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PREDICTING TOURISM SERVICE SUCCESS WITH TYPE-2 FUZZY LOGIC MODELS

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Abstract: *In an increasingly dynamic and interconnected global economy, businesses are confronted with mounting challenges driven by rapid technological advancements and shifting customer expectations. This ever-evolving environment compels organizations to pursue continuous innovation and strategic adaptability to maintain competitiveness. Relying solely on past achievements is no longer a viable approach; instead, companies must proactively embrace change to seize emerging opportunities and respond effectively to market disruptions. Agility, both operational and strategic, has become a key determinant of long-term success, enabling businesses to stay relevant and resilient in the face of technological and consumer-driven transformations. This paper underscores the importance of adaptability as a core element of sustainable business growth in the global market, highlighting the necessity for organizations to evolve continuously in order to avoid stagnation and obsolescence.*

Keywords: *Business Agility, Technological Innovation, Customer Expectations, Market Competitiveness, Sustainable Growth*

INTRODUCTION

In today's fast-paced globalized business environment, characterized by rapid technological progress and ever-increasing customer expectations, companies face immense pressures to remain competitive. The relentless pace of innovation and fierce market rivalry demands that businesses continually evolve and adapt, rather than resting on their laurels. Previous successes provide a foundation, but they are not sufficient to ensure future growth or relevance. To thrive, businesses must be agile, embracing new technologies and strategies that meet changing consumer demands and capitalize on emerging opportunities. Stagnation can lead to obsolescence, making adaptability a critical component of longterm business sustainability in a global market.

New Service Development (NSD) refers to the introduction of innovative services or processes aimed at enhancing efficiency and achieving superior outcomes. This strategic approach is essential for organizations seeking to improve service delivery and maintain their competitive advantage in dynamic markets [1]. A thriving NSD acts as a beacon for decision makers, guiding them to secure or maintain a competitive edge amidst the rapid changes of the business environment. The tourism industry in particular has not been immune to these shifts, necessitating continual adaptation and innovation to stay relevant.

The tourism sector has experienced significant expansion over the years and has become a fundamental component of the global economy [2]. As a result, competition within the industry has intensified, particularly among hotels, which are crucial to the tourism experience [3]. Hotel selection is a key focus for tourists when making decisions about their travels [4]. Thus, it is imperative for hoteliers to improve their marketing tactics to attract and retain customers and sustain their competitive position in the market [5]. Barney J argues that a company's competitive advantage is deeply rooted in its strategic approach to competition [6]. Porter outlines two main strategic paths: Low cost and differentiation [7]. Companies that focus on low-cost strategies prioritize operational efficiency to offer their products at competitive prices. Conversely, companies that pursue differentiation strategies concentrate on aspects of the value chain that increase the perceived value, distinctiveness, or quality of their offerings [8].

The introduction of new services is essential for both tourists and establishments such as resorts and hotels. By successfully launching innovative tourism services, these businesses can significantly boost their revenue and growth while enhancing customer satisfaction by surpassing expectations. The hospitality industry is perpetually evolving, with hotels frequently updating their offerings to align with the changing preferences of their guests. It is critical for hoteliers and industry stakeholders to comprehend the factors that contribute to the success of these services. The hotel industry is marked by its dynamism, continually introducing new services to meet the diverse demands of its customers. Effective implementation of these services is important for sustaining a competitive advantage in the sector [9].

Despite growing interest from scholars and industry experts in predicting the debut of new products and services, there is a noticeable gap in the literature on the subject. The majority of research leans towards new product development, with scant focus on NSD.

This study offers multiple contributions: 1) It presents the development and application of an innovative method combining a Type-2 Fuzzy algorithm with Particle Swarm Optimization, specifically designed to predict the success of new tourism services. To the best of our knowledge, this is the first systematized study of the impact of a Type-2 Fuzzy model to forecast a new service, 2) It utilizes a technique that cycles through all inputs to select the most relevant inputs, 3) By focusing on developing forecasting models for tourism services, this paper addresses a critical gap in the research. This contribution is particularly valuable given the economic importance of the tourism sector and the unique challenges it faces, such as seasonal demand fluctuations and sensitivity to external shocks (e.g., economic downturns, pandemics), 4) This paper proposes a methodology that is suited to the specific characteristics of tourism services. This includes a hybrid model that combines quantitative and qualitative data which can adapt to rapidly changing market conditions, 5) The development of dedicated forecasting models for tourism services aims to enhance predictive accuracy, which is crucial

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for strategic planning, resource allocation, and long-term sustainability in the tourism industry, 6) By expanding the scope of NSD research to include tourism services, this work contributes to a more comprehensive understanding of service development processes. This broader approach can inform cross-sectoral strategies and innovations, 7) This research extends the application of the fuzzy domain by employing Type-2 Fuzzy algorithm methods to forecast the success of emerging tourism services.

In addition to its academic contributions, this study also offers practical benefits. Launching new tourist services involves complex projects that require a high level of expertise and typically entail substantial initial costs. Given these factors, there is a significant risk of project failure. To mitigate this risk and enhance the effectiveness of these projects, it is important to employ forecasting techniques adeptly. This study advocates the use of Type-2 Fuzzy models, which are believed to reduce the risk of failure in launching tourism services.

The paper's structure is as follows: Section 2 delves into the literature surrounding new service development models. Section 3 outlines the research methodology. Data analysis and input selection are covered in Section 4. Section 5 showcases performance metrics, results, and a comparative review. Insights from the findings are discussed in Section 6, while Section 7 wraps up the paper.

Review of the related literature

While there has been growing interest among academic researchers and business practitioners in predicting the success of new services, scientific papers on this topic remain sparse. Most papers focus on new product development, with comparatively very few exploring new service development. This discrepancy highlights a significant gap in the research that needs to be addressed to better understand and predict the success of new service initiatives.

The literature review section of this study is structured in five distinct subsections. The first subsection delves into the critical issues associated with new service development, outlining the primary challenges and considerations. The second subsection presents some main models of product development. The third subsection focuses on the broader topic of new service development, discussing the methodologies and strategies employed in this area. In the fourth subsection, the discussion is narrowed down to the application of these findings, specifically to the development of new hotel services. The final subsection showcases various successful applications of fuzzy logic in forecasting across different fields, demonstrating the versatility and effectiveness of fuzzy theory in addressing complex problems in diverse sectors.

Factors influencing the success of newly launched hotel services

This section of the literature review aims to explore the factors that contribute to the success of newly launched hotel services. The hospitality industry is constantly evolving, with hotels introducing new services to meet the changing needs of guests. Understanding the determinants of success can provide valuable insights for hoteliers and stakeholders.

The hotel industry is characterized by its dynamic nature, with new services being introduced regularly to cater to the diverse needs of guests [9]. The success of these services is crucial for the competitive positioning of hotels. Some of the factors that influence the success of a new service are the following:

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Customer expectations and perceptions: Meeting and exceeding customer expectations is most important [10]. Services that align with guests' expectations and perceptions tend to be more successful.

Service quality: Service quality plays a pivotal role in determining guest satisfaction and loyalty [11]. Hotels that ensure high-quality services often witness higher success rates.

Technological integration: Incorporating technology into hotel services enhances efficiency and the guest's experience [12]. Services like online check-in, digital room keys, and AI-driven concierge services have gained popularity.

Customization: Personalized services cater to individual guests' needs, enhancing satisfaction [13]. Tailored experiences, from room preferences to curated experiences, can drive success.

Sustainability: With growing environmental concerns, sustainable hotel services are becoming increasingly important [14]. Green initiatives and eco-friendly services can attract niche markets, which also includes a growing segment of travelers.

However, there are also some challenges involved in the implementation of new services. The resistance to change, among both staff and guests, might hinder the introduction of new services due to unfamiliarity [15]. Proper training and communication can mitigate this. The high initial costs of introducing new services often requires significant investment [16]. However, the long-term benefits often outweigh the initial costs. The hotel industry is saturated in some regions, making it challenging for new services to stand out [17].

New Product Development (NPD)

New Product Development (NPD) is a critical process that involves the conceptualization, design, development, and commercialization of new products in the marketplace. It is a systematic approach used by companies to bring new products to consumers, consisting of several key stages. Effective NPD is essential for companies seeking to stay competitive, adapt to changing consumer preferences, and continue to grow in their respective markets. The process not only involves creativity and innovation, but also rigorous analysis and strategic planning to ensure that new products will succeed in the marketplace.

What follows is a review of some articles that provide a broad spectrum of perspectives and methodologies, offering valuable insights into the dynamic field of new product development.

The seminal paper "The new product development game" by Takeuchi and Nonaka discusses innovative approaches to new product development, emphasizing flexibility and speed [18].

In their paper "Issues and opportunities in new product development: An introduction to the special issue", Wind J and Mahajan V, explore the challenges and opportunities in new product development, with insights into market needs and product testing [19]. In their article "Identifying new product development best practice", Barczak G and Kahn KB, review best practices in new product development, focusing on benchmarks that enhance the efficiency and effectiveness of the process [20]. Strategic and practical aspects of successfully navigating new product development processes are discussed in the paper "Navigating the new product development process" [21].

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The article "Implementing the new product development process" by Bessant J and Francis D, covers the strategies and required framework for effectively managing and implementing new product development processes [22].

There are also many other studies which have contributed to the new product development domain, among which can be included the works of [23-33].

New service development

Mandal PC claims that the service industry is at a critical juncture where technology, customer empowerment, co-production, and the need for dual satisfaction of customers and employees are reshaping traditional service paradigms [34].

The study of Zhang G and Ravishankar MN contributes to an understanding of how start-ups can encourage cloud computing to deliver digital artifacts successfully [35]. By identifying and cultivating the capabilities discussed, start-ups can effectively utilize digital technologies to innovate and compete in the digital economy. The findings suggest that a combination of technological agility, customer-centric innovation, strategic resource management, and collaborative partnerships is critical to navigating the opportunities and challenges presented by digital entrepreneurship.

The primary aim of introducing a new service is to attract customers. However, if the service's creation is costly, its market price will likely be high, making it less appealing to potential buyers [36]. High-priced services tend to be less popular, reducing the new service's likelihood of success [37]. Reducing the price of an expensive service can compromise its profitability [38]. Thus, even if customers choose it, the service might not be profitable. Yao et al., studied green energy product innovation, emphasizing the importance of cost assessment for a project's effectiveness [39]. Similarly, Pojadas et al., and Timilsina GR highlighted the need for cost-benefit and cost evaluations, respectively, to enhance a project's performance and gain a competitive edge [40,41].

Mahavarpour et al., consider service innovation to be a key competitive differentiator for firms, which has gained significant attention over the past decade [42]. Their study delves deeper into the evolution and potential trajectory of service innovation by analyzing 255 articles from 1970 to 2021. The research uncovered four main clusters characterizing the domain: Resource, process, solution, and actors' focus. An analysis of thematic trends over time revealed that between 1992 and 2014, themes such as innovation, customer service, and product development were predominant. From 2014 to 2021, however, the focus shifted to service, customer, value and information, which also gained prominence. The study emphasizes the interdisciplinary nature of service innovation and its evolving research foundation.

Yuan et al., claimed that the rise of information and communication technologies has Spotlighted Smart Product-Service Systems (SPSSs) [43]. The success of these systems hinges on their ability to adapt to users' dynamic contexts, necessitating a context awareness approach. This research introduces a Context-Aware Spotlighted Smart Product-Service Systems (CA-SPSS) framework. Its development involves collecting user data, cloud-based context modelling, and context-driven service customization using neural networks and multi-criteria decision-making. When tested in nonprofessional sports competitions, the CA-SPSS outperformed traditional models; however, reliability concerns still arise.

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Hennelly et al., trace the collaboration between military and health systems in launching aeromedical services [44]. The restructuring of Ireland's health system led to greater reliance on both ground and air emergency services. Understanding the present model is crucial for future aeromedical enhancements.

Martínez et al., assess the NSD process for renewable energy investments using a novel fuzzy hybrid multi-criteria decisionmaking model [45]. The methodology incorporates a weighted criteria system and balanced scorecard-based project network. Alternatives are ranked using the ELECTRE approach, resulting in a “Project Evaluation and Review Technique” (PERT) diagram. Analysis is identified as essential in the NSD process for clean energy projects. The findings suggest a comprehensive evaluation of technical and financial aspects when introducing new products.

Huikkola et al., delve into the execution of Smart Solution Development (SSD) by established solution providers [46]. Addressing a gap in digital servitization research, they examine the integrated aspect of SSD beyond just product, service, and/ or software development. Based on 23 manager interviews, observations, and strategic documents, they enrich the literature on product-service innovations by pinpointing innovation routines and associated management processes.

Dahiru et al., Li et al., and Bose et al., posited that meeting customer expectations is vital for enhancing NSD performance [47-49]. To begin with, understanding customer needs is essential. Evaluations should consider diverse customer groups, including both older and younger individuals. Addressing these needs can make a company's products more appealing, boosting its competitive edge.

Xie et al., introduces a triadic collaborative service innovation model that explores the effects of an employer's customer focus, employee adaptability, and customer participation on service innovation [50]. Using data from hotel staff and guests, with 300 valid records, the study employs CFA and SEM for analysis. The findings reveal that understanding customer needs, influenced by the aforementioned factors, boosts service innovation. The study underscores the significance of recognizing customer needs for both employees and employers.

Through case studies, de Goeij et al., have investigated how Logistics and Financial Industries (LSPs) develop services and the factors influencing the process [51]. Findings reveal the challenges that LSPs face in transitioning from logistics to finance, and the potential enablers and inhibitors affecting this service development.

Yang et al., suggest that the creativity of staff on the front line can boost NSD, and that their Operational Improvement Competence (OIC) can further increase their creativity [52].

Tran T and Park JY introduced an innovative approach to crafting methodologies for Product Service System (PSS) challenges [53]. They identified eight categories consisting of 29 criteria for this objective. They demonstrated the application of this method with a practical example, guiding designers and practitioners in selecting the optimal solution for their PSS issues.

Zhang et al., introduced a multiple criteria analysis technique rooted in the fuzzy measure and the Choquet integral, which is tailored for assessing and enhancing airline service quality [54]. Data spanning a decade was analyzed to test the model's efficacy. The findings suggest that their method stands as a validated analytical approach for gauging airline service quality, especially in scenarios devoid of human-made interaction phenomena.

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Mosera et al., introduced a PSS development method influenced by genetic principles, contrasting the product and service development process with a PSS development approach [55]. This comparison yields fresh challenges, with some arising at particular development stages and others spanning the PSS's entire life-cycle. They tested their development procedure using a specific PSS example.

Homburg C and Kuehnl C explore the interaction between inner and exoteric completion methods and their impact on the success of new product and service innovations [56]. They propose the potential existence of an inverted U-shaped relationship between innovation success and its precursors. Their results reveal variances in how cross-functional integration, customer integration, and inter-firm collaboration relate (linearly or non-linearly) to innovation success, depending on whether this is in the context of a new product or a new service.

Kim S and Yoon B introduce an Agent-Based Simulation (ABS) approach for generating new service consent [57]. Their ABS model, which includes customer, service provider, and competitor agents, can predict the significance of service factors in new offerings based on future customers' needs. The findings suggest that ABS addresses the limitations of current concept design tools, capturing non-linear shifts and future patterns related to service components and real-time customer behavior. This method is tested in the healthcare sector, showcasing its practicality and benefits.

Using the Activity theory, Lin FR and Hsieh PS explore the intricate dynamics of service innovation systems, highlighting the interconnectedness of entities in telemedicine service projects [58]. They pinpoint key discrepancies affecting the longevity of new services, emphasizing the essential role of understanding customer needs, the integration of emerging technologies, and cross-industry collaborations.

Jaw et al., study the influence of service attributes, market orientation, and innovation efforts on NSD outcomes [59]. They use both qualitative and quantitative research techniques. The results indicate that service traits like heterogeneity and perishability, along with market orientation, positively affect a company's investment and recognition in innovation. Furthermore, innovation efforts and market orientation boost NSD performance.

Ozer M introduces two novel elements for forecasting the success of electronic shopping and sports services: Task organization and knowledge exchange [60]. A survey comparing preliminary forecasts with real outcomes for these services is conducted to validate the associated hypotheses. The findings indicate that the precision of predictions is notably enhanced by both elements. Furthermore, Ozer M emphasizes an interplay between the two factors, noting that utilizing just one of them yields meaningful outcomes [60].

Lee and colleagues introduced a Decision Tree model to forecast the success of various e-commerce services [61]. This model outperforms the regression and discriminant models with an accuracy rate of 70%-80%.

Menor L and Roth A describe a two-stage method to develop and validate a multi-item scale for a construct termed NSD competence, encompassing five dimensions: NSD process focus, market insight, NSD strategy, NSD culture, and IT experience [62]. The study first uses judgment-based data to evaluate the temporary validity and reliability of the suggested items, revealing a subset with solid

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psychometric traits. Subsequently, they undertake a confirmatory factor analysis for the NSD competence dimensions.

Smith et al., posit that an effective service design and NSD process result from merging a comprehensive NSD approach with micro-level precision [63]. Using five models (Prerequisites, quality function development, service blueprinting, stage gate, and stakeholder), they demonstrate the application of this approach in a multifaceted service like a hospital.

Development of new hotel services

Sembeta et al., propose that the ABSA framework for the hotel industry using Afaan Oromo texts represents a significant step forward in both the fields of AI and hospitality management [64]. By combining advanced machine learning techniques with strategic dataset development, their research is poised to offer meaningful insights that could revolutionize customer relationship management in the hospitality sector.

The research of Jeong N and Lee J illuminates the potential of AIdriven tools like Chat GPT in enhancing the analysis of customer feedback across various service industries [65]. By focusing on aspect-based summarization and explicit keyword extraction, their approach not only provides practical benefits to hotel management but also adds a valuable dimension to academic research in AI applications.

Atsalakis et al., introduced an algorithm to predict the failure or success of a service in hotels using an ANFIS technique [66]. This method blends fuzzy logic with neural networks to assess a data set of new tourism services. The model was developed using real data, ensuring its predictions aren't influenced by vague or imprecise subjective judgments. The research analyzed raw data from new hotel services using the neuro-fuzzy ANFIS technique. The results were promising, with a 91.75% accuracy rate and a forecasting error rate of 8.43%, outperforming seven other models.

Atsalakis SG and Kitsios F presented the creation of six computational models designed to predict the success of new services in the tourism industry [67]. The study employs both traditional models, such as the ANFIS and Neural Networks (genetically involved), and non-conventional models like Discriminant, Logit, Probit, and Weibull regression. These models utilize data pertaining to criteria variables determining the success or failure of new tourism services. In terms of forecasting accuracy, the ANFIS model stands out, achieving a classification accuracy of 91.57% in predicting the success or failure of new hotel services, making it a potentially effective tool for capturing uncertainties in the relationships between input and output variables.

Konu H effectively demonstrates that ethnographic approaches in NSD can provide comprehensive and detailed insights that are crucial for the successful development of new tourism services [68]. By embracing these methods, service designers and managers can enhance the effectiveness of their offerings, ultimately leading to improved business outcomes and enriched tourist experiences.

Research by Nilashi et al., on a new hybrid method for hotel recommendations highlights the potential of combining multiple advanced computational techniques to significantly improve the quality-of-service recommendations [69]. This approach not only enhances the accuracy of the recommendations but also contributes to the body of knowledge in the recommendation systems domain, offering a scalable and effective solution for the hospitality industry.

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Research by Kitsios et al., offers profound insights into the critical role of specific development process activities in the success of NSD in the hotel sector [70]. By employing a structured, methodical approach through the UTADIS method, they provide a quantifiable understanding of how different criteria contribute to the success of new services. This study not only aids hoteliers in refining their service development strategies but also enriches the academic discourse on service innovation and management.

Various sectors where fuzzy models have been applied successfully

Fuzzy systems have been applied across numerous scientific fields, offering researchers and practitioners effective models for predicting a range of issues. Several of these applications are outlined below:

Martinez et al., introduced a hybrid decision-making approach utilizing type-2 fuzzy logic for the NSD process in renewable energy investment [45]. Zhong et al., and Liu et al., determined the key issues to improve the effectiveness of the renewable energy investments [71,72]. In the proposed models, interval type-2 fuzzy sets were utilized specifically to address uncertainties more effectively.

Suganthi et al., examined the use of fuzzy logic within renewable energy systems. Their research involved the development of models using the fuzzy AHP method [73]. Cabalar et al., proposed several applications of neuro-fuzzy in "geotechnical engineering" [74]. Atsalakis G introduced a neuro-fuzzy forecasting model to effectively predict carbon emissions prices [75]. Adelkhani et al., crafted a model using image processing and neuro-fuzzy to characterize the taste of oranges [76]. Atsalakis et al., presented a neuro-fuzzy model that integrates the Elliot wave theory with neuro-fuzzy systems to predict stock market prices [77].

The literature review outlined in this paper highlights a critical gap in the field of new product and service development, particularly within the subsector of tourism services. The focus of existing research predominantly on quantitative methodologies and product-centric models underscores a significant opportunity for advancing knowledge in service-centric forecasting models tailored to tourism. Below is a detailed analysis of the findings from the literature review, followed by the contributions that this paper aims to make.

Quantitative methodologies: The review notes that most studies in NSD employ quantitative data analysis methodologies. This trend indicates a preference for statistical and numerical analysis, which can provide robust, generalizable findings. However, the emphasis on quantitative methods may overlook the nuanced insights that qualitative research could offer, especially in understanding complex consumer behaviors and preferences in the tourism sector.

Performance perspectives: The predominant use of classification into successful or failed outcomes in these studies highlights a binary approach to evaluating NSD performance. While useful, this perspective may simplify the complex factors that contribute to the success or failure of new products and services, particularly in nuanced and highly variable sectors like tourism.

Model development focus: The focus on products rather than services, as noted in the literature, suggests a gap in models that are specifically designed to address the unique characteristics of services, such as intangibility, heterogeneity and the simultaneous production and consumption of services. This gap is even more pronounced in tourism services, which are highly experiential and influenced by numerous external factors.

Sector coverage: This review also indicates that while some sectors are well-covered by existing methodologies, others like tourism services and particular hotel services have very few studies dedicated to them. This uneven coverage may lead to underdeveloped predictive capabilities in sectors that are economically significant and dynamically complex.

METHODOLOGY

Type-1 fuzzy: Theoretical background

The theory of Type-1 Fuzzy, often simply referred to as "fuzzy logic" or "type-1 fuzzy logic," is a mathematical framework that expands upon classical set theory to manage uncertainty, vagueness, and imprecision. Fuzzy logic was introduced by Zadeh LA in the 1960s as a means to model uncertainty in human reasoning [78]. Unlike classical set theory, which deals with binary membership (an element either belongs or doesn't belong to a set), fuzzy logic allows for degrees of membership. Each element has a membership value between 0 and 1 in a fuzzy set. For instance, in classical logic, an object is either "hot" or "not hot." In fuzzy logic, it might be "somewhat hot" with a membership value of 0.7. Fuzzy sets are defined by membership functions, which assign a membership value to each element. The boundaries of fuzzy sets are not sharp, making them suitable for modelling vague concepts. Fuzzy logic operations are extensions of classical logic operations. For example, the union of two fuzzy sets is determined by taking the maximum membership value of each element in the sets. Similarly, the intersection is determined by taking the minimum membership value. Fuzzy logic has been utilized across multiple domains such as control systems and decision-making processes, as well as artificial intelligence. Fuzzy controllers, for instance, have been used in appliances like washing machines and air conditioners. These controllers interpret inputs like "slightly dirty" or "almost cold" to make decisions.

Fuzzy logic's strength lies in its ability to handle ambiguity and make decisions based on imprecise data. It bridges the gap between purely logical reasoning and human-like reasoning. Type-1 Fuzzy systems deal with crisp inputs and produce outputs based on fuzzy rules. These rules often have the form: "If x is A, then y is B," where A and B are fuzzy sets. The method of transforming a fuzzy output into a precise value is known as defuzzification. Common defuzzification methods include the centroid method and the max membership principle. Fuzzy logic has been criticized for its lack of a solid theoretical foundation in some applications. However, its empirical success in various applications cannot be denied. It offers a more intuitive approach to problems that are hard to model with classical logic.

Fuzzy logic systems are inherently strong, as they can handle variations in input without drastic changes in output. They are particularly useful when the system being modelled is too complex for conventional mathematical modelling. The linguistic variables used in fuzzy logic, like "warm" or "cool," make it a user-friendly approach.

Over the years, fuzzy logic has been integrated with other computational paradigms, like neural networks, leading to hybrid systems. These hybrid systems aim to combine the strengths of both approaches. In conclusion, type-1 fuzzy logic provides a framework for reasoning under uncertainty.

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Its ability to model vagueness and imprecision has made it a valuable tool in various real-world applications. Type-1 Fuzzy systems are contrasted with Type-2 Fuzzy systems while type-1 systems deal with crisp uncertainties, type-2 systems handle uncertainties in the membership functions themselves.

Type-2 fuzzy: Theoretical background

Type-2 fuzzy sets extend the traditional type-1 fuzzy sets to better handle higher levels of uncertainty. Type-2 fuzzy sets were introduced as an extension of type-1 fuzzy sets to manage uncertainties in the membership functions themselves. While type-1 fuzzy sets have crisp membership grades, type-2 fuzzy sets have fuzzy membership grades [79,80]. This means that each point in a type-2 fuzzy set has a membership value that is itself a fuzzy set.

The primary motivation behind type-2 fuzzy logic is to handle situations where it's challenging to determine a precise membership value. The “footprint of uncertainty” is a concept in type-2 fuzzy sets that defines the region where membership values lie. Type-2 fuzzy sets can be categorized into interval type-2 and general type-2 fuzzy sets. Interval type-2 fuzzy sets have a membership function that is an interval across its domain, simplifying computations. General type-2 fuzzy sets, on the other hand, allow for more complex membership functions. The process of converting a type-2 fuzzy set to a type-1 fuzzy set is called type-reduction. Type-reduction is essential for real-world applications where a crisp output is needed.

The Karnik-Mendel iterative procedure is a popular method for type-reduction in interval type-2 fuzzy sets [81,82]. Type-2 fuzzy logic systems use type-2 fuzzy sets in their rules and decision-making processes. These systems are particularly useful in environments with significant noise or when the system's behavior is not well understood.

Type-2 fuzzy logic has found applications in areas like control systems, pattern recognition, and decision-making. It offers a stronger approach in situations with varying degrees of uncertainty. The added complexity of type-2 fuzzy logic, compared to type-1, means that it requires more computational resources. However, this complexity provides a richer framework to capture and model uncertainties.

The concept of type-2 fuzzy logic was also introduced by Zadeh LA, building on his foundational work with type-1 fuzzy sets [83]. Over the years, type-2 fuzzy logic has been refined and expanded upon by many researchers. Its ability to handle both aleatory and epistemic uncertainties sets it apart. Aleatory uncertainties arise from inherent randomness, while epistemic uncertainties come from a lack of knowledge. Type-2 fuzzy logic's strength lies in its capacity to model and manage both these uncertainties.

In real-world applications, type-2 fuzzy logic systems often demonstrate better performance and resilience to noise. They are especially valuable in situations where there is a lack of data or where the data is unreliable. The linguistic variables in type2 fuzzy logic can capture nuances that type-1 fuzzy logic might miss. As with type-1 fuzzy logic, type-2 has been combined with other computational paradigms to create hybrid systems. These hybrids aim to leverage the strengths of both approaches for more effective problem-solving. In conclusion, type-2 fuzzy logic offers a sophisticated framework for reasoning in environments riddled with uncertainty. Its ability to capture nuances and handle multiple types of uncertainties makes it a powerful tool. Continued research into and application of type-2 fuzzy logic promises more robust solutions to complex real-world problems [84,85].

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In a conventional type-1 membership function, any given value within the scope of discussion has a singular membership value. This means that while a type-1 membership function can represent the extent of membership in a specific linguistic set, it doesn't capture the uncertainty surrounding that membership degree. To represent this uncertainty, interval type-2 membership functions are employed. Within these functions, membership degree can span across a range of values.

An interval type-2 Membership Function (MF) is characterized by both an upper and a lower MF as depicted in Figure 1. The "Upper Membership Function" (UMF) mirrors a standard type-1 MF. The "Lower Membership Function" (LMF) is always less than or equal to the UMF across all potential input values. The space between the UMF and LMF is termed the "Footprint of Uncertainty" (FOU). A visual representation might depict the UMF in red, the LMF in blue, and the FOU as a shaded area between them, especially for a type-2 triangular MF. For every input value within the scope of discussion, the membership degree is the range between the LMF and UMF values.

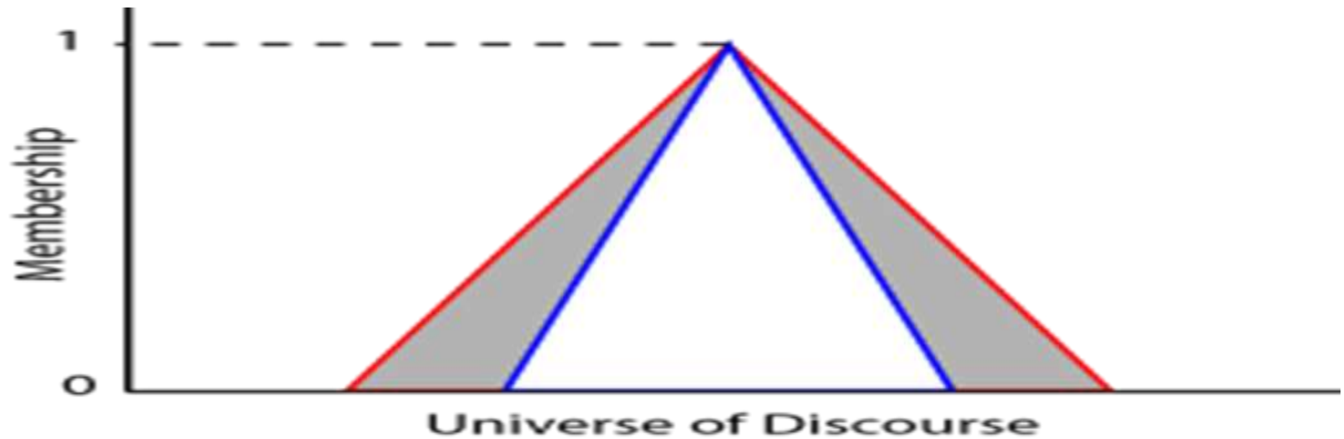

Figure 1: Type-2 Fuzzy membership function.

In type-2 Sugeno systems, only the input MFs are characterized as type-2 fuzzy sets. The output MF remains consistent with a type1 Sugeno system, either being constant or linear, based on input values.

Antecedent processing: In type-2 fuzzy inference systems, input values are fuzzified by establishing their membership degrees in both Upper Membership Functions (UMFs) and Lower Membership Functions (LMFs) as specified by the antecedent of the rule. Consequently, each type-2 MF generates two fuzzy values. For instance, in Figure 2, fuzzification might highlight the membership value in the UMF (fU) and the LMF (fL).

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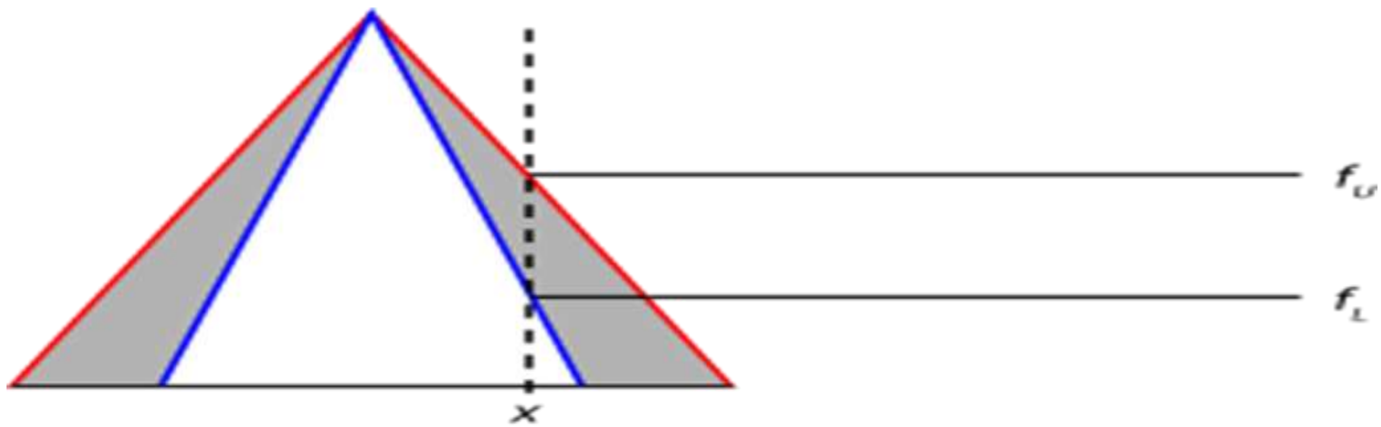

Figure 2: : Fuzzification of type-2 fuzzy membership function.

Subsequently, a spectrum of rule-firing strengths is calculated by applying the fuzzy operator to the fuzzified values generated by the type-2 MF. The peak value of this range (wU) emerges from applying the fuzzy operator to the UMF values, while the lowest value (wL) comes from its application to the LMF values. Antecedent processing remains consistent for both the Mamdani and Sugeno systems.

Aggregation: The aggregation phase is designed to consolidate multiple rule output fuzzy sets into a single type-2 fuzzy set. In a type-2 Mamdani system, this is achieved by implementing the aggregation method on both the Upper Membership Functions (UMFs) and the Lower Membership Functions (LMFs) of each rule's output fuzzy sets.

Type reduction and defuzzification: To derive the exact output value from the inference process, the aggregated type-2 fuzzy set is first transformed into an interval type-1 fuzzy set, characterized by a range that includes a Lower boundary (cL) and an Upper boundary (cR). This interval type-1 fuzzy set is often known as the centroid of the type-2 fuzzy set. Conceptually, this centroid signifies the average of the centroids of all the embedded type-1 fuzzy sets within the type-2 fuzzy set. Nevertheless, pinpointing the precise values for cL and cR can be complex in real-world applications.

As a result, iterative type-reduction techniques are employed for estimation. For a given aggregate type-2 fuzzy set, the estimated values of cL and cR represent the centroids of specific type-1 fuzzy sets.

Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a computational optimization technique inspired by the social behaviour of birds flocking or fish schooling. It was introduced by Kennedy J and Eberhart R in 1995 [86]. PSO is a meta-heuristic approach, implying that it operates with minimal or no assumptions about the problem being optimized and is capable of exploring vast spaces of potential solutions [86]. Following is a basic outline of how PSO works: A swarm (group) of particles (potential solutions) is initialized with random positions in the search space. Each particle has a position representing a potential solution to the optimization problem and a velocity that determines how much it moves in each iteration. Each particle's fitness or quality as a solution is evaluated using a predefined fitness function. Each particle remembers its personal best position (the position where it had the best fitness) throughout its journey. From all the particles' personal bests, a global best position is identified. Each

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particle updates its velocity based on its previous velocity, its personal best position, and the global best position. A stochastic (random) component is often added to the velocity updates to introduce some randomness in the movement of the particles. After updating the velocities, each particle's position is updated based on its new velocity. The process is repeated for a predetermined number of iterations or until a convergence criterion is met.

The beauty of PSO is that it is relatively simple compared to other optimization algorithms, yet it can be very powerful for many optimization problems. PSO is commonly applied in various domains, from tuning machine learning models to engineering design optimization.

Data preprocessing, selection of input variables, and their application

Data was gathered using a survey distributed across 167 hotels that had launched a new tourism service. Data collection primarily involved senior executives from the top levels of the companies. While there is no universally accepted method for dividing data, typically in modelling, data is categorized into two primary sets: training and validation. The training set shapes the model's logic, while the validation set tests its accuracy. Notably, the algorithm doesn't utilize the validation set during its operation. With a split value of 0.5, roughly half the data (84 samples) trains the model, and the other half (83 samples) assesses its performance. This division ensures a proportional representation of both successful and unsuccessful new services in both sets, which is especially crucial when there are fewer instances of unsuccessful services.

Table 1 showcases a survey with 20 variables. These variables, comprising a total of 104 items, were shared with tourism companies for responses. A 5-point Likert scale gauged these variables, indicating the extent to which companies implemented corresponding actions (from 0%-not implemented, to 100%-fully implemented). This scale leans more towards a quantitative interpretation rather than the typical qualitative nature of Likert scales. Such a method offers more dependable results compared to continuous scales, as noted by Churchill in 1987 [87]. While a 7-point scale might have provided even more accurate measurements, as per Churchill G and Peter P in 1984, preliminary testing revealed that hotel managers preferred and performed better with the 5-point Likert scale [88].

Table 1: List of input variables and their corresponding elements.

Number	Symbol variable	ofNumber Name of variable of items	
	E	Business/financial analysis	
1	E1	Identification of clear strategic action plans	6
2	E2	Idea generation	5
3	E3	Preliminary allocation of idea	4
4	E4	Preliminary market assessment	9
5	E5	Preliminary technical assessment	4
6	E6	Market research	8
7	E7	Business analysis	8
8	E8	Creation of the dysfunctional group	4
9	E9	Planning and development of the new Service	4
10	E10	Procedure	4
11	E11	System planning and assessment	4
12	E12	Staff training	4
13	E13	Pilot sales	2
14	E14	Business analysis before any promotion	3
15	E15	Service launching	6
16	E16	Breakeven and return on investment analysis	4
17	ST	Organization	10
18	Z	Resource allocation	5
19	H	Market potential	2

20	TH	Market synergy	7
Total	20		104

First, for each sub-variable from E1 to E16, the mean value of its items was determined by dividing the total of the item values by the number of items in that sub-variable. Subsequently, the mean value for the sub-variables E1 through E16 was computed by dividing the total value of these sub-variables by their count. Following this, the averages for the items of the variables ST, Z, H, and TH were derived by dividing the total of each variable's items by the item count. As a result, five input variables (Eall_avg, ST, Z, H, and TH), representing the average of their respective items, were employed. The ANFIS technique utilized these for further input reduction. This involved cycling through all five inputs and constructing 10 distinct ANFIS models [66,67]. The most effective model, with the lowest RMSE, uses the variables "H" (Market potential) and "TH" (Market synergy). The consistency between error curves suggests an even distribution of training and test data. This method of selecting the two most impactful inputs can lead to non-linear mapping with reduced error metrics.

Thus, the training data concerns the variables "H" (Market potential) and "TH" (Market synergy). A split value of 0.5 was applied to the data, so that 84 samples have been used to train the model, ensuring a proportional representation of both successful and unsuccessful new services in the training set, which is especially crucial when there are fewer instances of unsuccessful services. The training data are displayed in Figure 3.

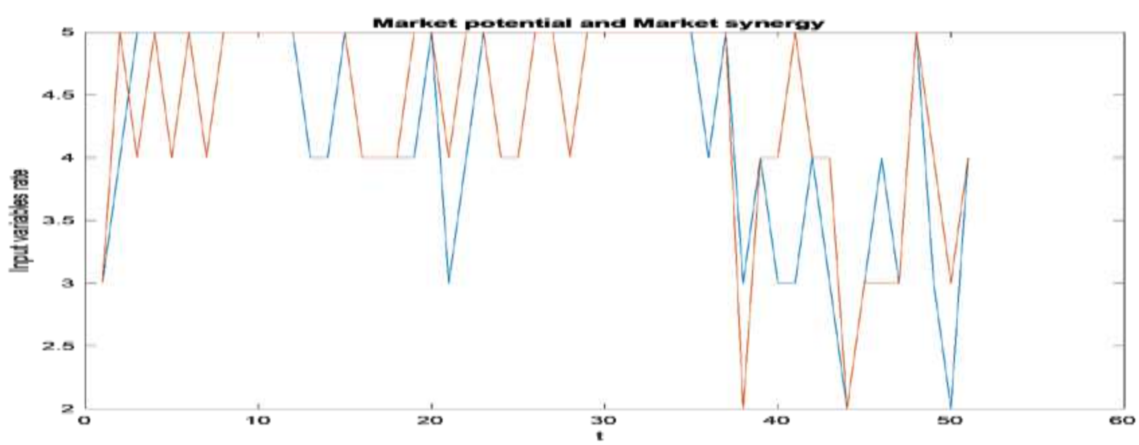


Figure 3: A two-dimensional plot of the two input variables: H: Market potential and TH: Market synergy. **Note:** (——) Market potential; (——) Market synergy.

The other half of the data (83 samples) assess its performance. This out-of-sample data for evaluation ensures a proportional representation of both successful and unsuccessful new services in both sets, which is especially crucial when there are fewer instances of unsuccessful services.

Initially, a Fuzzy Inference System (FIS) was created based on the default parameters from the Matlab toolbox. The FIS was trained using the data of the two inputs, having two Gaussian membership functions for each input. Subsequently, different versions of the model were created by increasing the number of MFs for each input. Starting from two membership functions for each input and keeping the same number of membership functions for both inputs, the tests reached up to 10 MFs. Then, a combination of a different number of membership functions per input was carried out, starting from 2 and reaching 10 MFs.

Further tests followed with different types of membership functions: Generalized bell-shaped MF, Gaussian MF, Gaussian combination MF, Triangular MF, Trapezoidal MF, Linear s-shaped saturation MF, Sigmoidal MF, and the difference between two sigmoidal MFs.

The overall accuracy was used as a comparison measure to select the optimal combination of the number of MFs for each input and the best type of MF.

The optimum configuration of the FIS was with 6 Membership Functions (MFs) for each input and the membership function type was “gauss2mf": Gaussian combination MF for the first input “H” (Market potential), and “trapmf”: Trapezoidal MF for the 2nd input variable “TH” (Market synergy).

The successful application of new services is categorized into two outcomes: Success and failure, represented by the output variable using a constant membership function with parameters set at 0 and 1. Through a process of trial and error involving different types of Membership Functions (MFs), the Gaussian2 MF was selected for the first input due to its effective handling of data variability. For the second input, the Trapezoidal MF was chosen, recognizing its ability to better accommodate the range and shape of data distribution. This methodical selection of MFs ensures precise modeling of input variables to predict service success accurately.

After transforming the Fuzzy Inference System (FIS) into a type2 system, Figure 4 illustrates the six type-2 fuzzy Membership Functions (MFs) for the first input, "H" (Market Potential), as they appear before the tuning process using the training data. This visual representation highlights the initial setup prior to optimization.

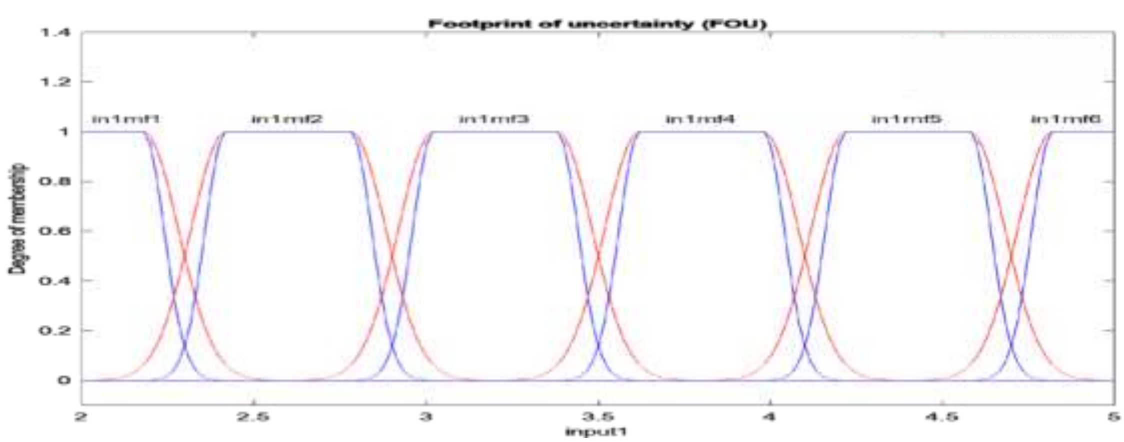


Figure 4: Plot of initial type-2 fuzzy MFs before tuning of the input variable “H” (Market potential). The linguistic labels of each MF are: “in1mf1”: Extremely low, “in1mf2”: Very low, “in1mf3”: Low, “in1mf4”: High, “in1mf5”: Very high, and “in1mf6”: Extremely high.

Note: ( ) Upper MF; ( ) Lower MF.

The fuzzification of input values is achieved by determining the degree of membership in both the Upper MF (UMF) and Lower MF (LMF), as dictated by the rule's antecedent. This results in two fuzzy values for each type-2 membership function. The space between the UMF and LMF is termed the "Footprint of Uncertainty" (FOU). The visual representation depicts the UMF in red, the LMF in blue, and the FOU as a shaded area between them.
Figure 5 depicts the 6 types-2 fuzzy MFs of the second input (TH=Market Synergy). The linguistic labels of each MF are: "in1mf1": Extremely low, "in1mf2": Very low, "in1mf3": Low, "in1mf4": High, "in1mf5": Very high, and "in1mf6": Extremely high. The fuzzification of input values is achieved by determining the degree of membership in both the Upper MF (UMF) and the Lower MF (LMF), as dictated by the rule's antecedent. This results in two fuzzy values for each type-2 membership function. The space between the UMF and LMF is termed the "Footprint of Uncertainty" (FOU). The visual representation depicts the UMF in red, the LMF in blue, and the FOU as a shaded area between them.

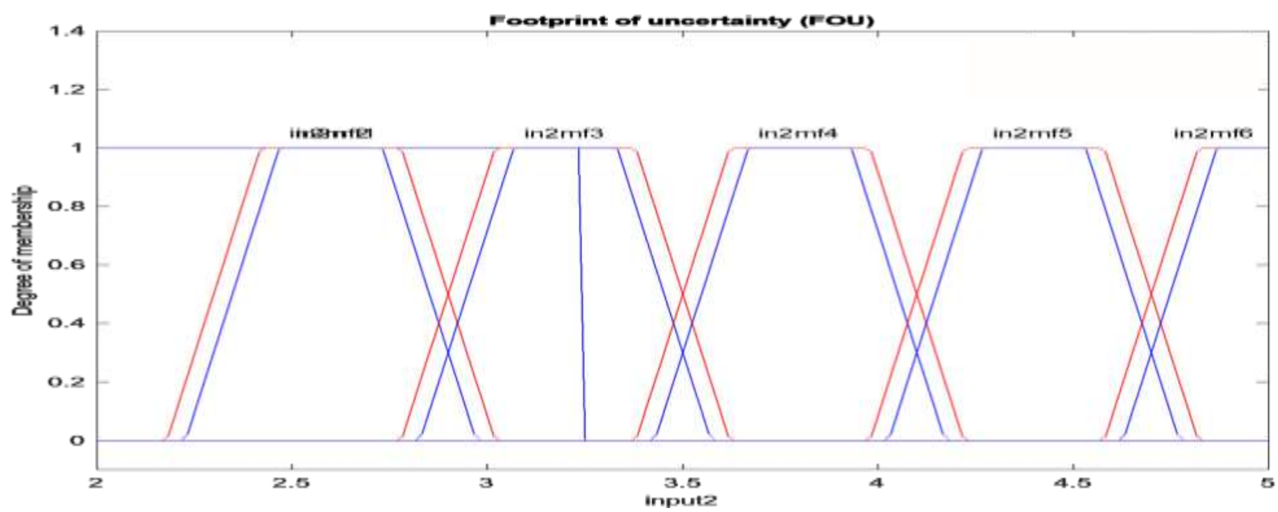
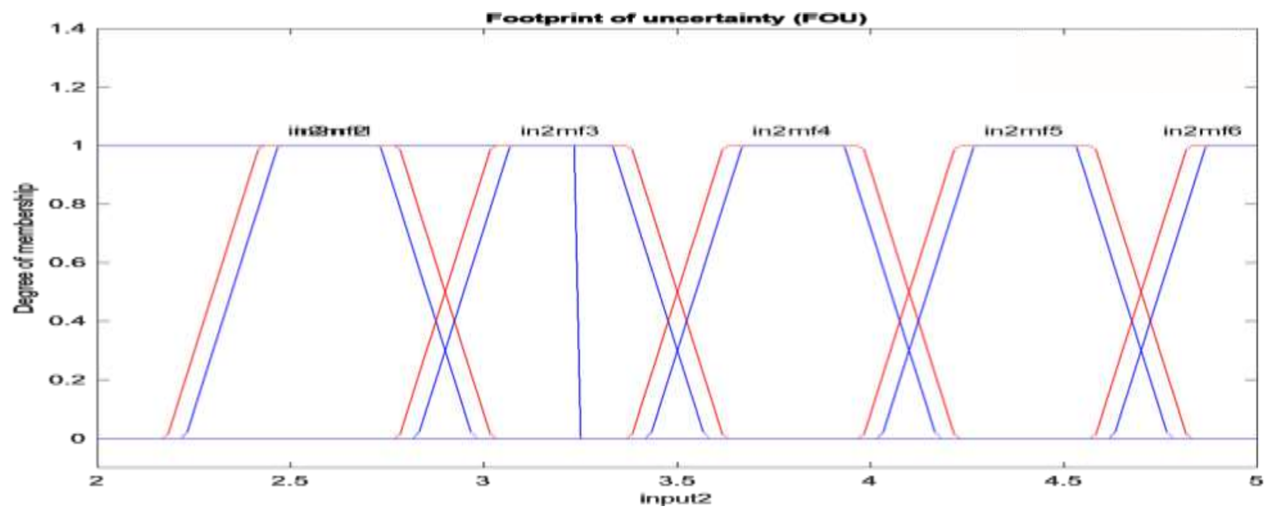


Figure 5: Plot initial type-2 fuzzy MFs before tuning for the 2nd input variable (TH: Market Synergy). **Note:** ( ) Upper MF; ( ) Lower MF.

Figure 6 presents the final shape of the six membership functions of input variable "H" (Market potential) after tuning it with the training process. The visual representation depicts the UMF in red, the LMF in blue, and the FOU as a shaded area between them and the linguistic labels, where a distinct shape is evident for most of the membership functions of this input.



variable "H" (Market potential). **Note:** ( ) Upper MF; ( ) Lower MF.

Figure 6: Plot of final type-2 fuzzy MFs after tuning for the input

Figure 7 depicts the final type-2 fuzzy MFs' shape after tuning of the 2nd input variable (TH: Market Synergy) with the training data. It presents the UMF in red, the LMF in blue, and the FOU as a shaded area between them and the linguistic labels, where a distinct shape is evident for most of the membership functions of this input.

Table 2 outlines the types and values of the Type-2 Fuzzy parameters for the two input variables, each with six Membership Functions (MFs). The input selection method employed has streamlined the number of inputs to two and the rules to 36.

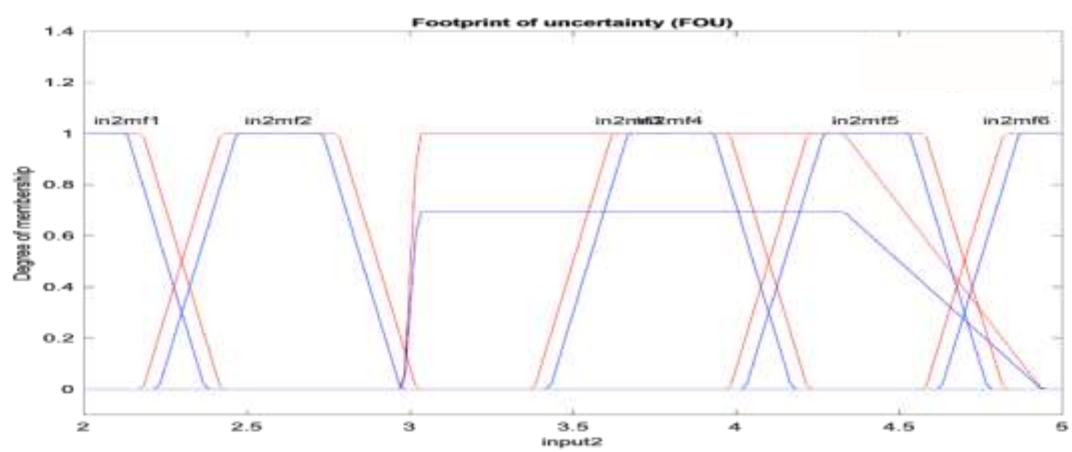


Figure 7: Plot of final type-2 fuzzy MFs after tuning for the 2nd input variable (TH: Market Synergy). **Note:** ( ) Upper MF; ( ) Lower MF.

Table 2: Parameter types and values of Type-2 Fuzzy used in training.

Type-2 Fuzzy parameter type	Value

MF type input 1 (TH: Market Synergy)	gauss2mf
MF type input 2 (H: Market potential)	trapmf
Count of linguistic variables (MFs)	6, 6
Output MF	Linear
Upper MF (UMF)	yes
Lower MF (LMF)	yes
Footprint of Uncertainty (FOU)	yes
Count of training data pairs	84
Count of evaluating data pairs	83
Count of fuzzy rules	36

Figure 8 represents the structure of the type-2 fuzzy model consisting of 2 inputs that correspond to the 2 input variables (H: Market potential and TH: Market Synergy), the Sugeno fuzzy inference system with 36 rules, and the output.

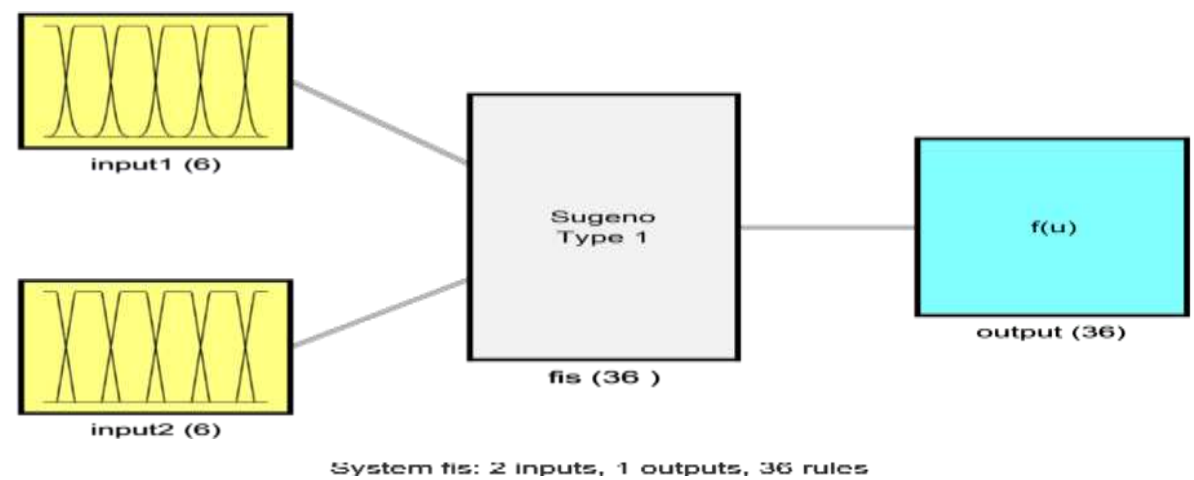


Figure 8: FIS structure of type-2 fuzzy MFs of the 2 input variables: H (Market potential) and TH (Market synergy).

RESULTS

Various metrics can evaluate the efficiency of a classifier or predictor, with preferences varying based on field objectives. In our data, the dependent variable y is labeled as 0 for successfully introduced services and 1 for failed ones. Out of 167 samples, 30 services have failed, marked by y=1.

In assessing the efficiency of a classifier or predictor, different metrics may be preferred, based on specific field objectives. In the dataset under analysis, the dependent variable y classifies services as either successful (0) or failed (1). Out of 167 samples, 30 services are marked as failures (y=1). This distribution is critical for evaluating the classifier's performance, especially in terms of sensitivity (ability to detect failures) and specificity (ability to identify successes). A good classifier should accurately distinguish between these categories, minimizing false positives and false negatives, to provide reliable support for decision-making processes in service introduction scenarios.

Following metrics to assess the proposed model's efficacy

False positive: A Type I error, also known as a False Positive (FP) error, arises when a successful service (y=0) is mistakenly classified as failed (y^=1). It is calculated as: (FP Rate = (count of FP/total samples of class 0) ×100).

False negative: A Type II error, or a False Negative (FN) error, takes place when a failed service (y=1) is misclassified as successful (y^=0). It is measured as: (FN Rate = (count of FN/total samples of class 1) × 100).

False weighted average: The Weighted Average False Error is the mean of the two aforementioned errors, each given an equal weight: ((FP rate 0.5+FN rate0.5) * 100).

True positive: The accuracy for class 0, known as True Positive (TP), is (TP Rate= (correct classifications for class 0/total samples of class 0) × 100).

True negative: The accuracy for class 1, referred to as True Negative (TN), is determined as (TN Rate= (correct classifications for class 1/total samples of class 1) × 100).

Accuracy of both classes weighted: The combined weighted accuracy for both classes is ((TP rate for class 00.5+TN rate for class 1 × 0.5) × 100).

Overall accuracy: The Overall Accuracy, which evaluates the proportion of all correctly classified services, is ((accuracy of class 0+accuracy of class 1)/total samples) × 100.

The Odds Ratio (OR) is a statistical measure used to assess the likelihood of a particular outcome, calculated as (OR) = (TP/FP)/ (TN/FN) = (TP×FN)/(FP×TN). It evaluates the probability of a service being classified as successful (class 0) over being deemed as failed (class 1). An OR greater than 1 indicates a higher chance of a service being assigned to class 0, signifying successful classification. An Odds Ratio (OR) of exactly 1 implies an equal probability of classification into either class, reflecting no particular bias or advantage in the classification process. Conversely, an OR less than 1 suggests a diminished likelihood of a service falling into class 0, indicating a tendency towards the classification as having failed. This measurement is essential for understanding the predictive power and bias of classification models in practical scenarios [89,90].

Table 3 reveals the performance of out-of-sample classifications, distinguishing between accurate and inaccurate results for two classes. In class 0 (successful services), there are 66 accurately classified instances, and 2 misclassifications where successful services are incorrectly marked as failures. Conversely, class 1 (failed services) shows 13 correct classifications of failure, with 2 services erroneously identified as successful. This data indicates a high degree of accuracy in identifying successful services, albeit with a small error rate. However, the error in classifying failed services, though equal in number, could imply a critical area for improvement given the potentially higher stakes of misclassifying failures.

Table 3: Classification of success or failure in an out-of-sample context.

	Class 0 (Positives)	Class 1 (Negatives)	Sum
Class 1 (reject/ negatives)	2 (false positives/ wrong/type 1=true but rejected)	13 (true negatives/ correct)	15
Class 0 (correct/ positives)	66 (true positives/ correct)	2 (false negatives/ wrong/ type 2=false but accepted)	68
Sum	68	15	83

Table 4 showcases the out-of-sample error percentages. False positives (correct instances but labelled as incorrect) stand at 2.94%, while false negatives (incorrect instances but labelled as correct) are at 13.33%. The weighted average error for both classes, considering incorrect classifications, is 8.13%. This average error is computed by averaging the two error percentages, with each given an equal weight of 0.5.

Table 4: Measurement of erroneous classifications.

Method	**Percentage error of False Positive (type I=True but rejected it) %**	**Percentage error of False Negative (type II=False but accepted it) %**	**False weighted average%**
Type-2 Fuzzy	2.94	13.33	8.13

The model under discussion employs a classification accuracy derived inversely from the rate of false errors, an approach that effectively highlights its predictive strength. (Table 5) provides a detailed breakdown of out-of-sample accuracy rates for the proposed model, demonstrating robust performance across different service classes. Specifically, the model achieves an impressive accuracy rate of 97.09% for services classified within class 0. This high rate indicates that nearly all services that were meant to be in class 0 are correctly identified, underscoring the model's effectiveness in recognizing attributes or outcomes specific to this group.

For class 1, the accuracy slightly dips to 86.67%, which, while lower than that of class 0, still represents a significant majority of services being correctly identified in this category. This variance between classes may reflect differing complexities or characteristics inherent to the services within class 1 that make accurate classification more challenging.

The model's combined weighted accuracy across both classes is calculated at 91.86%, which is a robust figure affirming the model's overall reliability in handling diverse datasets. The comprehensive accuracy rate, considering all samples from both classes, reaches an even higher mark at 95.81%, indicating a high level of predictive accuracy overall.

Additionally, the model boasts an odds ratio of 5.07, significantly above 1, which strongly suggests that a new service is over five times more likely to be correctly classified as belonging to class 0 rather than being misclassified. This odds ratio not only reinforces the model's effectiveness but also highlights its practical utility in scenarios where accurate initial classification is critical for subsequent analytical or operational processes.

Comparative analysis of the type-2 fuzzy algorithm

In evaluating the effectiveness of the Type-2 Fuzzy algorithm, a comprehensive analysis was conducted, comparing it to a range of established predictive models using the same dataset referenced by Atsalakis SG and Kitsios F [67]. This comparative study focused primarily on the overall error rate, providing a quantitative measure of each model's forecasting accuracy.

The models included in the comparison encompass a variety of statistical and machine learning techniques. These are: Linear Discriminant Analysis (LDA), Logistic Regression (LR), the k-Nearest Neighbours algorithm (k-NN), Proximal Support Vector Machines with both linear and Radial Basis Function (RBF) kernels (LPSVM, RPSVM), Classification and Regression Trees (CART), and the UTADIS method as detailed by Kitsios et al., [70]. The study also incorporated comparisons with models described by Atsalakis and Kitsios and McNelis, such as Neural Networks, Probit Regression, Weibull Distribution, Gompit, and the Adaptive Neuro-Fuzzy Inference System (ANFIS) as proposed by Atsalakis et al., [66,67,91].

This diverse array of models provides a robust framework for evaluating the Type-2 Fuzzy algorithm's performance. Each model brings distinct methodologies and assumptions into play, which affects their handling of data complexity and error sensitivity. The comparison is vital to ascertain which models deliver the most reliable forecasts and under what conditions they excel or falter.

The summarized results in Table 6 of the comparative analysis reveal how each model ranks in terms of error classification, offering insights into their operational strengths and weaknesses. By benchmarking the Type-2 Fuzzy algorithm against these varied approaches, we gain a clearer understanding of its relative efficacy and applicability in predictive modelling, particularly in environments where capturing complex, nonlinear relationships is crucial for accurate forecasting. This comparison not only highlights the algorithm's performance but also provides guidance on selecting appropriate models for specific predictive tasks in various fields.

Table 6: Comparative error measures.

Method	Success %	Failure %	Overall error %
LDA	10.79	37.13	15.74
LR	10.95	42.46	16.87
k-NN	16.14	23.73	17.57
LPSVM	12.1	35.53	16.5
RPSVM	12.15	26.22	14.8
CART	13.04	29.31	16.09
UTADIS	6.87	35.2	12.19
NN	7.35	33.33	12.05
Probit	10.29	46.67	16.87

Weibull	11.76	46.67	18.07
ANFIS	4.41	26.67	8.43
Type-2 Fuzzy	2.94	13.33	8.13

The Type-2 Fuzzy algorithm stands out among various forecasting models for its exceptional accuracy and minimal error rate. Recording the lowest overall error at 8.13% and a high overall accuracy of 95.81%, this algorithm demonstrates superior performance in forecasting tasks. The effectiveness of the Type-2 Fuzzy algorithm can be attributed to the synergistic combination of type-2 fuzzy logic and Particle Swarm Optimization (PSO). This integration leverages the strengths of both methods, enhancing the model's forecasting capabilities.

The primary advantages of the Type-2 Fuzzy algorithm lie in its ability to manage nonlinearity and its strong structural knowledge representation. These features allow it to model complex systems more effectively than other forecasting approaches, which may struggle with nonlinear data or require simplifications that strip away valuable information. Additionally, the adaptive capability of the Type-2 Fuzzy algorithm enhances its practical application, enabling it to adjust to new data or seamlessly changing conditions.

Moreover, the algorithm excels in areas where qualitative analysis is essential particularly in systems, where human reasoning and decision-making play significant roles. Traditional methods might fail to capture these subtleties effectively, but the Type-2 Fuzzy algorithm can integrate and analyze qualitative data, providing a more nuanced and comprehensive forecasting tool. This makes it particularly valuable in fields where conventional quantitative models cannot fully grasp the complexity of human-centered dynamics.

DISCUSSION

The failure of new services can lead to significant adverse impacts on a company's financial health and its capacity to meet business goals. Implementing a forecasting tool for the launch of new services is crucial for minimizing the risk of business failure. Given the importance of such innovations in this field, the development of accurate forecasting models for new services is critical.

Despite their significant value to decision-makers, there is a scarcity of empirical research focused on such forecasting models. Addressing this gap in the literature, the first hybrid model utilizing a type-2 fuzzy algorithm optimized by particle swarm optimization has been developed and tested through several trial-and-error iterations to optimize the prediction of a new service's success. This model represents a pioneering effort to enhance decision-making accuracy by providing robust tools capable of navigating the complexities and uncertainties inherent in launching new services.

The results affirm that the proposed Type-2 Fuzzy algorithm model is a robust tool for supporting decision-making in forecasting the success of new services launched by hotels. Fuzzy logic, when applied to forecasting models, allows researchers to encapsulate the qualitative elements of human reasoning and decision-making processes. The adaptive capabilities inherent in these models, especially when combined with optimization techniques, have facilitated the creation of hybrid type-2 fuzzy models. These models obviate the need for expert input or knowledge acquisition methods typically required to formulate 'if-then' rules and membership functions.

The Type-2 Fuzzy algorithm possesses several unique properties that enhance its utility and effectiveness. Specifically, it is distinguished by its capacity to learn and adapt over time, perform parallel operations to expedite processing, represent knowledge in a structured manner, and integrate seamlessly with other design methodologies, underscoring the algorithm's potential to improve forecasting accuracy and reliability in complex, dynamic environments such as the hospitality industry. Additionally, this paper broadens the application scope of fuzzy logic and Particle Swarm Optimization (PSO). The proposed hybrid optimization model employs a parallel operational framework and optimal integration strategies to develop a fuzzy type-2 model that skillfully mimics the dynamic variations in the success of new services. This approach particularly emphasizes the ability of fuzzy rules to effectively manage the uncertainties associated with the dynamic behavior inherent in launching new services.

The methodology outlined here facilitates a precise prediction of a new service's success without relying on prior assumptions. It presents a model-free, straightforward implementation strategy, distinguishing itself by employing a single-fitting procedure that adapts to nonlinear data without necessitating a predefined formal model. This feature is especially beneficial as it eliminates the requirement for researchers to possess a priori knowledge about the empirical relationships between the inputs and outputs of the model.

This model's design enhances flexibility and adaptability in research, offering a potent tool for decision-makers who require reliable forecasts but may lack detailed preliminary information about the factors influencing the success of new services. The fuzzy type-2 algorithm's ability to function effectively under such conditions underscores its suitability as an excellent forecasting tool in environments marked by high uncertainty and variability.

Moreover, the results generated by the proposed model are easily interpretable, thanks to the 'if-then' rule knowledge base embedded within it. This characteristic not only simplifies the understanding of the model's outputs but also highlights the significant value of the proposed system. The integrated synergies within the system adeptly capture the non-linear dynamics involved in launching new services, providing a nuanced understanding of the complexities at play.

In a broader context, this study offers a bridge between academic research and practical application, presenting a powerful resource for end-users. This tool can be effectively utilized to deal with the successful application of new services and to diminish the risks associated with uncertainty. By aligning academic insights with practical needs, the model serves as a valuable resource for both scholars and industry professionals, facilitating better decision-making processes and enhancing the likelihood of successful new service launches.

CONCLUSION

The purpose of this paper is to apply a hybrid method that merges fuzzy type-2 set theory with Particle Swarm Optimization (PSO) to assess data on new services in the tourism sector, aiming to predict successful launches of services in hotels. The model is developed from empirical data, ensuring it remains unaffected by the subjective and often vague judgments which are typical of uncertain environments. For this research, raw data from 167 new services were analyzed using a Type-2 Fuzzy

algorithm, evaluating the potential success of these services. The findings demonstrate that the input reduction strategy and the application of this model achieved an impressive accuracy rate of 95.81%.
This comparative analysis highlights the diverse capabilities of various forecasting models. The Type-2 Fuzzy algorithm, with its low error rate and high accuracy, shows substantial promise, especially in settings where traditional methods falter due to nonlinearity and uncertainty. By benchmarking it against other models using real-world datasets, stakeholders can make informed decisions about which model best suits their needs, balancing complexity, accuracy, and interpretability.
This research represents a significant step forward in the NSD literature, particularly in the underexplored area of tourism services. By addressing the lack of specialized forecasting models in this sector, this paper not only contributes to academic knowledge but also offers practical tools that can benefit industry stakeholders, practitioners, academicians, researchers, and policymakers who are involved in launching new services in the tourism sector, right from the planning phase.
Future research could build on this work by exploring specific applications of these models in different types of tourism services, such as eco-tourism, luxury tourism, and cultural tourism, among others, further refining the effectiveness and applicability of forecasting models in this vital sector.

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