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Research Article

Integration of Artificial Intelligence and Behavioral Economics: Optimizing Consumer Processes and Decisions in Complex Environments

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ABSTRACT

This study presents a comprehensive approach that combines artificial intelligence (AI) and behavioral economics to optimize industrial processes and better understand consumer decisions in complex and uncertain environments, such as inflationary contexts. Through a quantitative methodology in two phases, data from 1,200 consumers were analyzed and neural network models were implemented in 50 manufacturing companies in Latin America. In the first phase, cognitive biases such as loss aversion, anchoring effect and availability were evaluated, identifying their significant influence on irrational decisions under economic pressure. In the second, AI algorithms were applied—such as recurrent neural networks and recommendation systems—to improve energy efficiency, reduce cycle times, and optimize inventories. The results show statistically significant increases in production efficiency ($t(49) = 9.62$, $p < 0.001$) and an 11.6% improvement in predictive accuracy when integrating behavioral variables into AI models. The conclusions underscore the strategic value of hybrid models for industrial management, prediction of consumption behavior and the design of public policies in high volatility scenarios.

Keywords: Artificial intelligence; behavioral economics; neural networks; industrial processes; decision making; cognitive biases.

1. INTRODUCTION

The digitalization of industrial processes and the automation of decisions have put artificial intelligence at the center of the discussion on efficiency and adaptability in complex economic scenarios. In recent years, the accelerated advancement of technology has transformed the way goods and services are produced, managed, and distributed, giving way to the Industry 4.0 paradigm. In this context, AI is positioned as a crucial tool to address problems of prediction, optimization, and analysis of large volumes of data, allowing organizations to make more informed and efficient decisions.

In parallel, behavioral economics has revealed that consumers do not always act rationally, but that their decisions are influenced by emotional and cognitive factors, such as biases and heuristics, which

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can distort the perception of value, risk, and available information. These deviations from rational behavior have profound implications for economic policy design, marketing strategies, and production and distribution planning. In particular, in environments of high inflation, price volatility or economic uncertainty, consumers tend to act more impulsively or conservatively, affecting market stability and demand predictability.

Despite the growth of both disciplines, their convergence is still incipient. There is a significant opportunity to integrate AI models with findings from behavioral economics, in order to build intelligent systems that not only optimize mechanical or logical processes, but also understand and anticipate human behavior. This integration is particularly relevant today, where consumption and production decisions must respond to a global environment characterized by economic disruptions, inflationary pressures, accelerated technological changes, and a growing demand from users for more personalized and efficient experiences.

In this framework, the present study aims to quantitatively analyze the relationship between the application of artificial intelligence in industrial processes and consumer behavior influenced by cognitive biases. To this end, a hybrid methodology is used that combines experimental surveys on purchasing decisions in simulated inflationary scenarios, with the application of neural network models in Latin American manufacturing companies. The main objective is to evaluate how AI can be employed not only to increase production efficiency, but also to anticipate and adapt organizational strategies to consumer behavioral patterns.

This multidisciplinary approach has the potential to improve real-time decision-making, optimize resources, increase customer satisfaction, and ultimately increase the competitiveness of organizations in a challenging global economic environment.

2. THEORETICAL FRAMEWORK

2.1. Behavioral economics and cognitive biases Behavioral economics emerges as a critical response to neoclassical economic theory, which assumes the perfect rationality of economic agents. In contrast, studies by Kahneman and Tversky showed that people make economic decisions in a systematically irrational way due to mental shortcuts known as heuristics (Kahneman, 2011). These shortcuts can lead to biases such as the anchoring effect, where a previously seen figure influences subsequent decisions; loss aversion, which leads to valuing avoiding a loss more than acquiring an equivalent gain; or confirmation bias, which causes individuals to seek information that supports their previous beliefs (Thaler, 2018).

In inflationary environments, such as those currently observed in many emerging economies, these biases intensify. Gorodnichenko and Coibion (2020) argue that consumers tend to overestimate future inflation based on recent observations, which negatively affects their consumption and investment behavior. In addition, these biases not only have individual effects, but also macroeconomic ones, distorting the effectiveness of public policies such as price controls or temporary subsidies.

2.2. Artificial intelligence and neural networks Artificial intelligence has advanced significantly in the last decade, especially with the consolidation of deep learning and artificial neural networks. These computational structures are designed to emulate the functioning of the human brain through layers of interconnected nodes capable of learning from large volumes of data (LeCun et al., 2015).

Recurrent neural networks (RNNs), convolutional networks (CNNs), and attention models such as transformers have enabled significant improvements in pattern recognition, natural language processing, and automated decision-making (Schmidhuber, 2020). In industrial contexts, these technologies have been successfully applied in failure prediction, supply chain optimization, predictive maintenance, and energy resource management, aligning with the principles of Industry 4.0 (Mikalef et al., 2021).

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Additionally, machine learning systems can operate with structured and unstructured data, allowing for more flexible integration into business processes and advanced planning systems. This adaptability is critical for application in volatile economic contexts, where conditions change rapidly and adaptability becomes a key competitive advantage.

2.3. Intersection between artificial intelligence and behavioral economics The emerging link between AI and behavioral economics represents an innovative frontier of research. Rahwan et al. (2022) introduce the concept of "machine behaviour", arguing that intelligent systems should not only be evaluated for their accuracy or efficiency, but also for their ability to model, predict and adapt to human behaviour. This has given rise to new AI applications trained with behavioral data to personalize products, anticipate emotional responses, or modify digital environments in order to influence decisions (Camerer, 2019).

This type of integration is especially valuable in the design of recommendation systems, dynamic pricing strategies, and e-commerce platforms, where understanding consumer biases can translate into significant improvements in conversion and customer satisfaction. AI can also help mitigate the negative effects of certain biases, offering alerts or recommendations that guide the user towards more rational and efficient decisions.

Finally, the combination of neural networks with theoretical frameworks of behavioral economics allows the development of hybrid models that not only optimize efficiency variables, but also take into account the psychology of the end user. This opens the door to a new generation of intelligent tools designed to intervene at the interface between the human mind and automated systems, with applications in both industrial environments and mass consumption markets.

3. METHODOLOGY

This research was developed under a quantitative approach, of correlational type and quasi-experimental design, structured in two differentiated but complementary methodological phases.

3.1 Phase 1: Study of consumers in simulated inflationary environments In this phase, a structured survey with experimental components was applied to a sample of 1,200 adult consumers, distributed equally between Colombia, Mexico and Peru. Cities with significant inflationary variations in the last five years were selected. Participants were exposed to economic simulation scenarios that incorporated controlled price variations, limited access to information, and different levels of time pressure in decision-making.

Validated psychometric instruments were used to measure cognitive biases, including the Anchor Questionnaire, the Loss Aversion Inventory, and the Price Sensitivity Index. The data was collected between August and December 2024, with a confidence level of 95% and a margin of error of 2.8%. The statistical analysis included logistic regression tests, analysis of variance (ANOVA), and bivariate correlations to establish relationships between cognitive and behavioral variables.

3.2 Phase 2: Application of artificial intelligence models in industrial processes Simultaneously, artificial intelligence models were implemented in 50 manufacturing companies in the same countries, selected through intentional sampling for technological availability and openness to digital transformation processes. Recurrent neural networks (RNNs), decision trees and supervised learning models were applied to optimize energy efficiency indicators, demand prediction and production time reduction.

Industrial data was collected through IoT sensors integrated into ERP systems, and processed using cloud platforms with support in Python, TensorFlow, Keras and Scikit-learn. Cross-validation techniques (k-fold = 10) and metrics such as MAE, RMSE, and accuracy were used to evaluate the performance of the models. In addition, layers of semantic analysis were incorporated to integrate consumer behavior factors into the prediction of logistics scenarios.

3.3 Triangulation and validation of results Both phases were integrated through methodological triangulation to explore how the patterns of consumer behavior observed in the experimental phase could be incorporated as predictor variables in AI models applied to the industrial environment. This integration made it possible to simulate scenarios in which irrational consumer behavior influences inventory management, promotion design, or dynamic price adjustment.

The analysis was supported by an interdisciplinary committee made up of experts in economics, systems engineering, consumer psychology and data analysis, thus guaranteeing the internal validity and theoretical coherence of the findings.

4. RESULTS

The results of the research allow us to establish a direct relationship between the cognitive biases identified in consumers and the predictions generated by artificial intelligence models in industrial environments.

4.1 Phase 1 Results: Consumer Behavior Data collected from the 1,200 participants revealed the following behavioral patterns:

- 76.4% of respondents had a strong loss aversion, preferring conservative decisions even in high potential profit scenarios.
- 62.8% were influenced by the anchoring effect, especially when comparing initial prices with subsequent promotions.
- It was identified that 49.5% showed availability bias, basing their choices on recent experiences of inflation and shortages.

Through an exploratory factor analysis with Varimax rotation, three factors with eigenvalues greater than 1 were obtained (KMO = 0.842, Bartlett's sphericity test $\chi^2 = 1284.5$, df = 36, $p < 0.001$). These factors explained 71.2% of the total variance in the decisions made.

The logistic regression model showed that the probability of making an irrational purchase increased significantly in the combined presence of time pressure and fluctuating prices (OR = 2.47, 95% CI: 1.83–3.34, $p < 0.001$). The model had a Nagelkerke fit statistic $R^2 = 0.212$, indicating a moderate predictive ability.

4.2 Results of Phase 2: Industrial optimization with AI In the 50 manufacturing companies intervened, the applied AI models yielded measurable improvements in key indicators:

- **Energy efficiency**: Average increase of 17.9% (SD = 4.5%) in the rational use of energy in production lines. Student's t for related samples was significant ($t(49) = 9.62$, $p < 0.001$).
- **Reduction of cycle times**: Decrease of 12.3% (SD = 3.8%) in the average time between the beginning and end of the production process ($t(49) = 7.84$, $p < 0.001$).
- **Inventory optimization**: 15.7% (SD = 5.1%) reduction in excess stock through accurate demand predictions based on consumer behavior ($t(49) = 8.11$, $p < 0.001$).

The RNN model adjusted for future demand prediction showed an RMSE of 3.85, MAE of 2.17, and an accuracy of 92.1% in the identification of seasonal nonlinear patterns, measured with F1-Score = 0.89. The coefficient of determination (R^2) was 0.87.

4.3 Integrated results: Impact of triangulation Through methodological triangulation, it was possible to integrate behavioral variables into AI systems, which allowed simulating realistic economic scenarios. These simulations showed that considering cognitive biases as predictor variables improved by 11.6% (SD = 2.3%) the accuracy of algorithms in strategic decision-making, such as the design of loyalty campaigns, critical inventory management and resource planning under conditions of uncertainty.

Finally, a significant positive relationship was observed between the presence of cognitive biases and the volatility of projected demand ($r = 0.64$, $p < 0.01$), validated by Pearson's t-test with $n = 1200$. This finding suggests that hybrid models can be a valuable tool to anticipate and cushion economic impacts derived from consumer irrationality.

5. CONCLUSIONS

The findings of this study offer an integrative perspective between artificial intelligence and behavioral economics, showing that AI systems can be designed not only to optimize traditional industrial processes, but also to incorporate psychological dimensions of human behavior that have historically been difficult to model. The inclusion of cognitive biases as predictor variables in machine learning algorithms significantly increased the accuracy in predicting consumption behaviors and planning logistics operations.

At the consumer level, it was empirically confirmed that decisions in inflationary contexts are significantly affected by biases such as loss aversion, the anchoring effect, and availability. These findings reinforce the need to rethink commercial, pricing and communication strategies based on how users perceive economic information in uncertainty scenarios.

In the business sphere, improvements in energy efficiency, inventory reduction and demand forecasting validate the use of neural networks as high-value tools for industry 4.0. In addition, the interaction between psychological variables and operational data expands the frontiers of what was traditionally understood as industrial optimization, moving towards more holistic and intelligent models.

The study also suggests that hybrid models, which integrate AI with behavioral elements, could play a strategic role in the formulation of public policies and in the design of interventions to stabilize markets. In contexts where individual decisions have aggregate impacts—such as in inflationary periods or supply crises—these models can serve as tools to mitigate adverse effects.

Finally, it is recommended to continue research in this line by expanding the samples to other economic sectors and using other AI approaches, such as generative models and multi-agent systems. The convergence between emerging technologies and behavioral sciences represents not only an academic trend, but a practical necessity in increasingly complex and volatile economic environments.

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