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Impacts of artificial intelligence applications on prescriptive analytics: content analysis based on systematic literature review

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Abstract

AI applications have rapidly expanded and grown, providing significant advancements to prescriptive analytics in organizations. However, existing research has not yet capitalized on those advancements. While current research has focused on the fear of people losing their jobs or even lives and not being protected by legislative bodies, a significant gap remains in the absence of AI applications in organizations and how organizations utilize them for prescriptive analytics. This research aims to fill this gap by designing a framework to show the relationship between AI's three applications (reinforcement learning, computer vision, and fuzzy logic) and prescriptive analytics in organizations. Qualitative data were collected using an in-depth systematic literature review and were processed using content analysis. Hypotheses were tested using Chi-square analysis. Findings indicate that reinforcement learning, computer vision, and fuzzy logic have a positive impact on prescriptive analytics. Theoretical and practical contributions were offered.

Keywords: artificial intelligence, prescriptive analytics, reinforcement learning, computer vision, fuzzy logic, chi-square analysis

Introduction

All major industries, including healthcare, finance, manufacturing, retail, supply chain, logistics, and utilities, have begun employing AI applications and are being disrupted by their potential contributions to prescriptive analytics (Schmitt, 2023; Sariyer et al., 2024; Han et al., 2024; Weller et al., 2025). Indeed, AI applications have garnered significant attention since the emergence of deep learning, which has surpassed machine learning due to its ability to handle vast amounts of data. Additionally, the remarkable success of large language models (LLMs) has brought new excitement to AI applications in organizations (Fu et al., 2025). Moreover, decision-making based on AI applications has become indispensable in today's competitive market (Weller et al., 2024). Decision-making is a core component of prescriptive analytics (Weller et al., 2024). These significant advancements in AI have had a profound impact on many disciplines and in the business field. Therefore, efforts must be made to demonstrate how AI applications significantly enhance prescriptive analytics in organizations.

Some areas of AI applications (machine learning, natural language processing, deep learning) have been highly studied and researched in business (Xi & Shao, 2025; Cooper, 2025; Anukiruthika & Jayas, 2025;

Shafiee, 2025; Santos & Carvalho, 2025) while some areas have been subjected to small or neglected research in the business field such as reinforcement learning, computer vision, and fuzzy logic because of their technical underpinnings. This research adds to the limited research area of AI in business. The business field is characterized by decision-making that is prevalent due to its profit-oriented mentality (Gifford & Bayrak, 2023). Prescriptive analytics is one of the pillars of business analytics, where decision-making, simulation, and optimization play a dominant role (Hajipour et al., 2023; Han et al., 2024). As more organizations adopt AI to enhance their decision-making efficiency, it becomes increasingly important to focus on the relationship between AI applications and prescriptive analytics.

However, existing research has not yet capitalized on those advancements or the relationship between AI applications and prescriptive analytics. While current research on AI has focused on the fear that people may lose their jobs or even their lives and not be protected by legislative bodies, a significant gap remains in the absence of AI applications in organizations and how organizations utilize them for prescriptive analytics. This research fills this gap in literature by answering the following questions:

- *How do AI applications influence organizations' ability to make executive decisions?*
- *How do computer vision, fuzzy logic, and reinforcement learning contribute to prescriptive analytics?*

Furthermore, dynamic capabilities theory considers AI applications as organizational resources (Sariyer, 2024). The theoretical framework of this study encompasses AI applications such as computer vision, fuzzy logic, and reinforcement learning, which are viewed as dynamic capabilities and valuable resources for companies navigating uncertainties (Sariyer, 2024). Therefore, this work aims to investigate the impact of AI applications on prescriptive analytics in organizations.

The primary contribution of this research is to examine how AI applications impact the decision-making process in organizations through the lens of prescriptive analytics. Additionally, understanding these AI applications is crucial for informed organizational decision-making in the current AI landscape. This work expands dynamic capabilities theory to understand the relationship between reinforcement learning, computer vision, fuzzy logic, and prescriptive analytics. Moreover, this study applies content analysis to a systematic literature review. Furthermore, this research employs the chi-square test to evaluate hypotheses. In other words, quantitative analysis has been used to complete qualitative research in AI. Ultimately, this research confirms the existence of a connection between business analytics and AI applications.

The paper is organized as follows: Section 2 reviews the relevant literature. Section 3 outlines the research framework and hypothesis development. Section 4 presents the research methodology. Section 5 deals with the findings. Section 6 proposes a discussion. Section 7 concludes the study.

Literature Review

Dynamic Capabilities Theory

Dynamic capabilities theory defines an organization's ability to innovate, adapt to change, and improve for the benefit of its customers (Sariyer, 2024; Heikinheimo et al., 2025). The dynamic capabilities at the heart of this theory encompass the primary business processes and the sensing, integrating, learning, and reconfiguring of resources within organizations (Sariyer, 2024). In addition, these capabilities involve flexibility through the acquisition, assimilation, and restructuring of resources (Van Tran et al., 2024). Moreover, learning is crucial for deploying dynamic capabilities (Van Tran et al., 2024). In this research, we posit that merely using machine learning capabilities is insufficient for organizations to innovate, find new insights, and benefit from AI. Instead, the combination of computer vision, fuzzy logic, and reinforcement learning is essential to leverage AI in organizations to embrace new opportunities and improve for the benefit of their customers. However, to accept new challenges, businesses must understand the different internal and external resources necessary to develop a capability that integrates prescriptive analytics (Sariyer, 2024). Therefore, dynamic capabilities theory serves as a theoretical underpinning for this research. Thus, AI applications are another organizational capability in contemporary business environments. With the emergence of AI applications, organizations are adjusting to new circumstances to foster effective decision-making.

Prescriptive Analytics
Prescriptive analytics is rooted in the field of prescriptive decisions and seeks to recommend actions that align with the varying preferences of decision-makers across different scenarios (Feng et al., 2024). Equally important, prescriptive analytics mandates practical steps and dictates executable decisions (Weller et al., 2024). Therefore, prescriptive analytics aims to help experts automate their decision-making processes and provide actionable recommendations for enhancing efficiency, productivity, and effectiveness (Weller et al., 2024). In a different vein, prescriptive analytics is trying to answer the "What should I do?" and "Why should I do it?" questions (Sariyer et al., 2024). Furthermore, prescriptive analytics precedes predictive analytics, which is used in conjunction with prescriptive analytics. Prescriptive analytics employs various methods, but simulation, optimization, and logic-based models are the most popular. Simulation tests new ideas or how a probable modification will affect the system (Sariyer et al., 2024).

Collectively, prescriptive analytics is used to identify the optimal course of action for the future (Han et al., 2024). It comprises two parts: decision-making and decision-automation (Han et al., 2024). Decision-making involves providing recommendations, whereas decision automation involves utilizing AI applications to automate organizational decision-making processes (Han et al., 2024).

Impact of AI Applications on Prescriptive Analytics
AI applications have rapidly expanded, providing effective methods for analyzing and processing data (Santos & Carvalho, 2025). AI applications in organizations are diverse, spanning various functions and departments, including information systems, accounting, human resources, marketing, finance, and economics (Santos & Carvalho, 2025). Decision-making, optimization, and simulation have been challenging in these areas. This is why many authors have researched AI applications to improve decision-making in these areas. For instance, Xi and Shao (2025) found a positive impact of AI applications on green innovation in China, promoting green transformation in China's economic development. Also, early adopters applied AI to their business operations primarily due to expected improvements in efficiency and productivity (Cooper, 2025). They adopted AI applications for new product development (Cooper, 2025). Additionally, Anukiruthika and Jayas (2025) have shed light on the use of AI applications in grain storage to ensure production quality. Moreover, AI applications have revolutionized manufacturing processes because AI enables real-time monitoring and optimization. Similarly, generative AI has propelled the development of AI applications and advancements (Shafiee, 2025). Therefore, AI applications can synthesize novel content across various media, including images, audio, graphs, and vocal prompts, through generative models (Shafiee, 2025). Furthermore, Santos and Carvalho (2025) highlighted AI applications that could potentially democratize decision-making in organizations, while also emphasizing the ethical issues surrounding their practical implementation. Despite its potential, none of the existing AI applications paid attention to their impact on prescriptive analytics.

AI applications raise concerns about prescriptive analytics, prompting the need to develop a framework for effective solutions. Specifically, the contributions of reinforcement learning, computer vision, and fuzzy logic in AI applications must be addressed to ensure effective execution and achieve tangible organizational results.

Research Framework and Hypotheses Development

Diagnostic, descriptive, predictive, and prescriptive analytics are the four pillars of business analytics. Business analytics refers to the use of information technologies, statistical analyses, and quantitative methods to analyze large datasets, providing managers with relevant insights and improved decision-making (Boerner et al., 2025). Decision-making involves balancing intuition, analytics, judgment, and curiosity (Boerner et al., 2025). Among the four pillars of business analytics, prescriptive analytics is the best fit for decision-making. Therefore, this study's framework includes prescriptive analytics as the dependent variable.

The research framework adopted in this study includes computer vision selected from the task-oriented evaluation described by Hernandez-Orallo (2016). It also encompasses reinforcement learning as examples of AI applications pointed out by Berryhill et al (2019). Delanoe et al. (2023) noted that neuro-fuzzy interference was applied to photovoltaic forecasting in Tunisia (Delanoe et al., 2023). This project was part of the AI applications experienced in Tunisia and allowed us to incorporate fuzzy logic into this research framework. The relationship between AI applications and prescriptive analytics is discussed below.

Reinforcement Learning

Reinforcement learning is a technology that optimizes decisions (Xie et al., 2025). Thus, it focused on optimizing time-sequential decision strategies through learning (Anukiruthika & Jayas, 2025). However, reinforcement learning must heavily depend on the behavior of agents representing its backbone to work correctly. At each step of the reinforcement learning system, an agent uses input from its environment to perform actions and moves to the next step, following a transition probability (Anukiruthika & Jayas, 2025). Reinforcement learning operates on trial and error (Algherairy & Ahmed, 2025). That means an agent makes decisions, leading to transitions to new states, where it receives either rewards or penalties based on the quality of those states (Algherairy & Ahmed, 2025).

Literature distinguishes deep reinforcement learning and multi-agent reinforcement learning. Deep reinforcement learning combines deep learning and reinforcement learning (Xie et al., 2025). Deep learning enables reinforcement learning using a graphical processing unit (GPU) to store an unlimited amount of data. Multi-agent reinforcement learning focuses on the interaction of multiple agents within the same environment (Xie et al., 2025). In multi-agent reinforcement learning, the environment is dynamic because each agent’s strategy affects the strategies of other agents, hence creating the difficulty of strategy convergence (Xie et al., 2025). Deep learning integrated into multi-agent reinforcement learning solves the issue of communication and hardware limitations between different agents. The relationships, cooperation, and collaboration between agents can vary and affect the multi-agent environments. However, the black-box nature of reinforcement learning hinders our understanding of its decision-making process. Explainable reinforcement learning provides comprehension to its decision-making (Erlenbusch & Stricker, 2025) by explaining an agent's policy and the action it takes in a specific state (Erlenbusch & Stricker, 2025). Most importantly, explainable reinforcement learning explains the agents' decision-making process.

Collectively, reinforcement learning mimics the human learning process by continuously interacting with the environment through agents (Xie et al., 2025). It improved decision-making strategies iteratively through trial-and-error and feedback loops, allowing adjustment to an ever-changing environment (Xie et al., 2025). Erlenbusch and Stricker (2025) reported that an interactive user interface for solving optimization problems is achieved through reinforcement learning. Since optimization and decision-making processes are central to prescriptive analytics, this study highlights the following hypothesis:

Hypothesis 1 (H1): *Reinforcement learning systems positively impact prescriptive analytics in organizations.*

Computer Vision

Computer vision is defined as an AI application that 1) detects and classifies high-precision objects based on images and videos; 2) detects patterns from image data processing; 3) offers facial recognition techniques; 4) allows person identification; 5) allows optical character recognition; and 6) allows signature verification (Berryhill et al., 2019; Hajipour et al., 2023; Gifford & Bayrak, 2023).

Computer Vision offers many potential AI applications to organizations by allowing the analysis of historical visual data (Berryhill et al., 2019). Organizations should consider concrete visual data when making decisions. There is a slogan that suggests visual representations are more accurate and understandable in decision-making than lengthy speeches or texts. This sheds light on the debate between visual representation and textual representation. Equally important, computer vision has interdisciplinary applications, including face recognition, auto license plate readers, smart meter reading, optical character recognition, intelligent object cropping, and signature verification (Hajipour et al., 2023). Image recognition systems also allow law enforcement officers to scan vehicle license plates. Additionally, researchers have highlighted the combination of image-processing data and other sensor technologies in agriculture (Karanth et al., 2023). Moreover, facial recognition allows for person identification for hiring and recruiting screening in organizations (Berryhill et al., 2019). Furthermore, computer vision can recognize patterns and create prescriptive analytics models based on image and video mining. Similarly, computer vision can process historical image data and develop algorithms that can be applied to new images to inform prescriptions for actions and executive decisions (Li et al., 2023). Consequently, this subtopic of AI highlights the contributions of images, videos, and visualization techniques in decision-making and prescriptive analytics. Therefore, this study proposes the following hypothesis:

Hypothesis 2 (H2): *Computer vision has a positive impact on prescriptive analytics in organizations.*

Fuzzy Logic

Fuzzy logic is defined as an AI application that 1) can solve complex problems; 2) allows us to obtain approximate knowledge from uncertain situations; 3) has high adaptability to changeability; 4) changes imprecise qualitative data into numerical indicators; 5) can simulate human experience independently from the mathematical model of the system; and 6) uses probabilities to determine the likelihood of a phenomenon (Kang et al., 2023; Novas et al., 2023; Olmedo-Navarro et al., 2023; Rebelo et al., 2023; Mehra et al., 2023; Akhter et al., 2005; Keskin & Yazici, 2023; Niu & Feng, 2021; Delanoe et al., 2023).

Zadeh's fuzzy set theory was first introduced in 1973 (Keskin & Yazici, 2023). Fuzzy logic is derived from a theoretical fuzzy system and has three main components: fuzzy membership functions, relationships, and inference rules (Wang et al., 2021). According to this study, fuzzy logic can help organizations manage information uncertainty. Similarly, fuzzy logic has been used to forecast hydropower generation in China (Niu & Feng, 2021). However, a fuzzy logic system in China employs rigorous and advanced input-variable selection methods to forecast long-term electricity price fluctuations (Niu & Feng, 2021). Moreover, incorporating fuzzy inference into decision-making can enhance the reliability and capacity of prescriptive analytics. Rebelo et al. (2023) found that fuzzy systems are AI applications that use logic to predict the probability of an individual having COVID-19 based on symptoms. Furthermore, Keskin and Yazici (2023) found that a fuzzy-logic-based spatial framework for the prescriptive analytics of various spatiotemporal events is more accurate and scalable than conventional machine-learning techniques. Consequently, in organizations, fuzzy logic is appropriate for prescriptive analytics under uncertain conditions (Hassannayebi et al., 2022). Thus, this study proposes the following hypothesis:

Hypothesis 3 (H3): *A fuzzy logic system has a positive impact on prescriptive analytics in organizations.*

Research Framework

This study's framework comprises three independent variables that enable the development of AI applications: reinforcement learning, computer vision, and fuzzy logic. These three AI applications are related to prescriptive analytics through formulation testing of the hypotheses (H1 through H3). Figure 1 shows the research framework of this study.

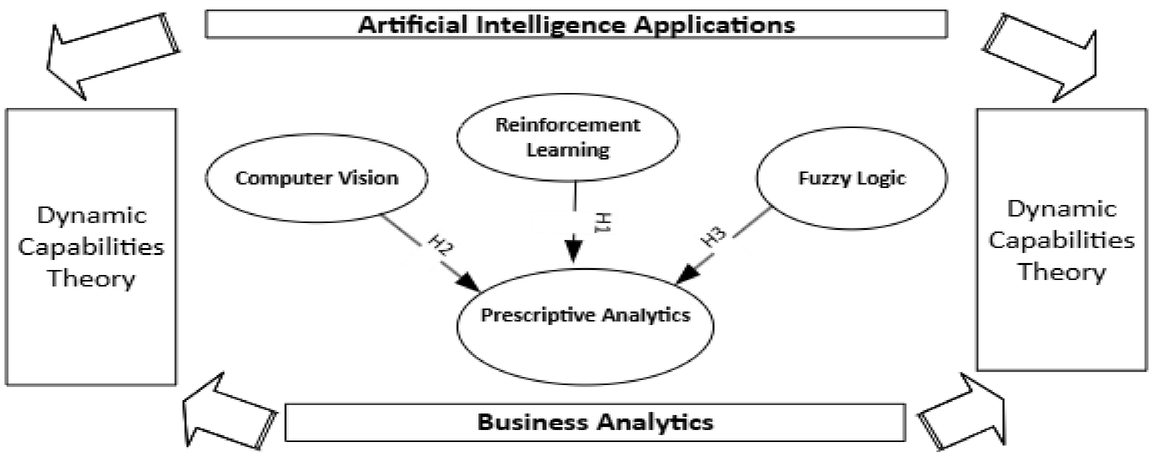

Figure 1. Research Framework

Research Methodology

Research Design

To achieve the study's objective, data were collected through a systematic literature review to identify articles that specified the content of the impact of AI applications on prescriptive analytics. Qualitative content analysis was employed to identify sentences (items) related to each AI application involving prescriptive analytics in the articles. The latter was followed by a quantitative content analysis based on chi-squared statistics. The systematic literature review and both content analyses are described below.

Search strategy

AI applications, including reinforcement learning, computer vision, and fuzzy logic, related to prescriptive analytics, were used as keywords to search publication databases (ScienceDirect, Google Scholar, Google Search, Scopus, and Scimago). More specifically, the keywords related to the impact of reinforcement learning on prescriptive analytics include transition probability, principle of trial-and-error, multi-agent reinforcement learning, deep reinforcement learning, and explainable reinforcement learning. The keywords related to the impact of fuzzy logic on prescriptive analytics include fuzzy inference, fuzzy membership functions, fuzzy membership relationships, and handling fuzzy and uncertain situations. The keywords related to the impact of computer vision on prescriptive analytics include concrete visual data, visual representations, textual representations, face recognition, image and video mining, optical character recognition, person identification, and signature verification. These keywords were combined with those related to prescriptive analytics: actionable decisions, optimization, simulation, actionable recommendations, decision-making, and decision automation.

Several articles relevant to each AI application connected to prescriptive analytics were identified and selected. Papers published between 2016 and 2024 were selected. This finding is consistent with a prior systematic literature review, which concentrated its search strategy on papers published within the last five years (Samad et al., 2022; Lawson-Body et al., 2024).

Study Selection

After retrieving the articles or papers correspondent to the search strategy, the following selection criteria were applied to exclude irrelevant papers to the objective of this study: 1) conference presentations, 2) peer-reviewed from predatory journals, 3) non-peer review papers, 4) letters to the editors, 5) only abstracts, and 6) letters for special issue invitations (Lawson-Body et al., 2024). Consistent with Lawson-Body et al. (2024), the following inclusion criteria were applied: peer-reviewed publications and conference peer-reviewed proceedings publications were retained.

Data Collection

The titles, abstracts, introductions, and conclusions of the selected papers were carefully considered and scrutinized during the final screening. Overall, 25 articles on the impact of reinforcement learning on prescriptive analytics, 19 on the impact of computer vision on prescriptive analytics, and 15 on the impact of fuzzy logic on prescriptive analytics were gathered for this study's qualitative content analysis and the chi-square statistics analysis.

Qualitative Content Analysis

Qualitative content analysis provides a deep and nuanced understanding of complex phenomena (Chaijani et al., 2024). Additionally, it provides flexibility for categorizing and interpreting textual data from various sources in a systematic manner. With qualitative content analysis, categories are derived from textual data rather than imposed a priori (Chaijani et al., 2024). It was utilized to identify and extract relevant content from communication messages through coding (Chaijani et al., 2024). This study used Bengtsson's qualitative content analysis process (Chaijani et al., 2024). Table 1 shows the Bengtsson content analysis process.

Table 1. The steps of qualitative content analysis adapted from Bengtsson (Chaijani et al., 2024).

Selection of a meaning unit	Every term from which the concepts were derived was considered a meaning unit.
Summary of meaning unit	Each of the units selected from the previous step was presented by mentioning the concepts in brief terms.
Coding	Each of the brief meaning units received a conceptual tag describing the meaning of that unit.
Creation of Subcategories and Categories	A category was classified by identifying codes with identical meanings and concepts in subcategories and by their integration.
Theme extraction	The themes were extracted based on concepts that lie in two or more classes with the same concept. Therefore, each theme's name represented the hidden meanings of those categories.

Quantitative Content Analysis (Chi-Square Analysis).

The chi-square distribution test is a non-parametric statistical test that can be used to test for equality of proportions, test independence, goodness of fit, or correspondence (Strzelecka & Zawadzka, 2023). Bahassine et al. (2020) used chi-square statistics to illustrate the total number of documents in a corpus. They divided the corpus into classes to illustrate the number of documents in each class that contain a specific term or item; the number of documents that contain the terms in other classes; the number of documents in each class that do not contain the term; the number of documents in each class that do not contain the term in other classes. Following Bahassine et al. (2020), Chi-square statistics analysis was used in this research to test hypotheses. In other words, chi-square statistics analysis was employed in this research to test the equality of proportions of articles (documents) in reinforcement learning, computer vision, and fuzzy logic in relation to prescriptive analytics classes. Most importantly, the chi-square analysis dealt with classes containing specific items relevant to AI applications. The formula proposed by Strzelecka and Zawadzka (2023) to calculate the chi-square can be expressed as follows:

$$x^2 = \sum_{ij} \frac{\left(f_{ij} - e_{ij}\right)^2}{e_{ij}}$$

Where: f_{ij} is observed frequencies; e_{ij} is expected frequencies.

Findings

Results of the Qualitative Content Analysis

The qualitative content analysis enabled us to categorize the items, or the sentences related to each item, that described the impact of AI applications on prescriptive analytics in the selected articles. In other words, the qualitative content analysis allowed us to determine the items that characterize each AI application's impact on prescriptive analytics. The items within the articles were identified as one or more. We found 15 items related to reinforcement learning, 9 items related to computer vision, and 8 items related to fuzzy logic. Table 2 shows the results of the qualitative content analysis.

In addition, the qualitative content analysis allowed us to determine the frequency of each item within each corresponding AI application's impact on prescriptive analytics. For instance, among the 25 articles selected after the systematic literature review for reinforcement learning, how many mentioned the 15 items found in the literature measuring reinforcement learning on the one hand, and how many did not mention those items? Tables 3 through 5 show, in columns 2, 3, and 4, respectively, the number of articles, the percentage of the articles, and the number of authors and co-authors who wrote the articles. The column entitled "Number of articles" contains the number of articles that contain the item (PREF), the number of articles that do not contain the item (PRENF), and the total number of articles. The third columns in Tables 3 through 5 show the content percentages of the second columns. The fourth column of Tables 3 through 5 shows the number of authors and co-authors of the articles that contain the items. Those numbers are greater than the number of articles that contain the items because more than one author writes many articles. They also contain the number of authors and co-authors of the articles that do not contain the items. Those numbers are greater than the articles that do not contain the items because more than one author writes many articles. Finally, the number of selected articles in each AI application must be related directly or indirectly to prescriptive analytics. In this sense, all 25 articles selected for reinforcement learning must contain prescriptive analytics or be concerning prescriptive analytics.

Table 2. The results of the qualitative content analysis.

Coded Items	Items and Variables
REL	Impact of Reinforcement Learning on Prescriptive Analytics
RELI	This system solves the optimization problems for an interactive user interface.
RELM	This system maintains relationships between agents that can vary and affect the multi-agent environments.
RELA	This system addresses the communication and hardware limitations between different agents.

Coded Items	Items and Variables
RELE	This system focuses on the interaction of multiple agents within the same environment.
RELD	This system utilizes a GPU to store an unlimited amount of data.
RELF	This system utilizes feedback loops, enabling adjustments to an ever-changing environment.
RELU	This system utilizes the trial-and-error approach.
RELS	This system improves decision-making strategies iteratively.
RELT	This system continuously interacts with the environment through agents.
RELH	This system mimics the human learning process.
RELO	This system is an optimization decision-making technology.
PREE	This system can prescribe what an expert should do.
PREA	This system helps experts to automate their decisions.
PREP	This system prescribes actionable decisions.
PRER	This system recommends actions that align with the varying preferences of decision-makers.
COV	Impact of Computer Vision on Prescriptive Analytics
COVI	This computer vision system accurately detects and classifies objects in images and videos with high precision.
COVP	This computer vision system detects patterns from image data processing.
COVT	This computer vision system offers facial recognition techniques.
COVA	This computer vision system allows for person identification.
COVR	This computer vision system allows optical character recognition.
COVV	This computer vision system allows signature verification.
PREI	This system can do simulations by testing new ideas.
PRED	This system provides the best choices based on generated prescriptions.
PREM	This system can prescribe why an expert should make simulations.
FUZ	Impact of Fuzzy Logic on Prescriptive Analytics
FUZP	This fuzzy system solves complex problems.
FUZK	This fuzzy system allows us to obtain approximate knowledge from uncertain situations.
FUZC	This fuzzy system is highly adaptable to change.
FUZI	This fuzzy system changes the imprecise qualitative data into numerical indicators.
FUZS	This fuzzy system can simulate human experience independently from the mathematical model of the system.
FUZL	This fuzzy system uses probabilities to determine the likelihood of a phenomenon.
PREF	This system identifies the optimal course of action for the future.
PREO	This system tests how modifications can affect the outcomes.

Results of the Quantitative Content Analysis

This research conducts quantitative content analysis to test hypotheses. Therefore, chi-square statistics analysis was performed on the results of the qualitative content analysis. It could be of interest whether there is a difference in the presence of the content of the items in the selected articles in the literature. The more the item's content is presented in the literature, the more important the item is in characterizing AI. Additionally, the chi-square test is used to determine whether the difference is statistically significant.

To calculate the chi-square statistics, we borrowed the formula from Bahassine et al. (2020), who illustrated the chi-square statistics using the number of articles (or documents) in a class and the number of articles (or documents) that are not in a class.

This study considered three classes: the impact of reinforcement learning on prescriptive analytics, computer vision on prescriptive analytics, and fuzzy logic on prescriptive analytics. For instance, the number of articles (documents) on reinforcement learning that contain the specific item. The number of articles (documents) on reinforcement learning does not contain the specific item. However, the number of articles (documents) on reinforcement learning containing items belonging to another class was not

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determined because all selected articles from the systematic literature review met the conditions related to prescriptive analytics.

Chi-squares of Impact of Reinforcement Learning on Prescriptive Analytics
Table 3 summarizes the coded observed items (taken from the first column of Table 2), the number of articles, the percentages, the number of authors, and the chi-squared statistics related to the impact of reinforcement learning on prescriptive analytics.

In addition, the results show that the proportion of articles mentioning items related to reinforcement learning and prescriptive analytics was significantly greater than the proportion of papers that did not mention such items (total chi-square =, $p < 0.001$). Thus, hypothesis H1 is supported.

Table 3. Chi-squares of Reinforcement Learning and Prescriptive Analytics

Coded Observed Messages	Number of articles	Percentages (%)	Number of Authors and co-authors	Chi-Squares
RELI	20	80	51	9.00
RELNI	5	20	16	
Total	**25**	**100**	**67**	
RELM	18	72	44	4.84
RELNM	7	28	20	
Total	**25**	**100**	**64**	
RELA	16	64	39	1.96
RELNA	9	36	26	
Total	**25**	**100**	**65**	
RELE	22	88	50	14.44
RELNE	3	12	7	
Total	**25**	**100**	**57**	
RELD	21	84	46	11.56
RELND	4	16	9	
Total	**25**	**100**	**55**	
RELF	17	68	42	3.24
RELNF	8	32	20	
Total	**25**	**100**	**62**	
RELU	18	72	43	4.84
RELNU	7	28	15	
Total	**25**	**100**	**58**	
RELS	23	92	54	17.64
RELNS	2	8	4	
Total	**25**	**100**	**58**	
RELT	20	80	47	9.00
RELNT	5	20	13	
Total	**25**	**100**	**60**	
RELH	22	88	49	14.44
RELNH	3	12	8	
Total	**25**	**100**	**57**	
RELO	16	64	36	1.96
RELNO	9	36	20	
Total	**25**	**100**	**56**	
PREE	18	81	70	13.44
PRENE	7	19	18	
Total	**25**	**100**	**88**	

Coded Observed Messages	Number of articles	Percentages (%)	Number of Authors and co-authors	Chi-Squares
PREA	19	84	68	16.00
PRENA	6	16	16	
Total	**25**	**100**	**84**	
PREP	16	75	59	9.00
PRENP	9	25	23	
Total	**25**	**100**	**82**	
PRER	19	84	72	16.00
PRENR	6	16	18	
Total	**25**	**100**	**90**	
*P<0.001	The total chi-square value is			147.36*

Chi-squares of Impact of Computer Vision on Prescriptive Analytics

Table 4 summarizes the coded observed items (taken from the first column of Table 2), the number of articles, the percentages, the number of authors, and the chi-squared statistics related to the impact of computer vision on prescriptive analytics. In addition, the results show that the proportion of articles mentioning computer vision related to prescriptive analytics was significantly greater than the proportion of papers that did not mention computer vision related to prescriptive analytics (total chi-square = 92.86, $p < 0.001$). Thus, hypothesis H2 is supported.

Table 4. Chi-squares of Computer Vision and Prescriptive Analytics

Coded Observed Messages	Number of articles	Percentages (%)	Number of Authors and co-authors	Chi-Squares
COVV	12	63	28	1.31
COVNV	7	37	16	
Total	**19**	**100**	**44**	
COVP	16	84	37	8.89
COVNP	3	16	7	
Total	**19**	**100**	**44**	
COVT	18	95	43	15.21
COVNT	1	5	3	
Total	**19**	**100**	**46**	
COVI	13	68	32	2.57
COVNI	6	32	15	
Total	**19**	**100**	**47**	
COVR	15	79	36	6.36
COVRN	4	21	10	
Total	**19**	**100**	**46**	
COVS	18	95	20	15.21
COVNS	1	5	4	
Total	**19**	**100**	**24**	
PREI	12	64	36	2.77
PRENI	7	36	20	
Total	**19**	**100**	**56**	
PRED	14	86	71	18.77
PREND	5	14	16	
Total	**19**	**100**	**87**	
PREM	15	89	84	21.77
PRENM	4	11	11	
Total	**19**	**100**	**96**	
*P<0.001	The total chi-square value is			92.86*

Chi-squares of Impact of Fuzzy Logic on Prescriptive Analytics

Table 5 summarizes the coded observed messages (taken from the first column of Table 2), the number of articles, the percentages, the number of authors, and the chi-squared statistics related to the impact of fuzzy logic on prescriptive analytics.

In addition, the results show that the proportion of articles mentioning items related to fuzzy logic and prescriptive analytics was significantly greater than that of papers that did not mention such items (total chi-square = 58.52, $p < 0.001$). Thus, hypothesis H3 is significant.

Table 5. Chi-squares of Fuzzy logic and Prescriptive Analytics

Coded Observed Messages	Number of articles	Percentages (%)	Number of Authors and co-authors	Chi-Squares
FUZP	11	74	25	3.26
FUZNP	4	26	11	
Total	**15**	**100**	**36**	
FUZK	12	80	28	5.4
FUZNK	3	20	7	
Total	**15**	**100**	**35**	
FUZC	14	93	31	11.26
FUZNC	1	7	3	
Total	**15**	**100**	**34**	
FUZI	10	67	24	1.66
FUZNI	5	33	13	
Total	**15**	**100**	**37**	
FUZS	13	87	32	8.06
FUZNS	2	13	5	
Total	**15**	**100**	**37**	
PREF	14	72	70	7.11
PRENF	1	28	23	
Total	**15**	**100**	**93**	
PREO	11	89	72	21.77
PRENO	4	11	5	
Total	**15**	**100**	**75**	
*P<0.001	The total chi-square value is			58.52*

Discussion

The findings revealed that reinforcement learning, computer vision, and fuzzy logic have a positive impact on prescriptive analytics in organizations. With the adoption of AI applications, organizations must rapidly adjust their business processes to match their capabilities. Dynamic capabilities theory provides the essential foundation for accomplishing these goals and making decisions accordingly. The research framework allowed us to use chi-square statistics to test three hypotheses. The results are discussed below.

The results of this study demonstrate that H1 is significant. This finding corroborates the conclusions of Xie et al. (2025) and Anukiruthika and Jaya (2025). These authors found that reinforcement learning utilizes single or multiple agents to imitate human biological neurons, capturing inputs from environments to prescribe decisions. This result also aligns with Anukiruthika and Jaya's (2025) perspective on optimizing the time sequence to trigger strategic-level decision-making processes in organizations. However, this result contradicts the study of Erlenbusch and Stricker (2025), who found that one of the disadvantages of reinforcement learning is its black-box nature, which makes decision-making cumbersome. As a solution, Erlenbusch and Stricker (2025) proposed explainable reinforcement learning to address the black-box issues, thereby facilitating the prescription of decisions in organizations.

Our results support Hypothesis H2: computer vision has a significant influence on prescriptive analytics. These results are consistent with those reported by Hajipour et al. (2023), Gifford and Bayrak (2023), Karanth et al. (2023), and Berryhill et al. (2019). These authors argue that computer vision can provide visual representations and videos, helping to inform decisions more effectively in organizations. Consequently, organizations can prescribe actions based on human interactions and body language in videos. Private businesses increasingly use computer vision algorithms to detect the traits and attitudes of their customers, suppliers, and partners. For instance, real estate agents can utilize computer vision to provide personalized solutions to prospective customers. Additionally, computer vision can be combined with virtual reality to distinguish between civilian installations and military facilities in combat zones. Additionally, in agriculture, computer vision can analyze videos of land to prescribe the optimal levels of fertilizers for crops and the land. Moreover, computer vision can detect unsecured activities in surveillance videos. Furthermore, immigration and customs experts should adopt computer vision for fingerprint identification.

The positive impact of fuzzy logic on prescriptive analytics (H3) is confirmed in this study, consistent with the results of studies by Kang et al. (2023), Novas et al. (2023), Olmedo-Navarro et al. (2023), and Rebelo et al. (2023). As pointed out by these authors, fuzzy logic is flexible and bridges the gap between qualitative and quantitative data. In addition, fuzzy logic operates under total uncertainty conditions and handles imprecise data more effectively than any other AI algorithm in prescribing organizational decisions. The private sector deals with challenging and uncertain data. Therefore, fuzzy logic can be used to execute simulations in complex scenarios. It can also optimize the occurrence of events. Additionally, on numerous occasions, organizations should refer to fuzzy logic to prescribe actions in inflationary economic circumstances.

Conclusion

A research framework was designed to empirically test the impact of AI applications, including reinforcement learning, computer vision, and fuzzy logic, on prescriptive analytics in organizations.

To fulfill the goal of this study, a systematic literature review was conducted to identify the most appropriate theoretical background supporting AI applications and prescriptive analytics. Dynamic capabilities theory is aligned with the purpose of this research. In this sense, AI applications and prescriptive analytics are utilized in today's organizations as resources and capabilities that enable adaptation to change through effective decision-making processes. Additionally, the systematic literature review, based on a thematic evaluation, enabled us to identify the impact of each AI application on prescriptive analytics. Qualitative content analysis was completed as part of the systematic literature review. As a result, 32 items were identified to form the impact of reinforcement learning, computer vision, and fuzzy logic on prescriptive analytics. Three hypotheses were developed to test the relationships between each AI application and prescriptive analytics. Chi-square statistics were calculated to test the hypotheses. Findings suggest that reinforcement learning, computer vision, and fuzzy logic have a positive impact on prescriptive analytics.

Theoretical Contributions

This research makes four primary theoretical contributions to AI and predictive analytics literature. First, this work extends the dynamic capabilities theory using reinforcement learning, computer vision, and fuzzy logic. The adoption of these AI applications enables organizations to leverage their internal and external resources. Thus, organizations can resist and survive in the competitive landscape by adapting to change and fostering effective prescriptive analytics. Second, this research proposed an innovative methodology and was one of the first to introduce a combination of qualitative and quantitative analysis using AI applications. Third, a qualitative content analysis based on a systematic literature review was conducted in the context of AI. Fourth, the chi-squared analysis constitutes another notable contribution to the literature in this study. This work has the merit of using chi-square analysis to test hypotheses using data collected from the systematic literature review. Collectively, this work bridges the gap between AI applications and prescriptive analytics, drawing on data analytics literature.

Practical Contributions

This research yielded findings that organizations can utilize to enhance their AI applications. The results of this study demonstrate that AI applications, such as reinforcement learning, computer vision, and fuzzy logic, can enhance prescriptive analytics. At the core of prescriptive analytics, organizations are willing to prescribe actions and executive decisions. Therefore, this work will help organizations, regardless of their size, sector, or industry, utilize appropriate AI applications to facilitate informed decision-making. Additionally, this study proposed fuzzy logic to control information and intelligence uncertainty in the simulation and optimization of prescriptive analytics. The managers can use the results of this work to determine which AI applications can be used to promote prescriptive analytics within their organizations.

Future Research and Limitations

This study uses a systematic literature review to collect data and analyze that using content analysis and chi-square statistics to test hypotheses. Thus, data bias can be an issue in this research because the literature on AI applications is vast and has become increasingly complex to review comprehensively. Another limitation is that the researchers conducted a literature review. Including practitioners and professional AI workers in the review will be fruitful because their opinions and perspectives may differ significantly from those of academic workers.

In terms of future research, reinforcement learning, computer vision, and fuzzy logic are not the only AI applications. Therefore, other new and existing AI applications can be included in the research design or framework, such as natural language processing (NLP), ChatGPT, and Deep Seek, among others. NLP is a subfield of AI that enables computers to understand, generate, and interpret human languages to support decision-making processes in organizations. ChatGPT is a type of NLP application that can be found in Chatbots used to facilitate conversations in organizations. Additionally, chi-squared statistical analysis was employed in this research; future work can utilize other statistical analyses, such as analysis of covariance (ANCOVA), partial least squares (PLS), and regression analysis, to test the hypotheses. Qualitative data was collected in this work; future avenues can concentrate on survey data collection.

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