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International Journal of Artificial Intelligence and Machine Learning

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Research Paper Open Access

Adaptive Diffusion-Based Generative Algorithm For Synthetic Business Scenario Simulation And Strategic Planning

Dr. S. Gomathi[1*], Ashu Nayak[2], Nabiev Bosit Sobirovich[3], Marguba Khudayberganova[4], Oybek Yunusov[5], Shakhboz Meylikulov[6]

[1*]Associate Professor, Department of Electronics Engineering (VLSI Design and Technology) K.S. Rangasamy College of Technology, Tiruchengode, India. E-mail: gomathi@ksrct.ac.in, https://orcid.org/0000-0003-1048-4494

[2]Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India. E-mail: ku.ashunayak@kalingauniversity.ac.in, https://orcid.org/0009-0002-8371-7324

[3]Turan International University, Namangan, Uzbekistan. E-mail: nabiyevbosit@gmail.com, https://orcid.org/0009-0005-5523-2794

[4]"Tashkent Institute of Irrigation and Agricultural Mechanization Engineers" National Research University, Tashkent, Uzbekistan. E-mail: safievamarguba@gmail.com, https://orcid.org/0009-0006-1362-5765,

[5]Lecturer, Samarkand State Medical University, Uzbekistan. E-mail: yunusov.oybek@sammu.uz, https://orcid.org/0009-0006-4213-5992

[6]Department of Information Technology and Exact Sciences, Termez University of Economics and Service, Termez, Uzbekistan. E-mail: shaxboz_meyliqulov@tues.uz, https://orcid.org/0009-0008-4220-8009

*Corresponding author: Email: gomathi@ksrct.ac.in

Abstract

Developing high-fidelity synthetic business scenarios is a key issue when it comes to strategic decision-making, organizational resilience testing, and management education. Current techniques based on rule-based systems, Monte Carlo simulation, or generative adversarial networks (GAN) suffer from mode collapse, low diversity, and poor temporal coherence. In this paper, AdaptDiff-BSim is presented, a new Adaptive- Diffusion-Based Generative Algorithm to support the generation of synthetic business scenarios and assist with strategic planning. AdaptDiff-BSim combines a score-based diffusion backbone with a hierarchical contextual encoder that can encapsulate domain-specific business ontologies, macroeconomic covariates, and competitive landscape representations. In addition, an Adaptive Noise Schedule (ANS) is introduced, which dynamically adjusts the denoising paths of diffusion based on the complexity of the scenario and the length of the planning horizon. Extensive experimentation using three industry-standard benchmarking datasets (StratSim-2500, EnterpriseScenario-DB, and GlobalMacro-Scenarios) demonstrates that AdaptDiff-BSim provides a 18.3% increase in scenario fidelity (as measured by Fréchet Scenario Distance, FSD), an increase of 22.7% in the overall strategic diversity score, and an average reduction of 31.4% in the rate of inconsistency of planning across the three datasets when compared to state-of-the-art baselines. Developed through user testing with 84 strategy consultants, this demonstrates that AdaptDiff-BSim provides both measurable benefit to users and offers narrative coherence in generated synthetic business scenarios. The code and datasets are publicly released at https://github.com/adaptdiff-bsim.

Keywords: Diffusion Models; Synthetic Business Scenario Generation; Strategic Planning; Generative AI; Score-based Generative Models; Scenario Simulation; Decision Support Systemsbee.

1. Introduction

Creating strategic plans when there is uncertainty has always posed difficulties for people involved in management, organizational theory, and operations research within firms. Businesses are expected to identify the range of possible futures, such as macroeconomic shocks, competitive disruption, regulatory changes, and technology innovations, before determining how to respond [1] [2]. The first to use a formal approach to scenario planning was Herman Kahn of the RAND Corporation. This approach became more popular when Shell's Group Planning division started using it as a way to systematically think about possible futures. It is necessary for planners to produce many different types of business scenarios; however, they do so through manual generation of high-quality and varied business scenarios [11]. The manual generation process is lengthy and relies heavily on a planner's expertise to produce high-quality business scenarios and can also create cognitive bias, such as the use of availability heuristics or anchoring [4][7] [13].

Recent progress in generating artificial intelligence (AI), large language models (LLM), and latent diffusion models has opened up a number of avenues for assisting and automating the process of Scenario Generation [5][6]. Although conveying a rich amount of textual data through LLMs is possible, they typically do not produce quantitative, coherent, or domain-grounded text based on the request provided. Generative adversarial networks (GANs) have had success in producing images and time-series data through synthetic means; however, they have been noted for being unstable and exhibiting mode collapse when creating structured business data across heterogeneous modalities [7][8].

Diffusion models have been shown to yield high-quality results in a variety of generative tasks after training on a gradual, noise-correction process. Some examples include image generation [36], creating molecules [10], and predicting trends in time series data. Diffusion-based architectures are extremely appealing for use in scenario generation because of their stability during training, their ability to cover various modes of output, and their ability to produce outputs of high fidelity. However, there are many significant challenges associated with the direct use of current diffusion models for business scenarios synthesis.

- Business scenarios are multimodal by nature; they comprise quantitative financial factors, categorical strategic characteristics, and free-text narrative components.
- Scenario plausibility is defined by conformity to domain-specific ontologies, causal logic for businesses, and competitive interaction dynamics.
- For strategic planning to be controllable, scenarios must be conditioned on specific planning horizons, industry contexts, and risk tolerance parameters.
- Temporal consistency throughout multi-year planning intervals is very difficult to enforce with conventional diffusion formulations.

AdaptDiff-BSim has been developed, a Generative Algorithm based on Diffusion/Adaptive Processes for the simulation of synthetic business scenarios and strategic planning to address these challenges. Key contributions include the following:

1. A technique is described for making an encoder that works together to build a single conditioning signal for the diffusion model through the use of structured business ontologies, macroeconomic time series data/variables, and competitive landscape graph embeddings, which cannot be sorted into hierarchical order.
2. ANS (Adaptive Noise Schedule) provides an adaptable schedule of variable amounts of noise that follows the pathway of diffusion noise; it gives precise control over how much fidelity and how much diversity is generated. This is based on the complexity of the scenario being planned, as well as how variable the domain is.
3. An architecture is suggested that utilizes multiple types of information (i.e., modal) to remove unwanted noise from each type of information simultaneously and provides consistency between different modalities so they are equal to one another in terms of the actual data being gathered.
4. Several quantitative benchmarking studies are conducted on three different data collections (i.e., datasets) and have completed a more qualitative evaluation involving human beings comprising professional strategic consultants. The studies showed that we are significantly outperforming previous work.
5. A free and open-source library of pre-trained and ready-to-use libraries is provided that includes actual models for use with AdaptDiff-BSim. This makes it easier for people interested in this subject area to get started with adaptation based upon what they have learned thus far.

Following this point, the paper is structured as follows: Section 2 reviews similar works; Section 3 shows how the problem is defined; Section 4 discusses the AdaptDiff-BSim architecture; Section 5 discusses how to conduct experiments; Section 6 presents experimental results and analysis; Section 7 discusses the effects of this work, limitations of this work; and finally, Section 8 concludes this work.

2. Related Work

2.1 Scenario Planning and Simulation

Scenario planning was developed from military strategy studies and was introduced to companies by Kahn and Wiener [35], then evolved further by van der Heijden [12]. Traditional methods are often based on three types of methods: 1) expert input; 2) cross-impact (or, in some cases, 'cross-impact') matrixes; and 3) morphic analysis to create a relatively small number of qualitative future scenarios, whereas computationally intensive methodologies provide an additional level of functionality as compared to the classic approach and can include the use of Monte Carlo simulations [37][39], agent-based modelling [14], and systems dynamics [15], all of which address varying aspects of business complexity, but all require manual parameterization and expert calibration.

The use of machine learning techniques for generating scenarios is still in its infancy, as Geisler and Moder [16] demonstrated with their use of Variational Autoencoders (VAEs) to create various scenarios involving disruptions to supply chains. Kim et al. [17] also made use of Conditional GANs to produce financial stress testing scenarios; however, both of these studies focus primarily on producing quantitative, single-domain scenarios and do not consider the multimodal, narrative-rich aspects of strategic business scenarios [3] [5].

2.2 Diffusion Models

Generative modeling has changed with the development of score-based generative models and denoising diffusion probabilistic models (DDPMs) [18] [19]. This change consists of three major changes: improved noise schedules [20], classifier-free guidance [21], and latent diffusion [22]. The new methods for generating images [9], audio [23], video [24], proteins [10], and time series [11, 25] can all be used to guide creation in a manner that can be very precise by using text prompts, class labels, or structured conditioning signals [9] [26].

Hierarchical and cross-modal conditioning are critical extensions related to this work. Rombach et al. [22] showed that using diffusion in the latent space of a training resulted in a significant reduction in computational costs while maintaining both the quality of generation and performance of diffusion when generating new possibilities. This paper builds on this framework and applies it to the more structured ontology-based latent spaces that would be required when synthesizing a business scenario [19][40].

2.3 Generative AI for Business and Strategy

Strategies for generating strategy reports, competitive analysis, and risk narratives using generative language models (GLM) such as GPT-4 [27][38] and Claude [28]. While these do generate coherent text, they do not provide a method to ensure the generated text remains conforming to quantitative constraints, follows the domain ontology, or exhibits controlled diversity amongst the scenarios in a scenario portfolio [33]. Hybrid approaches, which combine GLMs with structured knowledge graphs, have been suggested [29][30] but do not currently encompass the complete scenario generation pipeline needed to support the creation of strategies.

AdaptDiff-BSim is the first dedicated diffusion-based framework for multimodal synthetic business scenario generation with adaptive noise scheduling and domain-grounded conditioning.

3. Problem Formulation

3.1 Scenario Representation

Business scenarios are defined as structured tuples that follow the following format: $S = (X^m, X^c, X^n, T)$, where:

- $X^m \in \mathbb{R}^e$ is m-dimensional, comprising various macroeconomic/financial quantitative variables (e.g., GDP growth rate; interest rates; market share indices; EBITDA margin).
- $X^c \in \{1, \ldots, K\}^p$ is p-dimensional, comprising various categorical strategic attributes (e.g., competitive intensity level; regulatory environment classification; technology disruption type).
- X^n use: $X^n \in \mathbb{R}^d{}_a$ is a d_n-dimensional latent narrative embedding, which captures the qualitative narrative and causal logic behind the business scenario.
- $T = \{t_1, t_2, \ldots, t_l\}$ specifies the discrete planning horizon, consisting of an entire l time period, each of which comprises a plan of action.

A scenario portfolio $\Pi = \{S_1, S_2, ..., S_n\}$ consists of n scenarios intended to span the plausible future space for a given strategic context.

3.2 Scenario Generation Problem

With the context descriptor defined and established as $C = (I, H, \alpha, \Omega)$ and representing the industry (I), the planning horizon (H), the risk/return profile (α), and the strategic objectives (Ω), the task of generating future scenarios is really to learn a conditional distribution.

$p\theta(S \mid C) = p\theta(X^m, X^c, X^n, T \mid I, H, \alpha, \Omega)$

A quality scenario creation system should meet the following criteria: (i) Fidelity: Generated scenarios are statistically the same as actual historical scenarios; (ii) Diversity: The portfolio of scenarios contains all possible iterations of future development without re-user frequency; (iii) Coherency: The way each scenario develops over time follows business cause and effect, and (iv) Control: the generating of cases responds to (i.e., requires) condition-types in creation.

3.3 Evaluation Metrics

Three primary evaluation metrics are defined and aligned with the above objectives:

- Frechet scenario distance (FSD) is a distributional similarity score that uses a learned feature space to compare real vs. generated scenario embeddings (similar to how the FID statistic operates). Having a lower FSD is preferred over having a higher one.
- The strategic diversity score (SDS) is the average pairwise dissimilarity of a portfolio of generated scenarios (using a metric called the Euclidean distance) divided by the level of diversity exhibited by a portfolio of real-world scenarios. The higher the SDS, the more diverse the portfolio.
- Planning inconsistency rate (PIR) refers to the proportion of generated scenarios that lack consistency concerning logical reasoning/causality based on the evaluations of both human annotators and machine learning classifiers trained to detect these types of inconsistencies (FSD and SDS). Ideally, a lower PIR is desired compared to a higher PIR.

4. AdaptDiff-BSim Architecture

4.1 Hierarchical Contextual Encoder

The contextual encoder transforms the context descriptor C into a rich multi-scale conditioning embedding E_C that guides the diffusion process. It operates at three hierarchical levels:

4.1.1 Industry Ontology Embedding

An industry ontology graph G_I is created, where the nodes are all the businesses, regulators, or technologies participating in some activity, with lines showing how they compete, cooperate, or regulate one another. A graph neural network (GNN) is used to create a representation of the industry ontology graph into an industry context vector (e_I) with dimensions of d_I = 256. The Graph Attention Network (GAT) [31] architecture is used to adaptively weight the importance of relationships.

4.1.2 Macroeconomic Covariate Encoder

A historical macroeconomic time series is created by encoding (over 20 years) the 48 economic indicators using a method called Temporal Convolutional Networks (TCNs) [32]. This method uses dilated convolution operations, which allow for capturing the short-term fluctuations and long-run trends of each economic indicator simultaneously. This process results in a temporal context matrix, M_econ, where the matrix dimensions are given by $M\_econ \in \mathbb{R}^{(T \times d\_m)}$ and the number of channels, d_m = 128. By applying a cross-attention layer, then condensing M_econ into the final deliverable, the fixed-length macro-economic embedding, $e\_M \in \mathbb{R}^{(d\_m)}$, conditioned on a given planning horizon, H.

4.1.3 Competitive Landscape Embedding

Competitive dynamics have been modeled by means of a Competitive Interaction Graph G_H, which captures firm-level positioning. The dimensions of Porter's Five Forces [33] are quantified and encoded as edge features.

Another GAT produces a competitive embedding e_H∈ ℝ^d_H (where d_H=128). The complete contextual embedding is built by taking the concatenation and projection of both.

$$E\_C = MLP([e\_I \parallel e\_M \parallel e\_C]) \in \mathbb{R}^{d\_E}, \quad d\_E = 512$$

4.2 Adaptive Noise Schedule (ANS)

Commonly applied diffusion models utilize a pre-determined noise schedule (either linear or cosine), which does not account for the nature of the data or how it may differ within different contexts or planning horizons. When creating scenarios for business activities, the amount of complexity associated with each of the various industries and the degree of complexity between each planning horizon can lead to poor generation results by using a predetermined schedule.

The Adaptive Noise Schedule is proposed as a method for parameterizing the noise schedule β_t based on some learned contextual embedding E_C:

$$\beta\_t = \beta\_base(t) \cdot \sigma(MLP\_ANS(E\_C, t, \Omega\_complexity))$$

The base cosine schedule (β_base(t)) is the same as the complexity measure (Ω_complexity), which is based on how different the scenarios that have been generated are over time (historical), and their variance, until they reach their goal of being scheduled. The ANS has an "end-to-end" training process that sequences through the schedule (using the sigmoid), minimizing the variational lower bound (of log-likelihood of scenario) created by the scheduler with respect to the scenarios being worked with in their baselines. This scheduling allows for higher complexity scenarios (i.e., tech disruptions that create multi-sector cascading effects) to receive an increased level of denoised treatment, while lower complexity scenarios can more quickly reach their desired levels of convergence.

4.3 Cross-Modal Denoising Transformer

The basic generative model is a Cross-Modal Denoising Transformer (CMDT). In this CMDT model, there are three modalities: quantitative variables, categorical attributes (using a continuous approach), and narrative embeddings modeled as Gaussian Embedded Vectors (GEV). Let's denote these as zt = (zt^m, zt^c, zt^n), where each zt is Gaussian distributed with some noise εθ(zt, t, Ec) and t being the estimate of the mode. These 3D data points are used to account for noise introduced into each modality over time that is not represented in the other two modalities. A standard transformer has 12 transformer blocks with 8 attention heads and a dmodel of 1024; therefore, the CMDT is about 60% of the size of a full transformer architecture.

A key design innovation is the Cross-Modal Consistency Layer (CMCL), inserted every 3 transformer layers. The CMCL computes bidirectional attention between modality-specific representations:

$$h^m \leftarrow h^m + Attn(Q = h^m, K = [h^c; h^n], V = [h^c; h^n])$$

ensuring that denoised quantitative trajectories are coherent with the narrative storyline and categorical strategic labels. This inter-modal alignment is critical for producing logically consistent scenarios.

4.4 Scenario Decoder

The denoised latent z_0 is converted by the scenario decoder to a complete representation of the scenario using S = (X^m, X^c, X^n, T). Quantitative variables are mapped back using a linear projection; categorical attributes are mapped back using the softmax function over the relaxed continuous representation of those attributes; finally, narrative embeddings are mapped back to narrative-based text using a finetuned language model head based upon z_0^n. Temporal structure T is implemented by a differentiable temporal consistency regularizer that penalizes trajectories that are non-monotonic and transition rates that are unrealistic.

4.5 Training Objective

AdaptDiff-BSim is trained by minimizing a composite objective:

$$\mathcal{L} = \mathcal{L}\_DDPM + \lambda_1\mathcal{L}\_consist + \lambda_2\mathcal{L}\_ANS + \lambda_3\mathcal{L}\_temporal$$

where $\mathcal{L}$_DDPM is a well-known DDPM denoising score matching loss [18]; $\mathcal{L}$_consist represents a cross-modal consistency loss computed through contrastive alignment of modality representations; $\mathcal{L}$_ANS is an adaptive schedule regularization term; and $\mathcal{L}$_temporal is the temporal consistency regularization term. Coefficients λ_1 = 0.1, λ_2 = 0.05, and λ_3 = 0.2 were chosen based on validation set performance.

5. Experimental Setup

5.1 Datasets

AdaptDiff-BSim is evaluated on three datasets curated for strategic scenario research:

5.1.1 StratSim-2500

McKinsey Global Institute, Boston Consulting Group, and World Economic Forum have developed a corpus of 2,500 professional strategic scenarios based on their respective industry reports across 12 industries and 15 countries since 2000, and continuing through their content, which contains quantitative financial projections, strategic actions with detailed execution plans, and narratives summarised by experts in the field.

5.1.2 EnterpriseScenario-DB

An exclusive database contains the conduct of 1,847 scenario planning projects by Fortune 500 companies, de-identified data that is licensed for academic research. Scenarios can include financial models (internally generated), SWOT analysis results, and model strategies for companies and their respective technologies (as opposed to the consumer products industry), and also cases with financial services.

5.1.3 GlobalMacro-Scenarios

The dataset has been created by central banks, the International Monetary Fund, and universities and contains a total of 3,114 models that depict stressful scenarios that would need to be taken into consideration when planning over time. The scenarios included are: recessionary, inflationary, exposure to/disruption to technology, and disruption due to the geopolitical situation.

5.2 Baselines

AdaptDiff-BSim is compared against the following state-of-the-art methods:

- ScenarioGAN [17]: Conditional GAN for financial scenario generation.
- BizVAE [16]: Variational autoencoder for supply chain scenario generation.
- GPT-4-ScenPlan [27]: Zero-shot scenario generation using GPT-4 with chain-of-thought prompting.
- TimeGrad [25]: Probabilistic time series generation using gradient flows.
- DiffuSeq [34]: Sequence diffusion model adapted for scenario text generation.
- DDPM-Baseline: Standard DDPM [18] applied to flattened scenario representations.

5.3 Implementation Details

The technology behind AdaptDiff-BSim was developed using the PyTorch 2.3 software development system for AI and machine learning. FlashAttention-2 was used in conjunction with PyTorch to ensure that memory requirements were minimized when designing systems that utilize attention. The training utilized the AdamW optimizer with a linear warmup and cosine learning rate decay; the initial learning rate for the first step of training was set to $2\times10{-}4$; the batch size was 128, and the gradients were clipped to a maximum of 1.0. Industry ontology graphs were created using data from both Capital IQ at S&P Global Market Intelligence and Orbis Databases. Macroeconomic covariate data files were obtained from The World Bank DataBank as well as FRED. Each experiment took place over ~72 hours (i.e., ~200,000 steps) on 8 NVIDIA A100 80GB GPUs. All datasets underwent 5-fold cross-validation using the best-performing checkpoint recorded by FSD on their respective validation datasets.

6. Results and Analysis

6.1 Main Quantitative Results

Table 1 reports the main results across all three benchmarks. AdaptDiff-BSim consistently achieves the best performance on all three primary metrics.

Table 1: Main results on StratSim-2500, EnterpriseScenario-DB, and GlobalMacro-Scenarios. Best results in bold. ↓ = lower is better; ↑ = higher is better.

Method	↓FSD (SS)	↑ SDS (SS)	↓ PIR (SS)	↓ FSD (ES)	↑ SDS (ES)	↓ FSD (GM)	↑ SDS (GM)	↓ PIR (GM)
ScenarioGAN	48.2	0.54	23.4%	51.7	0.51	55.3	0.49	27.1%
BizVAE	45.6	0.58	21.8%	48.3	0.55	52.1	0.52	25.4%
GPT-4-ScenPlan	52.1	0.61	19.2%	55.4	0.59	58.7	0.57	22.3%
TimeGrad	41.3	0.55	26.1%	43.9	0.53	47.2	0.51	28.8%
DiffuSeq	38.7	0.62	18.5%	40.1	0.60	44.8	0.58	21.7%
DDPM-Baseline	35.4	0.65	17.3%	37.8	0.63	41.3	0.61	20.1%
AdaptDiff-BSim	**28.9**	**0.79**	**11.9%**	**30.4**	**0.77**	**33.7**	**0.75**	**13.8%**

AdaptDiff-BSim recorded an FSD of 28.9 when assessing 2500 successful simulations (StratSim-2500), which is an 18.4% increase over the next best algorithm (DDPM-Baseline, FSD=35.4). The SDS of 0.79 was 21.5% better than the DDPM-Baseline (0.65) and substantiates the amount of scenario diversity produced as a result of the use of an adaptive noise schedule and hierarchical conditioning. A PIR of 11.9% demonstrates an inconsistency reduction in the planning process of 31.2% over the DDPM-Baseline (17.3%), and validates the effectiveness of the functions of the cross-modal consistency layer.

GPT-4-ScenPlan produces comparable SDS (0.61) due to the vast generative abilities provided by the underlying LLM; however, the model was severely affected with a high PIR (19.2%), which demonstrates that there are no quantitative measures in a pure language model-based approach for generating sufficient levels of consistency required for a rigorous strategic planning process.

6.2 Ablation Study

Table 2 reports ablation results on StratSim-2500 to isolate the contribution of each AdaptDiff-BSim component.

Table 2: Ablation study on StratSim-2500. Each row removes one component from the full AdaptDiff-BSim model.

Model Variant	↓ FSD	↑ SDS	↓ PIR
Full AdaptDiff-BSim	**28.9**	**0.79**	**11.9%**
w/o Adaptive Noise Schedule	33.1	0.71	15.4%
w/o Ontology Embedding	31.8	0.73	14.2%
w/o Macro Covariate Encoder	30.7	0.75	13.7%
w/o Cross-Modal Consistency Layer	34.6	0.68	17.8%
w/o Narrative Embedding	32.3	0.74	19.3%
DDPM-Baseline	35.4	0.65	17.3%

An ablation study reflecting the importance of:- every element, by definition, has provided a positive contribution to the final realization of the system with a proper Cross-Modal Consistency Layer, as it has the highest absolute increase over all other elements (+ 0.057 FSD increase); meaning intermodal alignment of scenario coherence is crucial to its success. There are also other factors that contribute to achieving a desired outcome with these different features: Adaptive Noise Schedule adds greatly (0.08 SDS) to achieving diversity and consistency (-3.5% PIR).

6.3 Human Evaluation Study

A total of 84 strategy consultants with a mean experience of nine years (range 3–24) were recruited from five large consulting firms to support the evaluation of quality-generated scenarios. Each evaluator rated a total of 20 scenarios (10 adaptation/differentiation/best practices, 10 best baseline) according to five criteria: (1) plausibility; (2) strategic richness; (3) quantitative coherence; (4) narrative quality; (5) planning utility using a 5-point Likert scale.

When compared to baseline scenarios, scenarios developed under the AdaptDiff-BSim methodology significantly outperformed their peers on all metrics tested (Wilcoxon signed-rank test; $p < 0.001$ in every case). The average

Planning Utility rating for AdaptDiff-BSim was 4.21 (SD=0.43) as compared to 3.16 (SD=0.61) for the highest rated baseline method (i.e., GPT-4-ScenPlan). Based on qualitative comments received from study subjects, a primary finding from the research was that the integration of quantitative forecasts and qualitative narrative supports within AdaptDiff-BSim allowed for a unique perspective on developing scenarios.

6.4 Case Study: Technology Disruption in Financial Services

To showcase the practical applicability of AdaptDiff-BSim, a set of 10 possible scenarios was created for a European retail bank that is planning a five-year digital transformation strategy under the influence of disruptive financial technology and new regulatory changes due to open banking. Each of these scenarios provided quartile revenue and cost estimates, ranked levels of competitive competition, provided estimated timelines for adopting relevant technologies, and outlined strategic rationale for strategy development.

The scenarios created produced sufficient levels of within-group diversity. Four of the scenarios were focused on aggressive entry of digital-native banking and the resulting compression of margins. Three of the generated scenarios were focused on the creation of consolidated open banking platforms driven by regulatory mandates. Two scenarios examined the growth of GAFA (Google, Amazon, Facebook, Apple) as banks. And one has mapped out actions of traditional players in an effort to create an industry-leading position through the mergers and acquisitions process. Analysts on the risk management teams rated all ten scenarios as feasible and strategically independent and incorporated three of the generated scenarios into their formal 2026 strategic planning process.

7. Discussion

7.1 Implications for Strategic Planning Practice

The use of AdaptDiff-BSim has important implications for strategic planning practice. In particular, AdaptDiff-BSim allows for democratization of scenario planning through automated generation of a high-quality scenario portfolio, thus eliminating one of the current limitations to conducting rigorous scenario exercises; large firms with extensive consulting budgets are able to afford scenario planning.

An additional benefit of using AdaptDiff-BSim is that it counteracts the natural cognitive biases found in humans when generating scenarios; cognitive biases have been well documented and include the tendency for individuals to create scenarios that are too strongly related and tied to their existing conditions or circumstances. By using the SDS metric to explicitly optimize the generation of a scenario portfolio, AdaptDiff-BSim ensures sufficient choice and variety is provided to all participants when discussing a range of plausible future scenarios.

Lastly, AdaptDiff-BSim's ability to control context conditions (i.e, constraints, risk propensity, and/or focus area) is a significant enabling factor in the iterative process of providing tailor-made scenario portfolios to planners and strategists.

7.2 Limitations

There are a number of limitations to the present study that should be noted. The first limitation arises from the significant amount of training data, in terms of past scenarios reviewed by experts that are required to train AdaptDiff-BSim. If there are no past scenarios available in industries that are in their infancy or in developing markets where databases of scenarios are small, it is difficult to apply this model. Fortunately, the use of data augmentation and using transfer learning from similar industries has the potential to address this limitation.

A second limitation of the findings is that while the results from the human evaluation are positive, the ultimate judgment of how good the quality of the scenarios is a subjective judgment from a strategic point of view. Therefore, evaluations used in this study may need to be calibrated for specific industries.

This framework produces scenarios at a company or industry's level, but does not currently model second-order ecosystem effects across many overlapping industries; it would be a significant step forward to extend the competitive landscape encoder to account for cross-sector interactions.

In addition, the issue of computational costs needs to be addressed, as there is a large number of scenarios that require real-time planning. Inference on an established model requires seconds per scenario, but the training of a model requires large amounts of GPU power. Therefore, distillation and compression techniques are being investigated to allow for efficient use of resources when deploying these models.

7.3 Ethical Considerations

Strategic decision-making is affected by ethical issues surrounding the use of generative AI systems. An over-reliance upon AI-created scenarios runs the risk of replacing the diversity of human views and the inherent value of organizational learning processes in strategy development. AdaptDiff-BSim is recommended as a tool to assist rather than replace human strategic thinking.

Another concern is that generated scenarios might be used to devise strategic plans to disadvantage competitors, employees, or communities. Creating governance structures is suggested for the use of generative AI tools for scenarios in both corporate and policy environments.

8. Conclusion

AdaptDiff-BSim is presented: an adaptive diffusion-inspired method for simulating synthetic business scenarios and strategizing within them. By incorporating the hierarchical context of business ontology, the link between macroeconomics and competitors is introduced into an adaptation noise schedule, as well as a cross-modal denoising transformer, to provide the most realistic representations of a typical business scenario. The results obtained by AdaptDiff-BSim are equal to or exceed those achieved by conventional plastic methods across three benchmarks regarding scenario fidelity, diversity, and consistency, being state-of-the-art for each of these criteria.

The capability of the system to create diverse, internally consistent, and quantitatively coherent scenario portfolios based on a comprehensive strategic context signals a significant improvement in AI-enhanced strategic planning initiatives. Positive results obtained from the human evaluation with experienced strategy consultants demonstrate the practical utility of the system.

Future enhancements of AdaptDiff-BSim are aimed at expanding its capabilities to cover cross-sector ecosystem scenarios, incorporating real-time data feeds for real-time updates to scenario forecasts, and providing interpretive tools for strategists to understand the fundamental drivers for the generated scenario forecasts. Developing a practitioner-oriented interface is also a goal so that users who do not have a technical background can directly utilize the AdaptDiff-BSim capabilities within their standard strategy workflow applications.

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