The impact of artificial intelligence and natural language processing on the efficiency of the business process of standardizing unstructured textual data

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Aim: To examine the role of natural language processing (NLP) in supporting business processes by reliably transforming user-submitted unstructured textual data, specifically requests for medicines, into standardized product entries.

Methods: We collected a dataset of 24 medicine requests which we then processed using a Python-based pipeline that combined preprocessing, BERT embeddings, and fuzzy string matching. In this context, association refers to correctly linking a free-text request to a database entry, where impact is measured through accuracy, precision, recall, and F1-score; natural language refers to the unstructured text provided by users; processing denotes the computational steps used to clean, tokenize, and match the data; and the business process involves transforming user-submitted unstructured requests into structured database records.

Results: At a similarity threshold of 95%, the model achieved 0.94 accuracy, 0.89 precision, 1.0 recall, and an F1-score of 0.941. When the threshold was reduced to 85%, performance dropped to 0.25 accuracy, mainly due to false duplicate matches. The model consistently standardized strength and form (*e.g.*, "500 mg tab" → "500 mg Tablet"). Errors occurred when distinct medicines had highly similar names.

Conclusions: NLP methods can support the automation of unstructured textual data in business processes, provided high similarity thresholds and well-structured databases are maintained. Our findings highlight both the potential efficiency gains and the limitations of lightweight NLP models.

Keywords: natural language processing; artificial intelligence; Python; unstructured textual data

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Artificial intelligence (AI) today is a key emerging technology that can transform various industries and improve everyday life. Its contributions are evident in different fields, particularly in natural language processing (NLP). Before the rise of AI in its current form, NLP was a challenging endeavour due to the complexity of natural languages and its interdisciplinary nature, which encompasses formal and computational linguistics, machine and deep learning, cognitive psychology, and more (*1*, *2*). Machine and deep learning represent the technical aspect of building NLP models, while linguistics is crucial for creating language models that can be implemented in computers to facilitate language understanding and generation (*3*). Cognitive psychology also plays a similar role by helping to understand how language is formed, thus aiding in the comprehension of grammar, syntax, semantics, morphology, speech, and pragmatics. These elements serve as the foundation for NLP model development (*4*). Goldberg (*5*) defines NLP as the field of designing methods and algorithms that take natural language as input or generate it as output. Since natural languages were developed by humans and exist as unstructured textual and spoken data, they pose a challenge for computer processing, which primarily use artificial programming languages (*6*). Although they follow certain rules, a deep understanding of various linguistic disciplines is essential to design high-quality models. Moreover, natural languages are often ambiguous and evolve over time, making their understanding, analysis, and generation using computers more complex.

Most NLP models require preprocessing techniques such as tokenization, tagging, stemming, and lemmatization to help structure the text, ultimately enhancing the model's output quality and accuracy (*7*). A further challenge arises in big data environments, where data are becoming increasingly large, complex, and diverse, as it includes audio and video recordings, social media posts, emails, *etc*. Advancements in AI and more powerful computers have enabled the use of NLP to transform unstructured data into structured information (natural language understanding) or generate natural language from structured data (natural language generation) (*7*). NLP models typically rely on machine and/or deep learning in programming languages to enable computers to autonomously process human languages.

This paper explores the impact of AI – specifically, NLP models implemented in Python – on enhancing business processes. It seeks to address three key research questions within a single, narrowly defined business process:

– How do NLP models facilitate the conversion of unstructured textual data into standardized product names, highlighting practical benefits such as increased efficiency and faster workflows?

– What are the advantages and limitations of employing AI-driven approaches, including machine and deep learning models, in NLP for data transformation, and their integration into existing business systems for improved data analysis?

– How can assessing the performance of NLP models provide insights on the broader implications of AI adoption in business, leading to process optimization and a stronger competitive edge?

Methods

Data collection

Our dataset consisted of 24 simulated requests for medicines submitted through a Google Forms survey (*8*), which consisted of three questions: product name, where users enter the generic name of the medicine, *e.g.*, ibuprofen instead of neofen; strength, where users enter the medicine's strength, *e.g.*, 500mg; and form, where users enter the form in which the medicine is available, *e.g.*, tablet or capsule. The users were employees procuring these items through an ERP system to which requests are added once they are processed. The dataset was designed as a proof-of-concept sample, rather than a statistically representative corpus, while the entries within it represent natural language or free-text input provided by users without controlled vocabulary. Variations in spelling, capitalization, and formatting (*e.g.*, "ibuprofen 500 mg tab" *vs*. "Ibuprofen 500 mg tablet") were intentionally included to reflect real-world variability and to test the accuracy of the model in these situations. All responses were automatically stored in a Google Sheet (*8*) comprising eight columns (**Table 1**), following the rule that the most recent responses are saved at the top of the table. This Sheet served as the structured database for subsequent processing. The reference database used for matching consisted of more than 1000 standardized medicine entries, each defined by product name, strength, form, and a unique identifier.

Table 1. Explanation of Google Sheets document columns used to store survey responses

Column name	Explanation
Requested name	The requested product name provided in the survey
Requested strength	The requested product strength provided in the survey
Requested form	The requested product form provided in the survey
Status	The status assigned to the product after running the model. If the requested product is found in the database, it is assigned the status "duplicate". If the product is not found, it is assigned the status "new request".
Final product ID	A unique ID assigned to the new product after it is created. If the product is a duplicate, the product ID from the database is copied.
Final product name	The final product name assigned by the model
Final strength	The final strength of the medicine assigned by the model
Final form	The final form of the medicine assigned by the model

Evaluation

We assessed the performance of the NLP model by comparing the processed requests against the correct standardized database entries. A free-text request was then linked to the correct database entry, while impact was evaluated using accuracy, precision, recall, and F1-score. The business process of standardizing unstructured textual data refers to the organizational workflow of converting raw user requests into validated, consistent database entries. We considered a prediction correct if the model correctly identified a duplicate request and returned the correct existing product identifier, or correctly identified a new request and assigned standardized name, strength, and form consistent with the reference format. False duplicates and false new requests were counted as errors. We calculated evaluation metrics as simple proportions based on these definitions.

Model development and implementation

We used Python and supporting libraries necessary for NLP and data access for model development (*9*). Specifically, we implemented the model in Python (version 3.12) and executed it on a standard personal computer using CPU-based execution (no GPU acceleration). The main libraries used were PyTorch (version 2.4.0) (*10*), transformers (version 4.43.3), NumPy (version 2.0.1), fuzzywuzzy (version 0.18.0), and gspread (version 6.1.2). Processing time for one batch of requests was approximately 25 seconds.

The first part of the code loads the required libraries and their components for building the NLP model. The second part of the code loads the BERT tokenizer (*11*) and model, which converts raw text into a sequence of tokens that the model can process. The model itself is a neural network that processes the input data (tokens) and generates an output. Next, the code allows the model to access the Google Sheet where the data is stored. After that, a function is called that tokenizes the input text, which is then processed by the BERT model and returned as a NumPy array. The BERT embeddings were used to represent textual input, while the final matching decision was based on fuzzy string similarity scores computed on standardized text. This is then processed by functions that are responsible for standardizing the strength and form of the requested medicine. Once this is done, the code uses fuzzy matching to find the closest existing product name from the database and returns the most similar product based on a 0–100 similarity scale. We tested two similarity thresholds: 0.95 and 0.85. After collecting information about the medicine, the code checks whether the requested product already exists. If found, it returns a duplicate; if not, it creates a new product. Finally, the code generates a new unique ID and updates all the information in the database (**Figure 1**).

The purpose of the program code and NLP model is to automate the process of requesting new products and adding completely new ones when they are not duplicates. In other words, when users need a product that is not in the database (or they cannot find it), they fill out a survey entering all the necessary information about the product they want to add. Once submitted, the responses are recorded in a table which the program accesses, first checking if the requested product already exists in the database, then adding a new product if no duplicate is found (**Figure 1**).

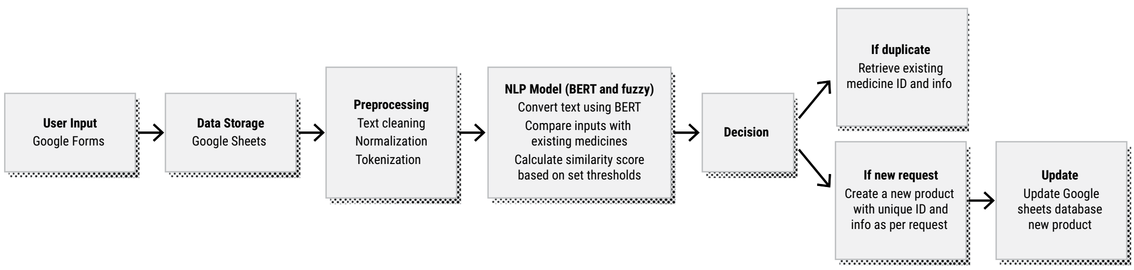

Figure 1. Visualisation of the natural language processing (NLP) model.

Results

We first filled out the survey requesting various medicines, which were either duplicates or completely new products not present in the database. Additionally, some medicines were intentionally written in lowercase or with misspellings to further train the model for different situations, while the strengths and forms were also written differently from the standardized naming conventions. This allowed us to evaluate how the NLP model functions in different scenarios.

At a 95% threshold, the model processed correctly processed 15 of 16 requests with an accuracy of 0.94, precision of 0.89, recall of 1.0, and an F1 score of 0.94. Errors primarily originated from confusion between medicines with similar names (*e.g.*, atorvastatin misclassified as alfacalcidol). These results deteriorated at an 85% threshold: accuracy dropped to 0.25, precision to 0.14, recall remained at 1.0, and the F1 score fell to 0.25.

The first group of new medicine requests mostly contained medicines that already existed in the database (**Table 2**), with the goal being to analyze the model's ability to recognize duplicates. Most requested medicine strengths and forms were not written according to standardized naming conventions, allowing us to assess how well the model performs in standardizing strengths and forms as defined in the program code. In other words, the final strength format always had follow the rule: "number" + space + "measurement unit" (*e.g.*, "500 mg"). Similarly, the final form had to be standardized, meaning it had to always be a full word, starting with a capital letter (*e.g.*, "Oral Solution" instead of "oral sol", or "Capsule" instead of "cap"). The processing results for group 1 were almost entirely accurate, with one exception: the first medicine, atorvastatin, listed in the first row. For all other medications, the model correctly identified whether the request was a duplicate or a new entry.

Table 2. Results of processing requests for adding new medications to the database – Group 1

Requested name	Requested strength	Requested form	Status	Final product ID	Final product name	Final strength	Final form
Atorvastatin	10 mg	Tab	Duplicate	MED-00010	Alfacalcidol	1 mcg	Capsule
Cefixime	400 mg	Tab	Duplicate	MED-00014	Cefixime	400 mg	Tablet
Acetaminophen	500 mg	Tab	Duplicate	MED-00001	Acetaminophen	500 mg	Tablet
Amoxicillin	500 mg	Cap	Duplicate	MED-00007	Amoxicillin	500 mg	Capsule
Vitamin C	500 mg	Cap	New request	MED-00919	Vitamin C	500 mg	Capsule
Etravirine	100 mg	Tab	Duplicate	MED-00756	Etravirine	100 mg	Tablet
Diosmin	600 mg	Tab	Duplicate	MED-00874	Diosmin	600 mg	Tablet
Captopril	25 mg	Tab	Duplicate	MED-00129	Captopril	25 mg	Tablet

The model returned the correct medications along with their IDs, names, strengths, and forms for duplicates and correctly assigned the necessary information for new requests. It also corrected errors in requested strengths and forms, where, for example, "400mg" was standardized to "400 mg", and "tab" was changed to "Tablet". Lastly, the model initially correctly identified incorrectly processed medication as a duplicate. However, instead of returning the requested "Atorvastatin (10 mg, Tablet)", it mistakenly returned "Alfacalcidol (1 mcg, Capsule)".

The second group of medication requests mainly consisted of medications not present in the existing database (**Table 3**). As with group 1, the names, strengths, and forms of some medications were intentionally written incorrectly or did not follow the standardized naming conventions (*e.g.*, "36mg" instead of "36 mg" or "Tab" instead of "Tablet"). The model accurately recognized duplicates and returned the appropriate medications as a result, while it correctly selected the name, strength, and form for new requests, adjusting them to the standardized naming format and assigning unique IDs.

The next group of medications was processed with a similarity threshold of 0.85, where the model incorrectly identified most of the medications either as duplicates or as new requests. For the former, it mostly assigned completely unrelated medications. The first request, haloperidol with a strength of 1 mg/ml in the form of oral drops, is a new request that the model incorrectly identifies as a duplicate and assigns it the medication acetaminophen. A similar situation occurs with the next two requests: pyrantel pamoate and paracetamol (**Table 4**).

Table 3. Results of processing requests for adding new medications to the database – Group 2

Requested name	Requested strength	Requested form	Status	Final product ID	Final product name	Final strength	Final form
Methzlphenidate	36 mg	Tab	New request	MED-00930	Methylphenidate	36 mg	Tablet
Methylphenidate	27mg	Tab	New request	MED-00931	Methylphenidate	27 mg	Tablet
Mwthylphenidate	18 mg	Tab	New request	MED-00932	Methylphenidate	18 mg	Tablet
Misoprostol	25 mcg	Tab	New request	MED-00926	Misoprostol	25 mcg	Tablet
Acetaminophen	16 mg /5 ml	Oral Sol	Duplicate	MED-00062	Acetaminophen	160 mg / 5 ml	Oral Solution
Amoxicillin	500 mg	Cap	Duplicate	MED-00007	Amoxicillin	500 mg	Tablet
Cholecalciferol	3500 IU	Oral drops	New request	MED-00923	Cholecalciferol (Vit D3)	3500 IU	Oral Drops
Flunitrazepam	2 mg	Tab	New request	MED-00925	Flunitrazepam	2 mg	Tablet

Table 4. Results of processing requests for adding new medications to the database – Group 3

Requested name	Requested strength	Requested form	Status	Final product ID	Final product name	Final strength	Final form
Haloperidol	1 mg/ml	oral drops	Duplicate	MED-00001	Acetaminophen	500 mg	Tablet
Pyrantel pamoate	100 mg/ml	susp	Duplicate	MED-00001	Acetaminophen	500 mg	Tablet
Activated charcoal	250 mg	tab	Duplicate	MED-00658	Activated charcoal	250 mg	Tablet
Carbocysteine	2%	syr	Duplicate	MED-00002	Acetylsalicylic Acid	500 mg	Tablet
Diltiazem HCl	120 mg	cap	Duplicate	MED-00002	Acetylsalicylic Acid	500 mg	Tablet
Paracetamol	240 mg/5 ml	susp	Duplicate	MED-00001	Acetaminophen	500 mg	Tablet
Gliclazide	30 mg	tablet	New request	MED-00950	Gliclazide	30 mg	Tablet
Lamotrigine	200 mg	tab	Duplicate	MED-00881	Dutasteride	500 mcg	Capsule

Discussion

Our main goal was to examine the role of NLP in upgrading a business process. To this, we note that AI can significantly contribute to business in several areas (*12*). By automating repetitive routine tasks, it can allow employees to focus on more demanding activities, increasing their productivity (*13*-*16*). It can also reduce the time required for key business processes (*17*) and minimize errors by automating tasks (*18*). Furthermore, AI can help identify hidden patterns in large datasets, leading to more effective, data-driven decision-making (*19*), while its implementation can significantly enhance business operations by achieving optimal productivity and improved efficiency. However, its introduction should be carefully studied, with attention to potential risks (*20*).

In terms of operational impact, AI contributes to the development of new products and services, as well as the improvement of existing ones (*12*). Some examples include creating chatbots on websites that can help users with simpler queries or using AI for personalized recommendations. We also note its potential financial impact: implementing AI in business automates tasks that would otherwise be performed by administrators, sales representatives, or contractors, leading to significant cost reductions for organizations (*18*). In the context of markets, AI can improve customer segmentation by analysing data on existing customers, their habits, lifestyles, and preferences, and can enhance customer satisfaction through personalized offers, better understanding, and prevention of potential negative events (*21*). Lastly, we are seeing an increasing emphasis on corporate sustainability today, where organizations must consider their environmental and social impacts. There, AI can contribute to sustainability by reducing costs, energy consumption, and waste (*22*, *23*). From a social perspective, a major concern is data privacy and how organizations will ensure data security while eliminating bias or discriminatory outcomes in AI models.

Our findings confirm that lightweight NLP approaches can automate the standardization of unstructured text in business processes. In our sample, high performance was achieved at stricter similarity thresholds, underscoring the need for conservative parameter tuning. Simultaneously, lower thresholds introduced significant risks of misclassification. compared to manual data entry, this NLP model could reduce manual effort and processing time under controlled conditions. Nevertheless, challenges remain, such as sensitivity to name similarity among medicines, absence of user feedback loops for model refinement, limited generalization beyond the medicine domain without retraining.

From an organizational perspective, this approach is low-cost and feasible to implement with open-source tools. However, adoption must consider issues such as data privacy, workforce impact, and system integration. These broader implications highlight opportunities for scalability and sustainability but lie beyond the immediate scope of this study. Additionally, the contribution of this study is reflected in the analysis of the effectiveness of NLP models, which can provide insight into the benefits of implementing AI in a business environment. The implementation of such a model in a business organization would save time and resources, and reduce the need for manual labour.

Our study offers insight into the advantages and limitations of using AI in NLP, where it shows that a relatively simple NLP model can be built utilizing free tools while still achieving fairly good results in processing requests. The complexity of the database should also be considered here, as it consists exclusively of generic medications with highly specific names that are not part of conversational language, making text processing and contextual understanding significantly more challenging. Unlike common words like “house” or “dog”, medication names lack inherent meaning. The similarity threshold of 95%, which is highly sensitive to changes, further adds to this complexity, as even a slight adjustment worsens the model’s performance. In fact, lowering the similarity threshold from 95% to 85%, which is still relatively high, resulted in poor outcomes where the model frequently returned the first two products from the database as results, even when they had no resemblance to the requested products. In other words, NLP models are not perfect, and it is impossible to always achieve satisfactory results due to the complexity of natural language. We note, however, that AI-based models improve with each run, as well as with the growth and quality of the database from which they learn.

Although the model performs well and delivers satisfactory results, it is not without limitations. One major issue is the lack of feedback that the model could receive after processing requests, which would aid in its learning and training, ultimately leading to better outcomes. Additionally, the model could be adapted to process not only medications, but also other types of products, such as household goods, automotive parts, electronics, *etc*. Another limitation is the way the model is currently executed, since it operates manually; if it were continuously running and processing requests in real-time as they arrive, it would create a fully automated system. Additionally, our dataset represented only a small, illustrative subset of data selected to demonstrate the model’s performance. The NLP model showed high accuracy within this subset; however, further testing on a larger dataset is necessary to fully validate its reliability and efficiency. Lastly, we note that the requests were processed in batches, rather than one by one, with the goal of improving efficiency without affecting the results. Overall, our results should be interpreted as indicative, rather than conclusive.

This exploratory study contributes primarily to a practical understanding of the importance and potential of applying NLP models in Python within a business context, providing valuable insights into the benefits, challenges, and opportunities these technologies offer to organizations that rely on unstructured text data analysis for successful operations.

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participation in writing and revising intellectual content, and approving the final version of the paper to be published.

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