trends. If more sophisticated relations are given (say, usage increases as user base increases due to network effects), those can be encoded as well.

Revenue Calculation: Revenue Rt is computed as a deterministic function of the other metrics. We allow this to be model-independent by design. Two common formu- lations are:

- $R_t = ARPU_t \times U_t$ where $ARPU_t$ is the average revenue per user (like sub- scription fee or average customer spend in that month). If pricing is stable, $ARPU_t$ might be constant; if there are upgrades or pricing changes, $ARPU_t$ can be set accordingly over time.

– $R_t = AdRate_t \times M_t$, where $ARPU_t$ is the revenue earned per unit of usage (like advertising yield per hour or per click). Again, this rate can be constant or increase (if monetization improves) $R_t = U_t \times a_t \times m_t$, where M_t is the monetization per usage (so $a_t \times m_t$ would be revenue per user). This formulation covers both cases above: in a subscription scenario, at could be 1 and M_t would be the fee; in an ad scenario, a is usage per user and M_t is revenue per usage. The model does fixate on any particular revenue formula. It allows users of the framework to plug in the appropriate revenue equation reflecting their business metrics.

These equations form a system that deterministically evolves the state of the business metrics month over month. The model's deterministic assumptions mean that if we run the simulation forward with the same initial conditions and the same parameter choices, we will always get the exact forecast. There is no randomness in variables, we use point esti- mates for growth rates. This is useful for scenario comparison, since differences in outcomes can be directly attributed to changes in assumptions rather than random fluctuations. It also aligns with most common business planning models where forecasts are often built in spreadsheets with fixed numbers (a form of deterministic simulation). However, it is important to note that real outcomes will of course deviate from a single line forecast. So, in practice one might explore multiple scenarios or incorporate safety margins.

4 Incorporating Causal Interventions ("What-If" Scenarios

A pivotal feature of our model is its ability to simulate **"what-if" scenarios** by inducing interventions at some different future points. An intervention is a deliberate change to parameters at a given time, reflecting a hypothetical event(like launching a new product feature, starting a marketing campaign or a pricing changes). We treat interventions in a **causal modeling** sense: an intervention is an external action that changes the under- lying data generating process. In causal inference terms, this is similar to performing a do- operation (do(X)=x) on the system, forcing a variable to take a new value. In our forecasting model, the direct way to implement an intervention is to modify the growth rate or other parameters from the intervention point onward. For instance, a new feature that increases user growth by X% YoY can be termed as increase in the monthly growth rate starting at the time of launch. If the feature is launched at month $t = T_{launch}$, we could model:

For $t < T_{launch}$: $g(t) = gbase$ (the baseline monthly user growth rate, estimated from history)

For $t >= T_{launch}$: $g(t) = g + \Delta g$

Here Δg is chosen such that the annual growth is higher by X percent. For example, if baseline growth $g_{base} = 0.02$ (2% per month, ~26.8% per year) and we want to boost growth by X = 10% points yearly (to ~36.8% YoY), we solve $(1 + g_{base} + 6g)^{12} - 1 = (1 + g_{base})^{12} - 1 + 0.10$

This would yield $\Delta g \approx 0.00646$ (0.646% additional monthly growth). In practice, one can easily set a new monthly rate (e.g. use 2.6% per month as an "boosted" rate if 2% was baseline). The key is that at T_{launch} , we deterministically change the growth parameter. This structural change leads to a different trajectory for Ut after the inter- vention, which then flows through to usage and revenue.

Mathematically, we can show an intervention as a function that modifies the model's parameters as a function of time. Let θ represent the set of model parameters (like growth rates, ARPU, etc.). We can define θ(t) piecewise, with different values before and after the actual intervention time. For example, if θ1 is the user growth rate param- eter:

$$\theta_t(t) = \begin{cases} g_{base} & , t < T_{launch} \\ g_{base} + \delta g, & t >= T_{launch} \end{cases} ,$$

and all other parameters might remain the same (unless the intervention affects oth- ers too). In general, an intervention could potentially affect multiple parameters. For instance, launching a new feature might not only accelerate user acquisition (growth rate) but also can reduce churn, or increase user engagement. The framework allows for all such affects in the scenario configuration. Each scenario can be a different set of parameter functions $\theta_{scenario}(t)$

This approach is related to the concept of **intervention analysis** in time series fore- casting, where one estimates the impact of any given event on a time series [10] . How- ever, classic intervention analysis is generally retrospective. Here we inject a hypothetical future event and propagate its impact going forward. By doing so in a deterministic model, we get a clear view of the causal effect on the forecast. The difference between the intervention scenario forecast and the baseline forecast can be attributable to the intervention by design.

Multiple and Timed Interventions: The model will be able to handle multiple in- terventions at different times. For example, we can simulate a scenario where a feature launches at 12th month and another major change (say, a price increase) happens at 24th month. Each intervention would adjust the relevant parameters from its point on- ward. Because the model is deterministic, the order and timing of interventions strictly determine the outcome this lets analysts evaluate, for instance, whether launching a feature earlier yields significantly more cumulative revenue than launching later (due to compounding growth effects). We demonstrate such comparisons in the case study section.

In summary, our causal scenario methodology treats the forecasting model as a structural causal model of any business metrics. By explicitly encoding the causal links (users –> usage –> revenue) and allowing outside interventions (like feature launch –> changes in user growth), we can simulate counterfactual scenarios: “If we launch feature X at month 12, what happens to revenue vs if we don’t?” The output is a deterministic forecast. This provides valuable insight for decision makers, as they can project impact and plan accordingly.

For illustration, A flexible Python module was built for forecasting business metrics using historical data and optional intervention scenarios, with customizable parameters like user growth and ARPU. The model iteratively updates forecasts month by month and allows easy scenario modeling.

5 Illustrative Use Case and Results

To demonstrate our forecasting framework, we can consider a hypothetical software business with a subscription based revenue model. We have historical monthly data which indicate that the user base has been constantly growing around 2% per month and each user brings in an average of extra $50 per month in revenue (it can be via subscription fee or combined ARPU). For simplicity, assume usage per user is constant, and revenue per user remains at $50 (this could represent a fixed subscription price). We will forecast revenue for the next 36 months (3 years) under different scenarios:

- **Baseline (No Intervention):** Assume the current trends continue with no changes in business strategy. User count growth remains at the baseline of 2% monthly (~27% YoY).
- **Feature Launch at 6 Months:** An intervention scenario where a new feature is launched in 6th month. We expect this will boost the user growth rate by an additional ~10% yearly (i.e. growth increases from 2% to ~2.65% per month from month 7).

– **Feature Launch at 12 Months:** Similar intervention but occurring later, at the 1-year mark
– **Feature Launch at 24 Months:** Late intervention, 2 years out

We run our deterministic model for each scenario, starting from an initial user count of 1,000 and initial monthly revenue $50,000 (which corresponds to 1,000 users * $50 each at t=0). The model updates user count and revenue forward month by month. Because the only difference between scenarios is the timing of the growth-rate boost, we can directly attribute differences in outcomes to that timing.

As shown in Figure 1, the intervention scenarios diverge upward from the baseline once the feature is introduced. In all cases, introducing the growth boosting feature leads to higher revenue by the end of the 3-year period compared to doing nothing (baseline). However, the timing of the intervention significantly affects the magnitude of the gain:

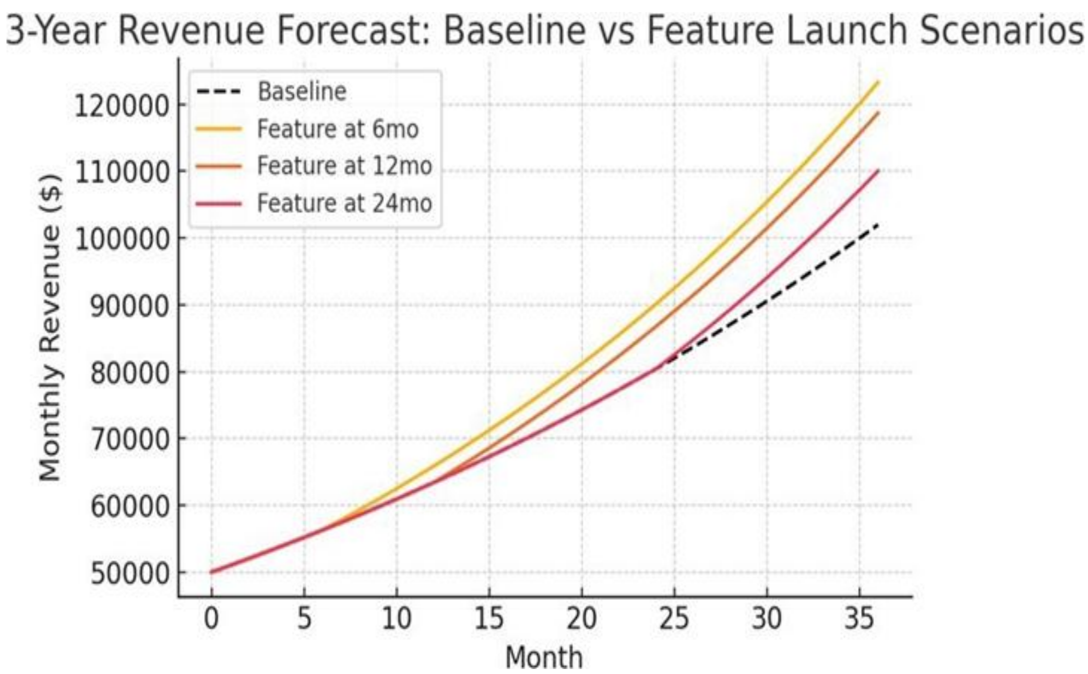

Fig. 1. 1. Projected revenue trajectories under baseline and feature-launch scenarios at different times. The baseline (no intervention) is shown as a dashed black line. Colored lines show scenar- ios where a growth- boosting feature is launched at month 6 (orange), month 12 (red-orange), and month 24 (pink). All scenarios assume the feature yields an additional ~10% YoY user growth after launch. The vertical axis shows monthly revenue in USD.

– Launching the feature earlier (at 6 months) yields the greatest revenue by year 3, reaching about $123k per month vs $102k in the baseline. The earlier boost allows compounding to work longer – the user base starts growing faster from month 7 onward, so by the end of 36 months the gap has widened substantially.

- Launching at 12 months still provides a boost, but less cumulative impact by year 3 (revenue ~$119k). The delay means the first 12 months had only baseline growth, so the compounding period for the higher growth is shorter (24 months of boost vs. 30 months in the 6-month scenario).
- Launching at 24 months yields the smallest uplift by year 3 (revenue ~$110k). In this case, for the first 2 years the growth is at baseline; only in the last 12 months does the higher growth rate kick in. Thus, by the 36th month, the user count and revenue haven't had time to diverge far from the baseline – though if we projected further out, eventually the 24-month launch scenario would overtake the baseline more significantly.

These results quantitatively illustrate a common strategic insight: earlier interventions have a larger compounded effect on growth. The deterministic model makes this ex- plicit and measurable. Decision-makers can use such analysis to evaluate the trade-offs of launching a feature sooner versus later [6,11] . Of course, launching earlier might involve higher cost or risk, but the model shows the revenue upside in concrete terms.

Another insight from the model is that all else being equal, delaying an intervention means the revenue "lost" (versus an earlier launch) during the delay period cannot be recovered. You end up at a lower revenue level even after the boost has applied, because growth is multiplicative. This kind of insight is exactly what causal scenario forecast- ing is meant to provide, complementing financial considerations and feasibility in the overall decision.

While the above use case focused on a subscription model and an intervention af- fecting user growth, the framework can handle other casesIf our business relied on ad monetization, we would model revenue as $R_t = AdRate \times M_t$. An intervention could be something like a new product feature that increases user engagement (usage per user) by, say, 5% after launch, or a new ad technology that increases monetization rate. We would then adjust the usage growth rate or monetization factor in the model accordingly. The deterministic simulation would show how revenue grows with more usage or higher ad yield. The causal chain in that scenario might be: feature launch → higher a_t (usage per user) → higher M_t → higher R_t. The methodology is the same.

Multiple simultaneous interventions: Suppose the company plans two actions, e.g., a price increase and a feature launch in different future periods. We can model both: at the price increase month, bump up ARPU (or ad rate) by the intended percentage; at the feature launch month, bump user or usage growth. Running the simulation yields a scenario with both effects. If needed, we could also isolate their individual contributions by running scenarios with each alone.

Causal sensitivity analysis: By trying different values of the intervention effect (e.g., what if the feature only gives 5% YoY boost vs 15% YoY?), we can determine how sensitive the 3-year revenue is to the strength of the intervention. In a deterministic model, this is straightforward: change the parameter and re-run. This helps in under- standing best-case and worst-case scenarios if there is uncertainty about the actual im- pact of a planned action. Through these use cases, the deterministic causal model proves to be a powerful tool for **scenario planning**. It accepts a baseline grounded in historical data and then explores divergent futures based on explicit assumptions. This is in con- trast to purely statistical forecasts that might only give a confidence interval assuming no structural change. Here, we are injecting knowledge of potential structural changes. The results are not "predictions" in the probabilistic sense, but rather **conditional fore- casts:** If X happens at time Y, this model predicts Z outcome. Such conditional forecasts are immensely valuable for planning and "answering questions before they come up," as scenario analysis enables companies to be proactive. These features align with scenario planning principles emphasized by Schlenker and Armstrong [4,5].

6 Conclusions

We have constructed a deterministic forecasting framework that combines conventional trend-oriented forecasts with causal scenario simulations to predict business revenue through out an extended multi-year period. In an era of increasingly complex business environments and rapid technological evolution, the need for more robust, transparent, and adaptive forecasting tools is more pressing than ever. Traditional forecasting mod- els, while statistically sophisticated, often fall short in strategic planning contexts due to their inability to simulate the impacts of deliberate interventions or sudden market shifts. This paper introduced a deterministic forecasting framework augmented with causal scenario analysis, aimed at bridging this critical gap in business forecasting methodology.

The strength of our model lies in its structured decomposition of revenue generation into three core causal components: user growth, usage intensity, and monetization rate. By modeling each of these independently and linking them through deterministic equations, we offer a flexible, plug-and-play framework adaptable to a wide range of business models—be it subscription-based, advertising-supported, or hybrid revenue structures. This modularity empowers businesses to tailor the framework to their specific operational metrics, industry norms, and strategic priorities.

The deterministic nature of the model ensures reproducibility and transparency. Each simulation run yields a unique, point-based forecast directly traceable to a set of clearly defined assumptions and input parameters. This clarity is invaluable in decision- making contexts, particularly in corporate finance, strategy, and executive leadership. Decision-makers are often not data scientists; they require tools that provide reliable in- sights with minimal ambiguity. Our model addresses this need by emphasizing causality, interpretability, and practical implementation.

Central to the model’s utility is its capacity to simulate counterfactual scenar- ios—commonly referred to as "what-if" analyses. These simulations allow planners to evaluate the downstream impact of strategic initiatives such as launching new prod- uct features, adjusting pricing strategies, or initiating marketing campaigns. The causal modeling framework operationalizes interventions by directly modifying the param- eters influencing growth, engagement, or monetization. These adjustments then flow deterministically through the system, offering a realistic and measurable projection of potential outcomes.

The use case presented in this paper illustrates the tangible benefits of scenario modeling. The analysis demonstrated how varying the timing of a feature launch could significantly alter long-term revenue trajectories, even when the intervention itself re- mains constant. This insight—that earlier interventions yield compounding effects over time—is not only intuitive but now quantifiably demonstrable through our framework. Such insights can directly inform go-to-market strategies, capital allocation decisions, and organizational prioritization.

Furthermore, the model supports advanced strategic planning techniques such as sensitivity analysis and multi-scenario evaluation. By altering intervention parameters (e.g., growth boost magnitude, monetization uplift), analysts can assess the robustness of their forecasts and plan for best-case, worst-case, and most-likely outcomes. These capabilities help organizations adopt a proactive rather than reactive stance in managing uncertainty.

It is important to acknowledge the limitations of deterministic models. Real-world outcomes are seldom perfectly predictable, and any model that does not account for stochastic variability may overlook risks stemming from unexpected external shocks or internal fluctuations. However, the deterministic foundation can be enhanced through probabilistic overlays. For instance, a Monte Carlo simulation could be run atop the deterministic outputs to generate confidence intervals or risk-adjusted scenarios. This hybrid approach—blending deterministic and probabilistic modeling—offers a promis- ing avenue for future research and tool development.

Another potential area for expansion lies in integrating real-time data streams. By feeding live metrics into the model, organizations could continuously update their fore- casts and interventions, thereby moving toward adaptive or real-time scenario planning. Incorporating feedback loops would also enable self-correction and learning, ultimately aligning the forecasting framework with the broader trend toward autonomous decision-support systems in business intelligence.

From an academic standpoint, this work contributes to the growing literature on ap- plied causal inference, scenario planning, and business analytics. While the conceptual underpinnings draw from well-established research in these domains, the primary inno- vation lies in synthesizing these elements into a coherent, applied forecasting method- ology. Future work could explore deeper integrations with causal graphical models, dynamic optimization, or reinforcement learning to further enhance scenario evaluation and intervention design.

In conclusion, the deterministic causal forecasting framework proposed in this pa- per offers a powerful, interpretable, and adaptable tool for business revenue projection and strategic decision-making. It combines the rigor of mathematical modeling with the practicality required in real-world business contexts. By making assumptions explicit and effects traceable, the model fosters greater trust and usability among non-technical stakeholders. As organizations increasingly seek foresight tools that are not only accu- rate but also actionable, our framework stands out as a robust and scalable solution. We hope this work lays the foundation for future advancements in scenario-driven forecast- ing and inspires further research into the convergence of causal inference, deterministic modeling, and strategic planning.

References

[1] Lenahan, M.G.: Deterministic Forecasting: A Practical Approach. (2015)

[2] Lucas, J.M., Lawson, R.B.: Forecasting with causal models. J. Forecasting 1(1), 3–28 (1982)

[3] Holland, P.W.: Statistics and causal inference. J. Amer. Statist. Assoc 81(396), 945–960 (1986)

[4] Schlenker, B.R.: Scenario planning: A tool for strategic thinking. MIT Sloan Manage. Rev 36(2), 25–40 (1995)

[5] Armstrong, M.J.: Scenario planning: A tool for navigating strategic uncertainty. Harvard Bus. Rev

[6] Box, G., Tiao, G.: Intervention analysis with applications to economic and environmental problems. NPS Library Guides 70, 70–79 (1975)

[7] Davenport, T.H., Harris, J.G.: Competing on Analytics, Harvard Business Press (2007)

[8] Murphy, K.P.: Machine Learning: A Probabilistic Perspective, MIT Press (2012)

[9] Gelman, A.: Bayesian Data Analysis, CRC Press (2013)

[10] Hamilton, J.D.: Time Series Analysis (1994)

[11] Ghosh, S., Reilly, S.: The impact of new product launches on firm value: The case of the U.S. pharmaceutical industry. J. Product Innov. Manage 31(2), 302–318 (2014)

Citation: Dharmateja Priyadarshi Uddandarao. (2025). A Deterministic Forecasting Framework with Causal Scenario Analysis. International Journal of Management (IJM), 16(3), 172-186.

Abstract Link: https://iaeme.com/Home/article_id/IJM_16_03_012

Article Link:
https://iaeme.com/MasterAdmin/Journal_uploads/IJM/VOLUME_16_ISSUE_3/IJM_16_03_012.pdf

✉ **editor@iaeme.com**