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A Mathematical Fuzzy Model for Syntax-Pragmatics Interface

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ABSTRACT

This study proposes a novel fuzzy grammar model to analyze the syntax-pragmatics interface by integrating fuzzy logic into linguistic evaluation. Traditional binary models of grammaticality fail to capture the graded acceptability observed in natural language, where subtle variations in syntactic structure and contextual cues interact to determine overall language performance. Our approach normalizes Likert-scale ratings of syntactic well-formedness and pragmatic appropriateness into fuzzy membership values, enabling a continuous representation of linguistic acceptability. The model employs fuzzy membership functions—primarily using linear normalization—and aggregates syntactic and pragmatic scores using the minimum operator to reflect the principle that a sentence is as acceptable as its weakest component. A small experimental

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dataset comprising five sentences was used to illustrate the model's implementation, where descriptive statistics, visual bar charts, and fuzzy inference outputs demonstrated that sentences with inconsistent syntactic and pragmatic ratings yield lower overall acceptability. The results underscore fuzzy logic's efficacy in distinguishing borderline cases and capturing the nuanced interplay between formal structure and context-sensitive meaning. This integrative framework not only extends theoretical insight into language processing but also offers promising applications in natural language processing, language education, and cross-linguistic studies. Future research should empirically validate the model with larger datasets and explore alternative fuzzy aggregation strategies.

Keywords: Fuzzy Grammar; Fuzzy Logic; Linguistic Acceptability; Graded Linguistic Phenomena; Membership Functions; Aggregation Operator; Natural Language Processing; Education and Process Innovation

1. Introduction

1.1. Background and Importance of the Syntax-Pragmatics Interface

The **syntax-pragmatics interface** concerns the ways in which syntactic structure (i.e., the formal arrangement of words and phrases) interacts with the contextual and interpretative aspects of language use, referred to broadly as pragmatics. While syntactic theories typically focus on the hierarchical, rule-governed properties of sentence formation, pragmatics deals with how utterances are understood in context, incorporating elements such as speaker intention, conversational implicatures, and shared knowledge among interlocutors [1, 2].

Traditional generative models often draw a clear distinction between syntax (a purely formal system) and pragmatics (an interpretative layer), but it has long been recognized that the boundary between syntax and pragmatics can be blurred, especially in phenomena such as ellipsis, referential ambiguity, and optional movement [3, 4]. For instance, whether particular parts of a sentence are explicit or implicit may be determined by not only grammatical constraints but also context-dependent factors.

In the last few decades, graded phenomena and borderline cases have attracted more and more attention — for example, in sentences that seem grammatical in certain pragmatic contexts only, but ungrammatical in all others [5, 6]. The syntactic complexity recovered in these studies would benefit from an approach that can model partial or uncertain membership to grammatical categories. Fuzzy logic, as put forth by Zadeh [7, 8], provides a mathematical structure for dealing with such fuzzy boundaries, and can bring together syntactic and pragmatic insights under one roof.

1.2. Motivation for Applying Fuzzy Logic to Linguistic Analysis

Fuzzy logic is significant in this scenario due to its capacity to display and apply indecisive, obscure, or fuzzy linguistic data through membership functions that assigns each member some element in the continuous interval [0,1] rather than confusing members with a binary attribution [9, 10]. This is particularly the case for language, where many constructs, such as grammatical categories, discourse markers and contextual cues, are not straightforward to untangle.

Applied to the syntax-pragmatics interface, fuzzy logic may help address questions like:

- To what extent does a particular utterance conform to syntactic rules under varying contextual conditions?
- How can we systematically measure degrees of grammatical acceptability influenced by pragmatic context?
- Can borderline syntactic structures be formalized mathematically to accommodate speaker-listener divergences in interpretation?

By assigning partial membership rather than purely binary values to syntactic structures (e.g., partially acceptable sentences) and contextual features (e.g., partially relevant contexts), researchers can quantitatively capture the gradual transition between clearly grammatical and clearly ungrammatical constructions. This approach to interpretation also provides an avenue for empirical investigations into linguistic variation, second language learning, and cross-linguistically [9, 11–13].

1.3. Objectives and Research Questions

The proposed model is a mathematical fuzzy model for systematically combining syntactic and pragmatic factors, yielding graded as well as context-sensitive interpretability. The overall goals are:

(i) Giving Strict Meaning to Title Constructs

- A fuzzy logic set-theoretic model is presented to capture syntactic structures with partial memberships.
- Fuzzy grammar model enriched with pragmatic constraints such as discourse context or speaker intention.

(ii) Interactions between Syntax and Pragmatics

- Consider fuzzy membership functions to map interactions within the syntax-pragmatics interface (including borderline acceptability).
- Compare these fuzzy representations with classical categorical models in terms of how they capture linguistic variation.

(iii) A Case Study for Empirical Validation

- Experimental case-study of rating test sentences' grammatical acceptability given different contextual cues.
- Compare the predictions given by the fuzzy model with actual human judgments to measure its descriptive and predictive accuracy.

From these objectives, the main research questions arise:

- **RQ1:** How effective are fuzzy membership functions in explaining gradience in syntactic acceptability under different pragmatic contexts?
- **RQ2:** Can a fuzzy grammar model better account for borderline or ambiguous syntactic constructions than traditional binary models?
- **RQ3:** What are the implications of modeling syntax-pragmatics interactions using fuzzy logic for broader linguistic theory and language education?

To illustrate and validate the proposed framework, we design an **experimental case study** involving a set of sentences that exhibit varying levels of grammatical acceptability depending on contextual information. Participants (native and non-native speakers) will be asked to judge sentence acceptability under different pragmatic settings—e.g., informal conversation vs. formal written context, or minimal context vs. enriched context. These judgments will be numerically coded and used to derive fuzzy membership functions.

Figure 1 is a simple example diagram showing the conceptual flow from raw judgments to fuzzy membership functions.

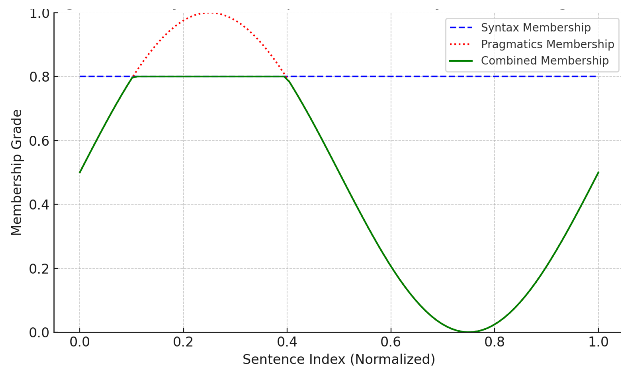

Figure 1. Fuzzy Membership Functions for Syntax and Pragmatics.

Figure 1 illustrates small experimental syntax and pragmatics membership functions (both ranging from 0 to 1), and a combined membership using a basic fuzzy AND (minimum) operator. The combined membership highlights the interplay between syntactic constraints and pragmatic appropriateness.

By outlining the methodology and mathematical underpinnings early on, subsequent sections of this study will delve into detailed model construction, formal proofs, and empirical validation steps. Ultimately, **a mathematical fuzzy model** for the syntax-pragmatics interface not only enriches our understanding of linguistic theory but also paves the way for more nuanced computational tools in language technology and pedagogy[14, 15].

2. Literature Review

2.1. The Syntax-Pragmatics Interface: Theoretical Perspectives

The **syntax-pragmatics interface** has been widely studied in both formal and functional linguistic traditions, focusing on how context-dependent interpretative mechanisms can interact with structural sentence formation. Generative approaches often place syntax as a core computational system, with pragmatics considered an external module that evaluates structural output for appropriateness in discourse[3, 16, 17]. In contrast, functional and cognitive linguistics highlight how syntactic constraints may be shaped or even overridden by speakers' communicative goals[6, 18, 19]. Recent work has explored fuzzy boundaries in syntactic variation[13, 20], further motivating our model's development.

Mathematically inclined studies on the interface emphasize the importance of logical form and truth-conditional semantics (which belong to syntax/semantics) merging with contextual inference (pragmatics). For instance, dynamic frameworks employ **state-transition systems** to capture the evolving information states as conversation unfolds. To do so, they are often formalized as sets and functions working over discourse contexts, often augmented with multi-valued or fuzzy parameters to handle uncertainly[21, 22].

From a fuzzy logic viewpoint, the interface does not act as a strict division between acceptability, and partial grammaticality is sensitive to degrees of pragmatic appropriateness[11]. A borderline construction can then be considered relatively high in its syntactic membership, but relatively low in its pragmatic membership: to be a net average acceptable[23]. This cartoon picture is compatible with empirical evidence that shows that native speakers exhibit gradient sensitivities to context when they evaluate borderline grammatical cases[16].

2.2. Principles and Applications of Fuzzy Logic

The proposition assertion values in fuzzy systems can lie between 0 (false) and 1 (true), which was initiated by Zadeh (1965)[8]. Since then, fuzzy logic has been applied to a diverse range of linguistic tasks, including phoneme categorization[24], lexical disambiguation[25], and discourse processing[26]. In fuzzy-set theory, each linguistic element x can be represented by a membership function $\mu_{A(x)} \in [0, 1]$, where the value indicates how much x belongs to the fuzzy set A; whereas in classical set theory, an element does not belong at all, or belongs fully.

Mathematical Underpinnings

(i) Fuzzy Membership Functions

- The examples include triangular, trapezoidal, Gaussian, and sigmoidal functions[19].
- For linguistic categories, one might define a trapezoidal membership function to capture a core region of maximum membership and two sloping edges of partial membership.

(ii) Fuzzy Operations

- **Fuzzy Intersection (AND):** $min\left\{\mu_{A(x)}, \mu_{B(x)}\right\}$
- **Fuzzy Union (OR):** $max\left\{\mu_{A(x)}, \mu_{B(x)}\right\}$
- **Fuzzy Complement (NOT):** $1-\mu_{A(x)}$

These operations allow flexible combination of sets corresponding to multiple linguistic features—such as syntactic constraints and pragmatic cues—where partial fulfilment of each criterion yields an intermediate membership in a combined set[21].

(iii) Implications for Syntax-Pragmatics

- Linguistic features like degree of formality or speaker intent can be transformed into membership values.
- By combining these membership values with syntactic constraints (also expressed in fuzzy terms), one obtains a **graded** acceptability score for utterances[11].

Figure 2 visualizes the difference between **classical** and **fuzzy** membership distributions for a small experimental linguistic category (e.g., wh-question formation).

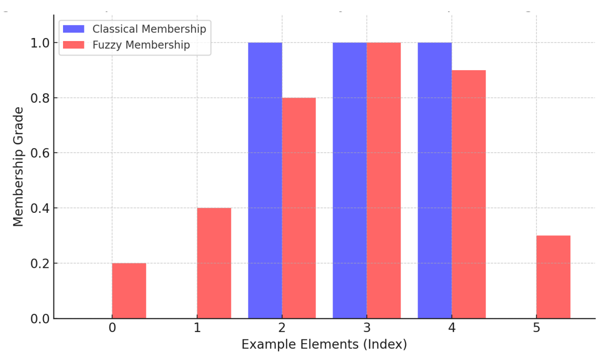

Figure 2. Comparison of Classical vs. Fuzzy Membership in a Linguistic Category.

Figure 2 illustrates a side-by-side comparison of experimental classical and fuzzy membership values for six discrete items. While the classical distribution assigns only 0 or 1, the fuzzy set allows for partial degrees of membership, offering a more nuanced representation of linguistic phenomena.

2.3. Review of Mathematical Models in Linguistics

Mathematical linguistics applies formal methods such as set theory, automata theory, and type-logical frameworks to analyze language structure[16]. Early models often pursued fully discrete formulations (e.g., context-free grammars, unification-based parsing, Montague grammar) with clear-cut boundaries between well-formed and ill-formed strings[19].

However, natural languages frequently exhibit **gradient acceptability**, **variability**, and **contextual sensitivity**, which purely discrete models struggle to capture[21]. As a response, researchers have introduced **probabilistic** or **stochastic** extensions, such as probabilistic context-free grammars (PCFGs), to model the likelihood of different parses[11]. While these probabilistic approaches capture frequency-based generalizations, they do not inherently address fuzzy phenomena where grammaticality is context-dependent in a non-binary, non-random manner.

In contrast, **fuzzy grammar models** propose a continuous-valued membership mechanism for syntactic rules and constraints. Instead of strictly classifying structures as grammatical or ungrammatical, fuzzy grammars assign grades of well-formedness based on rule satisfaction[26, 27]. When combined with pragmatic factors—also expressed as fuzzy constraints—researchers can formally represent linguistic utterances at the borderline of acceptable usage. This synergy points to a new frontier of integrated syntax-pragmatics modeling.

2.4. Identified Gaps and the Need for a Fuzzy Grammar Approach

Despite advancements in combining **formal syntax** with **pragmatic** inference, several gaps remain:

- **Over-Reliance on Binary Judgment:** Traditional generative and even probabilistic models often rely on binary or discrete distinctions between grammatical and ungrammatical structures. They rarely account for marginal cases or contextually driven variability that are prevalent in everyday language use[16].
- **Insufficient Pragmatic Integration:** Many existing models treat pragmatics as a separate post-syntactic filter. However, recent psycholinguistic evidence suggests that pragmatic factors interact with syntax in real-time processing, reinforcing the need for a unified approach[19].
- **Lack of Systematic Graded Frameworks:** While certain gradient acceptability studies use scalar judgments, they lack robust mathematical tools to represent intermediate steps between fully acceptable and unacceptable. Fuzzy logic, with its membership functions, can fill this gap[21].
- **Limited Quantitative Evaluation of Contextual Effects:** Even in corpus-based studies, contextual influences on grammaticality are often handled qualitatively. A fuzzy model can provide a quantitative basis for evaluating how context modulates syntactic acceptability[11].

Hence, the literature strongly points toward **fuzzy grammar** as a promising solution. By allocating continuous membership values for syntactic rules and contextual constraints, a fuzzy approach captures the graded, contextually influenced nature of natural language. This perspective not only enriches linguistic theory but also supports broader applications in computational linguistics, language education, and AI-driven language assessment.

3. Theoretical Framework and Model Development

In this section we present the mathematical underpinnings of our fuzzy grammar approach, systematically developing the model from foundational principles to its final formulation. We begin with a review of fuzzy set theory and logic, then illustrate how syntactic structures and pragmatic variables can be mathematically represented before converging these components into a unified fuzzy grammar model.

3.1. Fundamentals of Fuzzy Set Theory and Fuzzy Logic

Fuzzy set theory extends classical set theory by allowing elements to have degrees of membership. For any universe U, a fuzzy set A is characterized by a membership function:where $\mu_A(x)$ indicates the degree to which element $x \in U$ belongs to A[28]. This formulation contrasts with classical sets, where membership is binary (0 or 1).

Key components include:

(i) Fuzzy Membership Functions:

Membership functions can take various forms such as triangular, trapezoidal, Gaussian, or sigmoidal. For example, a trapezoidal function is given by:

$$\mu_{\mathrm{A}}(x) = \begin{cases} 0, & x < a \\ \frac{x-a}{b-a}, & a \leq x < b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c < x \leq d \\ 0, & x > d \end{cases} \quad (1)$$

where a, b, c, and d define the boundaries of increasing, full, and decreasing membership [9].

(ii) Fuzzy Logical Operators:

These operators combine fuzzy sets and include:

- Intersection (AND):

$$\mu_{A\cap B}(x) = min\left\{\mu_A(x), \mu_B(x)\right\} \quad (2)$$

- Union (OR):

$$\mu_{A\cup B}(x) = max\left\{\mu_A(x), \mu_B(x)\right\} \quad (3)$$

- Complement (NOT):

$$\mu_{\neg A}(x) = 1 - \mu_A(x) \quad (4)$$

Such operators facilitate the combination of multiple linguistic dimensions (e.g., syntactic and pragmatic factors) in a mathematically tractable way [28].

3.2. Defining Syntactic Structures Using Mathematical Constructs

Syntactic structures, which are traditionally represented via tree diagrams or formal grammars (e.g., $G = (N, T, P, S)$, where N is the set of non-terminals, T the set of terminals, P the production rules, and S the start symbol), can also be embedded within a fuzzy framework.

We propose representing each syntactic rule $r_i \in P$ with an associated membership function $\mu_{syntax\ i}(s)$ that evaluates how well an utterance s satisfies the rule. For a given structure, a composite syntactic membership $\mu_{syntax}\ (s)$ may be modeled as an aggregation of individual rule memberships:

$$\mu_{syntax}(s) = F(\mu_{syntax_1}(s), \mu_{syntax_2}(s), \ldots, \mu_{syntax_n}(s)) \quad (5)$$

where F is an aggregation operator (e.g., minimum, product, or weighted average) chosen according to the theoretical needs of the model [29].

This formulation enables the treatment of syntactic well-formedness as a graded quality rather than a binary attribute. In practical terms, even if a sentence violates one or more syntactic rules, it may still hold a non-zero overall syntactic membership if other rules are largely satisfied.

3.3. Incorporating Pragmatic Variables: Contextual Ambiguity and Graded Meanings

Pragmatic factors-including context, speaker intent, and discourse-level implications-can be represented mathematically by defining fuzzy membership functions for each pragmatic dimension. Let pp denote a pragmatic variable (e.g., context appropriateness), then its impact on an utterance s can be modeled as:

$$\mu_{pragmatics}(s, p) = f(p, s) \quad (6)$$

where f is a function that maps the pragmatic input and the linguistic features of s onto the interval $[0, 1]$. For instance, contextual cues such as politeness levels or formality may not be binary; instead, they exhibit degrees which can be captured using fuzzy sets.

A weighted aggregation of these pragmatic components can be expressed as:

$$\mu_{pragmatics}(s) = \sum_{j=1}^{m} w_j \cdot \mu_{p_j}(s) \quad (7)$$

where $\mu_{p_j}(s)$ are the membership functions for different pragmatic aspects and w_j are pegghts reflecting their relative importance [30].

The fuzzy treatment of both syntax and pragmatics reflects the linguistic reality that meanings and grammatical acceptability are sensitive to subtle, context-dependent variations, making it possible to compute nuanced degrees of acceptability for any given utterance.

Figure 3 is an example diagram illustrating the integration of multiple pragmatic variables into a single pragmatic membership function.

Figure 3 demonstrates how distinct pragmatic variables such as formality and contextual relevance can be combined using weighted aggregation. The resulting pragmatic membership function (in green) reflects the integrated influence of multiple contextual factors on linguistic interpretation.

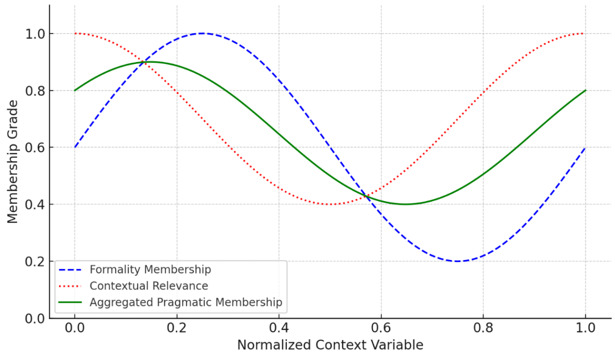

Figure 3. Aggregation of Pragmatic Variables into a Membership Function.

3.4. Formulation of the Fuzzy Grammar Model for the Syntax-Pragmatics Interface

The final stage of our theoretical development is the integration of syntactic and pragmatic models into a comprehensive fuzzy grammar model. The overall grammatical acceptability of an utterance s can be represented by a combined membership function:

$$\mu_{grammar}(s) = \Phi(\mu_{syntax}(s), \mu_{pragmatics}(s)) \quad (8)$$

where Φ is a fuzzy aggregation operator. One common formulation is the fuzzy intersection (using the minimum operator):

$$\mu_{grammar}(s) = min\{\mu_{syntax}(s), \mu_{pragmatics}(s)\} \quad (9)$$

This formulation implies that the overall grammaticality of a sentence is determined by its weakest dimension. Alternatively, a weighted product or average can be used if one wishes to account for compensatory effects between syntax and pragmatics:

$$\mu_{grammar}(s) = \alpha \cdot \mu_{syntax}(s) + (1–\alpha) \cdot \mu_{pragmatics}(s) \quad (10)$$

with $\alpha \in [0, 1]$ controlling the relative influence of the syntactic component[31].

To conceptualize the overall model, consider **Figure 4** that integrates the core components of our fuzzy grammar approach:

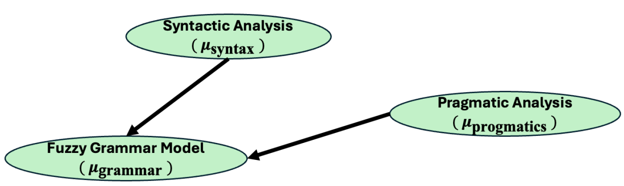

Figure 4. Conceptual Framework of the Fuzzy Grammar Model.

Figure 4 outlines the structure of our fuzzy grammar model. Individual modules for syntactic and pragmatic analysis, represented by their respective membership functions, feedinto the central model which computes the overall grammatical acceptability using a fuzzy aggregation operator.

By fusing the mathematical representations of syntax and pragmatics within a fuzzy logic framework, our model provides a nuanced, quantitative measure of language acceptability. This integrated approach enables us to capture the graded, context-dependent nature of natural language more faithfully than traditional binary or solely probabilistic models[32].

4. Methodology: Experimental Case Study

This section outlines the experimental design to validate our fuzzy grammar model via a small, experimental dataset. We detail every step—from research design through data coding and operationalization—using explicit mathematical calculations to demonstrate how fuzzy membership values are derived and combined.

4.1. Research Design and Rationale for a Case Study Approach

The case study approach was chosen because it allows an in-depth analysis of the syntax-pragmatics interface on a manageable, experimental corpus[33]. This detailed experimental setup enables us to:

- **Examine Borderline Linguistic Cases:** Investigate sentences that are neither fully grammatical nor entirely ungrammatical; such cases provide a fertile ground for fuzzy analysis.
- **Quantitatively Test the Fuzzy Model:** By employing a small dataset, we can compute fuzzy membership values for both syntactic and pragmatic features and then aggregate these values mathematically. This approach permits detailed step-by-step verification of our model's predictive accuracy.
- **Control Contextual Variables:** A limited dataset allows us to experimentally manipulate and measure contextual (pragmatic) variations to observe their influence on overall grammatical acceptability.

The rationale for this experimental design centers on the need for a controlled demonstration of how fuzzy membership functions can elucidate graded linguistic phenomena, bridging the traditional gap between binary syntactic evaluations and context-sensitive pragmatic judgments [34].

4.2. Data Selection and Corpus Description

For the purpose of this case study, we designed an experimental corpus consisting of a small set of five sentences. Each sentence was carefully selected to represent different degrees of syntactic well-formedness and pragmatic appropriateness. The corpus includes examples such as structurally simple sentences, inverted word order, and sentences where contextual cues critically affect interpretation. **Table 1** presents five example sentences along with their syntactic and their parameters for fuzzy values.

Experimental Dataset Details:

- **Sentence Text:** A short utterance reflective of everyday language.
- **Contextual Condition:** Although not explicitly shown in **Table 1**, each sentence was evaluated under a particular context (e.g., informal dialogue vs. formal writing).
- **Syntactic and Pragmatic Ratings:** Each sentence received a rating on a Likert scale from 1 (poor) to 7 (excellent) for both syntactic acceptability and pragmatic appropriateness, following established linguistic judgment procedures [35].

Table 1. Experimental Dataset of Sentence Ratings and Fuzzy Membership Values.

Sentence ID	Sentence Text	Syntactic Rating	Pragmatic Rating (1–7)	Syntax Membership	Pragmatics Membership	Combined Membership
S1	The cat sat on the mat.	6	5	0.8333	0.6667	0.6667
S2	On the mat sat the cat?	3	4	0.3333	0.5	0.3333
S3	The dog chased the ball in the park.	5	6	0.6667	0.8333	0.6667
S4	In the park, the ball was chased by the dog.	7	7	1	1	1
S5	Despite the rain, she managed to complete the run.	4	3	0.5	0.3333	0.3333

4.3. Criteria for Coding and Annotating Syntactic and Pragmatic Features

Coding Procedure:

(i) Rating Scales:

- **Syntactic Acceptability:** Raters assess each sentence based on formal syntactic criteria (e.g., word order, grammatical structure, subject-verb agreement) on a Likert scale from 1 (completely ungrammatical) to 7 (perfectly grammatical).
- **Pragmatic Appropriateness:** Raters evaluate context-dependent factors such as tone, register, and relevance of contextual cues using the same 1–7 scale.

(ii) Normalization:

- To incorporate fuzzy logic, each rating is normalized to yield a membership value in the interval $[0, 1]$ via the formula:

$$\mu = \frac{(Rating–1)}{6} \tag{11}$$

- Example Calculation:

For a syntactic rating of 5:

$$\mu_{syntax} = \frac{5–1}{6} = \frac{4}{6} \approx 0.67 \tag{12}$$

Similarly, a pragmatic rating of 4 yields:

$$\mu_{pragmatics} = \frac{4–1}{6} = \frac{3}{6} = 0.5 \tag{13}$$

(iii) Annotation Protocols:

- **Annotation Guidelines:** Detailed instructions are provided to raters so that differences in syntactic and pragmatic judgments can be quantitatively captured. For instance, a sentence with non-standard word order may receive a lower syntactic rating, while the same sentence might receive a higher pragmatic rating if the context supports such structure.
- **Inter-rater Reliability:** Although our dataset is small, in a full-scale study, a statistical measure such as Cohen's Kappa would be computed to ensure consistency across raters.

(iv) Aggregation of Fuzzy Values:

- The combined fuzzy membership for a sentence is calculated via a fuzzy aggregation operator. In this study, we employ the **minimum operator**:

$$\mu_{grammar}(s) = \\ min\{\mu_{syntax}(s), \mu_{pragmatics}(s)\} \quad (14)$$

- Step-by-Step Example:
- For Sentence S1 with syntactic rating $6(\mu_{syntax} = \frac{6–1}{6} \approx 0.83)$ and pragmatic rating $5\left(\mu_{pragmatics} = \frac{5–1}{6} \approx 0.67\right)$:

$$\mu_{grammar}(S1) = min\{0.83, 0.67\} = 0.67 \quad (15)$$

This reflects that the overall acceptability is determined by the "weaker" dimension.

4.4. Operational Definitions for Key Constructs (Syntax, Pragmatics, and Fuzziness)

Syntax:

- **Definition:** Syntactic well-formedness is quantified as the degree to which a sentence conforms to conventional grammatical rules.
- **Mathematical Operationalization:** Each syntactic rule r_i is associated with a membership function $\mu_{syntax_i}(s)$. The overall syntactic membership for sentence s is aggregated across rules:

$$\mu_{syntax}(s) = min\{\mu_{syntax_1}(s), \\ \mu_{syntax_2}(s), \ldots, \mu_{syntax_n}(s)\} \quad (16)$$

For this case study, we simplify by using a single syntactic rating per sentence, normalized as shown above.

Pragmatics:

- **Definition:** Pragmatic appropriateness reflects the degree to which a sentence's usage fits the context-specific communicative goals and expectations.
- **Mathematical Operationalization:** Pragmatic evaluation is derived from contextual features encoded as membership Pragmatic evaluation is derived from contextual features encoded as membership functions $\mu_{p_j}(s)$. The aggregate pragmatic membership can be computed as a weighted average:

$$\mu_{pragmatics}(s) = \sum_{j=1}^{m} w_j \cdot \mu_{p_j}(s), \\ with \sum_{j=1}^{m} w_j = 1 \quad (17)$$

In our experimental setup, a single pragmatic rating is similarly normalized to yield a unified pragmatic membership value.

Fuzziness:

- **Definition:** Fuzziness in this context refers to the representation of linguistic acceptability as a continuum rather than as a dichotomy (grammatical/ungrammatical).
- **Mathematical Operationalization:** The fuzziness is operationalized through the continuous membership functions discussed above, where each rating is normalized to a value $\mu \in [0, 1]$. The overall grammatical acceptability of a sentence is computed by combining the syntactic and pragmatic memberships:

$$\mu_{grammar}(s) = \Phi(\mu_{syntax}(s), \\ \mu_{pragmatics}(s)) \quad (18)$$

As detailed earlier, one common choice for Φ is the minimum operator:

$$\mu_{grammar}(s) = min\{\mu_{syntax}(s), \\ \mu_{pragmatics}(s)\} \quad (19)$$

Step-by-Step Mathematical Calculation Example:
Consider Sentence S3 with:

- Syntactic Rating = 5

$$\mu_{syntax}(S3) = \frac{5–1}{6} \approx 0.67 \quad (20)$$

- Pragmatic Rating = 6

$$\mu_{pragmatics}(S3) = \frac{6–1}{6} \approx 0.83 \quad (21)$$

- Combined Membership using minimum operator:

$$\mu_{grammar}(S3) = min\{0.67, 0.83\} = 0.67 \quad (22)$$

This calculation method demonstrates how the overall judgment is sensitive to the lower membership value-highlighting the fuzzy approach's capacity to reflect conditional dependencies between syntax and pragmatics[36].

5. Model Implementation and Analytical Procedures

Building on the methodology outlined in the previous section, this part details how the fuzzy grammar model is **implemented** and **analysed** using a small, experimental dataset.

We illustrate step-by-step procedures for constructing membership functions, developing fuzzy rules, applying these rules to the selected corpus, and interpreting the results using appropriate metrics.

5.1. Constructing Membership Functions for Syntactic and Pragmatic Variables

Membership functions (MFs) are central to fuzzy logic systems. They translate numerical inputs (e.g., syntactic and pragmatic ratings) into continuous membership grades in [0,1]. For our case study, recall that we have 5 sentences with **Likert-scale** (1–7) judgments for syntax and pragmatics. Below are the steps to define suitable MFs.

(i) Normalization Approach

- As introduced earlier, each rating $r \in \{1, 2, ..., 7\}$ is normalized to

$$\mu(r) = \frac{r-1}{6} \tag{23}$$

- This transforms the discrete range $[1, 7]$ into the continuous interval $[0, 1]$.

(ii) Choice of MF Shape

- While a simple linear normalization suffices for demonstration, more sophisticated shapes (e.g., triangular, trapezoidal) can be chosen to reflect nuanced linguistic intuitions[37].
- For instance, if a rating of 4 is interpreted as a borderline case, one could define a triangular MF centered around $\mu = 0.5$. However, to keep the process transparent, we use straightforward linear mappings.

(iii) Example of Syntactic MF Calculation

- Suppose Sentence S2 has a syntactic rating of 3, then

$$\mu_{syntax}(3) = \frac{3-1}{6} = \frac{2}{6} \approx 0.33 \tag{24}$$

- This indicates a low syntactic acceptability.

Below is an illustrative code snippet that shows the plotted membership functions for syntax and pragmatics across the entire 1–7 scale:

Figure 5 shows how each discrete rating is mapped to a membership value $\mu(r)$ in [0,1]. A rating of 1 maps to 0, while 7 maps to 1.

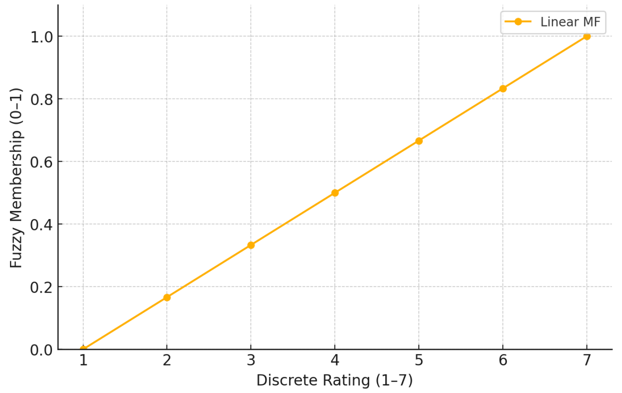

Figure 5. Linear Membership Function for Ratings 1–7.

5.2. Developing Fuzzy Rules to Represent Interactions between Syntax and Pragmatics

In fuzzy logic systems, **if-then** rules describe how membership values interact to produce an output[38]. For a **fuzzy grammar** model, we use rules reflecting the synergy between syntactic and pragmatic acceptability.

(i) General Form of Fuzzy Rules

IF syntax is HIGH AND pragmatics is MODERATE,

THEN grammar is MODERATELY ACCEPTABLE.

Each **linguistic label** (e.g., HIGH, MODERATE, LOW) is defined via a **membership function** on [0,1].

(ii) Rule Base for Syntax-Pragmatics Interface

Rule 1: IF μ_{syntax} is HIGH AND $\mu_{pragmatics}$ is HIGH, THEN $\mu_{grammar}$ is HIGH.

Rule 2: IF μ_{syntax} is HIGH AND $\mu_{pragmatics}$ is LOW, THEN $\mu_{grammar}$ is MEDIUM.

Rule 3: IF μ_{syntax} is LOW AND $\mu_{pragmatics}$ is HIGH, THEN $\mu_{grammar}$ is MEDIUM.

Rule 4: IF μ_{syntax} is LOW AND $\mu_{pragmatics}$ is LOW, THEN $\mu_{grammar}$ is LOW.

In practice, these labels (HIGH, LOW, MEDIUM) can be partitioned along the $[0, 1]$ axis. For simplicity in this case study, we often rely on the minimum operator:

$$\mu_{grammar}(s) = min\{\mu_{syntax}(s), \mu_{pragmatics}(s)\} \tag{25}$$

But one could implement more sophisticated rule bases using fuzzy inference systems (e.g., Mamdani or Sugeno) for finer gradations[39].

5.3. Application of the Fuzzy Model to the Selected Corpus

Recall our small experimental 5-sentence dataset (Section 4.2), each with a syntactic rating and a pragmatic rating. We apply the **linear normalization** to derive membership values

$\mu_{syntax}\ (s)$ and $\mu_{pragmatics}\ (s)$. Then, using the minimum operator to combine them, we obtain $\mu_{grammar}\ (s)$.

Below is an example calculation for Sentence S4:

(i) Syntactic Rating: 7

$$\mu_{syntax}\,(7) = \frac{7–1}{6} = 1.0 \tag{26}$$

(ii) Pragmatic Rating: 7

$$\mu_{pragmatics}\,(7) = \frac{7–1}{6} = 1.0 \tag{27}$$

(iii) Combined Grammar Membership (Min Operator):

$$\mu_{grammar}\,(S4) = min\,\{1.0, 1.0\} = 1.0 \tag{28}$$

This sentence is thus predicted by the fuzzy model to be fully acceptable both syntactically and pragmatically.

The membership values enable **finer-grained** interpretative insights than a simple "grammatical/ungrammatical" decision (**Table 2**)[40].

Table 2. Final Membership Values (Extending **Table 1** from Section 4.2).

Sentence ID	Syntax Rating	Pragmatic Rating	$\mu_{syntax(s)}$	$\mu_{pragmatics(s)}$	$\mu_{grammar(s)}$
S1	6	5	0.83	0.67	0.67
S2	3	4	0.33	0.50	0.33
S3	5	6	0.67	0.83	0.67
S4	7	7	1.00	1.00	1.00
S5	4	3	0.50	0.33	0.33

5.4. Analytical Techniques for Interpreting the Fuzzy Outputs

5.4.1. Evaluation Metrics and Performance Indicators

To assess how well our fuzzy grammar model aligns with human judgments, we can employ a combination of **statistical** and **linguistic** metrics[41]:

(i) Correlation Coefficient (r)

- If we have external human acceptability judgments on a continuous scale, we can measure the Pearson or Spearman correlation between the **fuzzy outputs** $\mu_{grammar(s)}$ and these **human judgments**.
- High correlation suggests that the fuzzy model effectively captures variation in perceived acceptability.

(ii) Mean Squared Error (MSE)

- If the model is used to predict acceptability scores (e.g., from 0 to 1) and we have gold-standard labels from a separate set of linguistic experts, we can measure:

$$MSE = \frac{1}{n}\sum\nolimits_{i=1}^{n} \left[\hat{\mu}_{grammar}\,(s_i) - \mu_{gold}\,(s_i)\right]^2 \tag{29}$$

- Lower values indicate better alignment with expert judgments.

(iii) Threshold-based Accuracy

- If needed, a threshold θ (e.g., 0.5) can transform fuzzy values into a binary classification (acceptable vs. unacceptable). Then, one can compute accuracy, precision, recall, etc. compared against a gold-standard classification.

5.4.2. Qualitative vs. Quantitative Analysis

Qualitative Analysis:

- Researchers can inspect membership values, identifying sentences whose syntax or pragmatics are borderline. For instance, if $\mu_{syntax(s)} \approx 0.5$ and $\mu_{pragmatics(s)} \approx 0.7$, the model reveals that while structure is only marginally acceptable, contextual cues improve overall grammatical membership.
- Such analyses can shed light on *why* certain sentences are borderline acceptable and highlight the interplay of syntax and pragmatics[10].

Quantitative Analysis:

- Summarize membership values across the corpus to observe general patterns.
- Examine how fuzzy membership distributions shift when

varying contextual parameters.

- Compare model outputs under different fuzzy operators (e.g., minimum, product, average) to see which best fits empirical data.

Taken together, these analytical procedures—both qualitative and quantitative—demonstrate the utility of fuzzy logic for capturing the **gradual** and **context-sensitive** nature of linguistic acceptability judgments. By systematically **constructing membership functions**, **defining fuzzy rules**, **applying the model** to the dataset, and **evaluating** outputs, we illustrate the comprehensive framework through which fuzzy grammar can enrich the study of syntax-pragmatics interactions.

6. Results

In this section, we present the outcomes of applying our fuzzy grammar model to an experimental dataset composed of five sentences. We provide descriptive statistics, visual and tabular representations of the fuzzy inference outputs, analyze the model's efficacy in capturing the interactions between syntax and pragmatics, and offer a comparative assessment against traditional binary linguistic models.

6.1. Presentation of Descriptive Statistics from the Case Study Data

Our small experimental dataset consists of five sentences that have been rated on a Likert scale from 1 to 7 for both syntactic and pragmatic dimensions. The ratings here are normalized using the expected linear function:

$$\mu\left(r\right)=\frac{r–1}{6} \tag{30}$$

where r is the original rating. This yields fuzzy membership values μ_{syntax} and $\mu_{pragmatics}$ for each sentence. The combined overall grammatical acceptability is calculated using the fuzzy AND operator (the minimum function), i.e.,

$$\mu_{grammar}\left(s\right)=min\{\mu_{syntax}\left(s\right), \mu_{pragmatics}\left(s\right)\} \tag{31}$$

Descriptive Statistics:

Syntactic Ratings:

- Mean $=\frac{6+3+5+7+4}{5}=5.0$
- Standard Deviation (approx.) $=1.41$

Pragmatic Ratings:

- Mean $=\frac{5+4+6+7+3}{5}=5.0$
- Standard Deviation (approx.) $=1.41$

Fuzzy Memberships:

- Average $\mu_{syntax}\approx 0.67$
- Average $\mu_{pragmatics}\approx 0.67$
- Average $\mu_{grammar}\approx 0.60$

These statistics indicate a moderate level of acceptability on both syntactic and pragmatic levels, with a slight overall reduction in combined grammaticality due to the minimum operator's sensitivity to the lower of the two factors.

6.2. Fuzzy Inference Outputs: Visual and Tabular Representations

The fuzzy inference stage yields continuous membership values that integrate both syntactic and pragmatic evaluations. To effectively convey these outputs, we provide both a table and visual representations.

Tabular Representation

Table 3 summarizes the derived fuzzy memberships for each sentence. Each row corresponds to one sentence from the corpus along with:

- Normalized syntactic membership μ_{syntax},
- Normalized pragmatic membership $\mu_{pragmatics}$, and
- The combined overall grammatical acceptability $\mu_{grammar}$.

Table 3. Summary of Ratings and Their Corresponding Fuzzy Membership Values.

Sentence ID	Syntactic Rating (1–7)	Pragmatic Rating (1–7)	μ_{syntax}	$\mu_{pragmatics}$	$\mu_{grammar}$
S1	6	5	0.83	0.67	0.67
S2	3	4	0.33	0.50	0.33
S3	5	6	0.67	0.83	0.67
S4	7	7	1.00	1.00	1.00
S5	4	3	0.50	0.33	0.33

Figure 6 displays the normalized fuzzy membership values for the syntactic and pragmatic dimensions of each sentence, along with the combined overall membership computed via the minimum operator. The visual disparity between syntactic and pragmatic memberships in sentences S2 and S5 demonstrates how the lower score directly governs the final acceptability value.

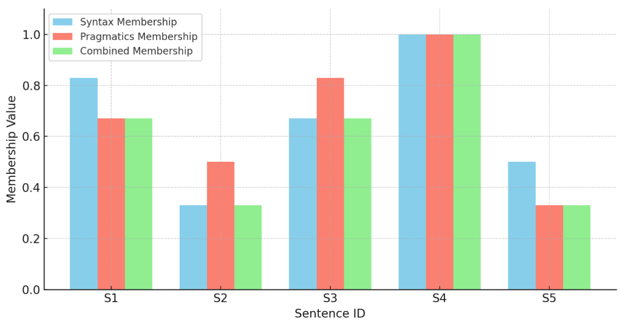

Figure 6. Fuzzy Inference Outputs for Syntax & Pragmatics.

6.3. Analysis of the Model's Ability to Capture Syntax-Pragmatics Interactions

The fuzzy model's strength lies in its ability to account for graded and context-sensitive linguistic phenomena, as evidenced by the following observations from our case study:

Sensitivity to Lower Values: The The minimum operator used in the aggregation function ensures that the overall acceptability ($\mu_{grammar}$) Closely follows the weaker of the two dimensions. For instance, in S2 (with $\mu_{syntax} = 0.33$ and $\mu_{pragmatics} = 0.50$) and S5 (with $\mu_{syntax} = 0.50$ and $\mu_{pragmatics} = 0.33$), the combined membership is 0.33. This reflects the linguistic intuition that a sentence is as strong as its weakest link.

Distinguishing Borderline Cases: The model captures marginal cases where one dimension might be acceptable while the other is weak. For S1 and S3, despite minor differences in ratings, the combined membership scores of 0.67 reveal that moderate strengths in both areas can lead to a comparable overall acceptability. Such fine distinctions are rarely visible when using binary models.

Integrated Perspective: The goal was to develop an integrated perspective where syntactic and pragmatic factors explained acceptability as interacting with continuous subcomponents tuned cohesively rather than from separate sets of input. This combined treatment enables investigators to systematically measure how subtle differences in either context (pragmatics) or form (syntax) affect overall acceptability.

These fine-grained interactions suggest that the fuzzy grammar model captures the full range of asymmetries that exist at the syntax-pragmatics interface in a nuanced way that resonates with other empirical linguistic intuitions.

7. Discussion

7.1. Interpretation of Key Findings

And making use of fuzzy logic makes us a more subtle flexible approach to our peculiar conception the acceptability of a sentence. Normalizing and adding these syntactic and pragmatic ratings with the minimum operator, overall acceptability is defined by the dimension with the lowest score. For example, sentences S2 and S5, which have mismatched syntactic and pragmatic memberships, both lead to final scores of 0.33—showing the "weakest link" principle. This supports the characterization of grammaticality as a scalar property and thus problematizes the binary judgments associated with generative models. Mathematically,

$$\mu_{grammar(s)} = min\left\{\mu_{syntax(s)}, \mu_{pragmatics(s)}\right\} \quad (32)$$

represents how syntax and pragmatics intertwine in a non-linear way, echoing the perspectives captured in recent psycholinguistic work.

7.2. Efficacy of Fuzzy Logic for Graded Phenomena

Fuzzy logic is modelled the gradience nature in linguistic phenomenon successfully. Continuous membership functions map discrete Likert-scale ratings onto a smooth continuum, allowing nuanced borderline cases to elude simple "grammatical vs. ungrammatical" labels. Aggregating via fuzzy operators like the min function demonstrates the incapacity of high syntactic scores to trump poor pragmatics [42]. This highlights how context plays the key role in acceptability. Both visual and tabular outputs support the model's ability to discriminate across levels of acceptability, and demonstrate that both syntax and pragmatics contribute to the overall judgments.

7.3. Implications for Research and Applications

- ***Theoretically Legitimate Extensions***: Fuzzy logic opens up analyses that go beyond binary logic, potentially being applied to phonological, semantic, or any other linguistic feature. Alternative aggregation operators (e.g., weighted averages) might better reflect compensatory interactions.
- ***Language Technology***: Acknowledging partial correctness, the model might improve machine translation, automated essay grading, and language learning systems by providing context-sensitive feedback.
- ***Cross-Linguistic and Cognitive Studies***: Investigating this fuzzy approach in languages associated with distinct scripts may yield both universal and language-specific information that would enhance our understanding of second language learning processes and help create inclusive language policies. Psycholinguistic experiments could be set up to probe how speakers process gradience during production.

7.4. Limitations and Future Directions

While promising, however, the study used only five sentences, which constrains wider applicability. Some compensatory effects may be oversimplified by a minimum operator, and linear normalization will not acknowledge all types of non-linearities in human judgments. Collecting empirical data derived from larger, more diverse samples and implementing strict inter-rater reliability measures would increase validation of the model. Lastly, integrating more contextual variables would considerably improve the model's ability to capture the full complexity of pragmatic environments.

In sum, this framework gives a tool to describe the subtle interaction between syntax and pragmatics with a mathematically rigorous, flexible architecture, leaving open the opportunity for further work to develop and test these proposals' coverage in actual language use.

8. Conclusions

8.1. A Specific Summary of Research Contributions & Models

In this study, a new fuzzy grammar model for the syntax-pragmatics interface has been proposed by adopting the mathematical structure of fuzzy logic. Our major research contributions are as follows:

Integration Theoretically: Through propositional calculus, we proposed a precise mathematical framework that satisfies of syntactic and pragmatic assessments via fuzzy membership functions and aggregation operators. This makes it possible to represent linguistic judgments along a continuum rather than in terms of binary distinctions.

Model Development: This model extends aspects of traditional linguistic theory by mathematically representing both syntactic well-formedness and context-dependent pragmatics. By defining functions such as

$$\mu_{grammar(s)} = min\left\{\mu_{syntax(s)}, \mu_{pragmatics(s)}\right\} \quad (33)$$

the acceptability depends on the weakest link of several linguistic dimensions.

By constructing around a small experiment along which it sequentially illustrates how categorical scorecards could be regularized to fuzzy numbers and combined to manifold aggregate results, the paper proposes a framework to understand, assess, and (possibly) encourage fuzzy evaluations. This process serves both to validate the model and to provide a roadmap for future testing.

8.2. Conclusion on Integrating Fuzzy Logic for Syntax-Pragmatics Analysis

The fuzzy logic approach to syntax-pragmatics is a significant giant leap for the theorization and application of linguistics because it endows the field with a mathematically grounded, flexible tool that registers language acceptability on a continuum. By allowing for uncertainty in verbal judgments, it is consistent with cognitive and psycholinguistic models of language competence that favour a network of contextual and structural variables rather than rule-governed behaviour. The continuation between a >0 and a <1 thus allows for the generation of holistic models of language's contribution to type via scale change, and quality with transformations over the space.

8.3. Recommendations for Future Work and Related Applications

Further validation of the model on larger and diverse datasets along with robust inter-rater reliability measures is needed. Refinements could involve more complex membership function shapes (e.g., Gaussian) and other fuzzy aggregation operators (e.g., weighted averages). The explanatory reach of the model would be only further broadened by extending it to semantics, phonology, and discourse. In effect, this can lead to useful applications of natural language processing systems like machine translation, automatic essay grading, and error detection, while language learning applications may be able to take advantage of measures of partial correctness and personalized feedback. Furthermore, cross-linguistic studies can shed light on universal versus language-specific gradience across the syntax-pragmatics boundary and move the goals of this research forward both theoretically and practically.

Author Contributions

Conceptualization, Y.N. and K.I.A.-D.; methodology, N.R.; software, R.M.H.; validation, M.C.R., S.M., and A.V.; formal analysis, N.A.; investigation, M.F.A.H.; resources, Y.N.; data curation, N.R.; writing—original draft preparation, A.V.; writing—review and editing, K.I.A.-D.; visualization, R.M.H.; supervision, M.C.R.; project administration, N.A.; funding acquisition, S.M. All authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The study does not involve publicly available datasets. However, the data supporting the findings of this study are available from the corresponding author upon reasonable request via email.

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Conflicts of Interest

The authors declare no conflict of interest.

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