LaTeX Example Doc

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CS 800

Current draft: 2/7/26 at 2:09am EST

Look at the source `main.tex` to see how this is done.

1 URIs

These are my professional accounts:

Academic Webpage: `https://cs.odu.edu/~cs_ychit001/`

Google Scholar: `https://scholar.google.com/citations?user=-XV8_74AAAAJ&hl=en`

ORCID: `https://orcid.org/0009-0007-1764-6544`

LinkedIn: `https://www.linkedin.com/in/yaminichitikela/`

2 Images

All figures must have a caption and must be referenced in the text. See the example below.

Figure 1 shows an original PNG with no scaling or cropping. Figure 2 shows an example of cropping the image using the `trim, clip` options to `includegraphics`.

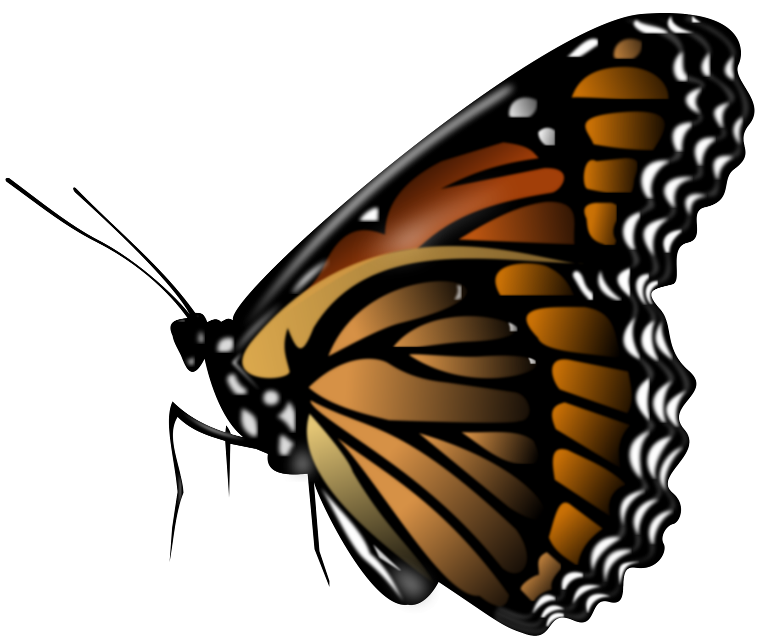

Figure 1: Original PNG

Figure 3 shows the same cropping as Figure 2 but scaled up. It is blurry because the original image was low resolution.

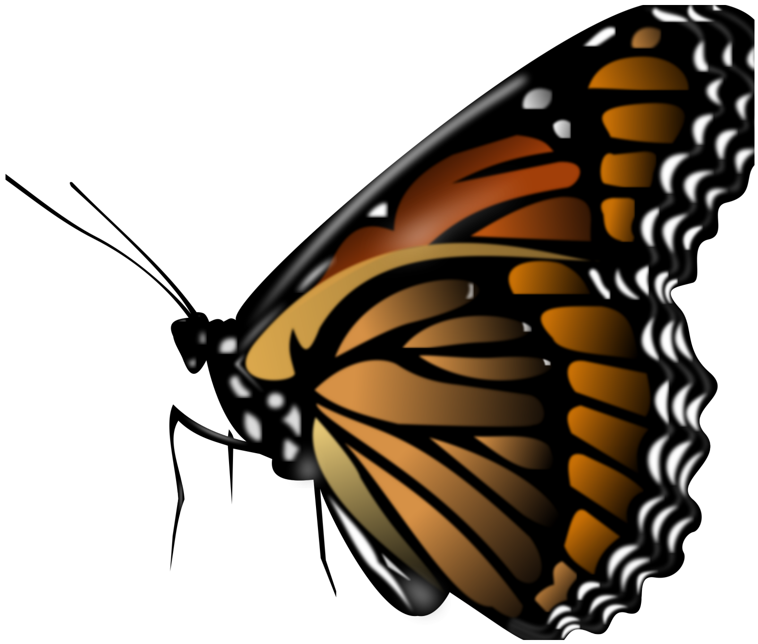

Figure 2: Cropped PNG

We can insert PDFs into the document in the same way as images.

3 Quotation Marks

Quotation marks are weird in LaTeX. Here is using ”double quotes”. *Not quite right.* Here is the “proper way”. It uses two backticks and two single quotes: ``proper way''

4 Tables

Table 1 shows a simple example table. Table 2 shows an example confusion matrix from https://en.wikipedia.org/wiki/Confusion_matrix.

Table 1: Simple Table

Week	**Date**	**Topic**
1	Sep 1, 3	Introduction, What's Vis and Why Do It?
2	Sep 8, 10	Data and Data Cleaning
3	Sep 15, 17	Marks and Channels

Table 2: Example Confusion Matrix from Wikipedia

		Actual	
		Cat	Dog
Predicted	Cat	5 (TP)	3 (FP)
	Dog	2 (FN)	3 (TN)

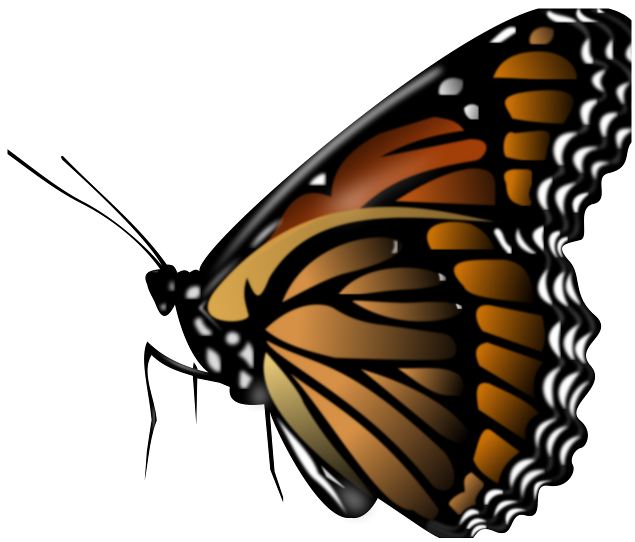

Figure 3: Cropped and scaled PNG

Illuminating the Unseen: A Large-Scale Exploration of Bias in ICU Discharge Summaries via Language Models

Anonymous Author(s)

***Abstract*—Discharge summaries (DS) are pivotal to patient care transitions, yet their completeness and quality can vary widely. This study uses large language models (LLMs) to evaluate DS quality across more than 50,000 ICU discharges from the MIMIC-IV dataset, aiming to quantify compliance with standardized documentation criteria and identify potential biases among different demographic subgroups.**

In this study, we adopted 19 established clinical metrics, grouped into five major DS components (e.g., *Reason for Hospitalization*, *Significant Findings*, *Procedures and Treatment*, *Patient's Discharge Condition*, and *Patient and Family Instructions*). Each DS was automatically annotated via LLM-based prompt engineering, producing categorical labels (*Fully, Partial, Unacceptance, Missing*). We then conducted numeric score-based and level-wise statistical analyses to detect variations in DS quality across race, insurance type, chief complaints, and admission types.

For the results, while *Reason for Hospitalization* was generally well documented, up to 10% of DSs lacked sufficient *Patient and Family Instructions* and 3–10% had incomplete *Discharge Condition* details. Statistically significant disparities ($p < 0.05$) were observed among subgroups, with higher negative scores (i.e., *Missing* or *Unacceptable*) in certain demographic categories, notably Asian males insured under less common plans (not in Medicare or Medicaid), where over 7% of DSs contained deficiencies—more than twice the overall average.

***Index Terms*—Large Language Model, Discharge Summary, Bias**

I. Introduction

Discharge summaries (DS) are critical documents that encapsulate a patient's hospital course, diagnoses, treatments, and follow-up instructions. They serve as an essential communication tool between healthcare providers, ensuring continuity of care and reducing the risk of medical errors as patients transition between care settings [1], [2]. In the Intensive Care Unit (ICU), this role becomes even more pronounced due to the complexity and acuity of patient conditions. ICU patients often undergo multiple procedures, experience rapid physiological changes, and require intricate medication regimens [3]. Consequently, accurately captured discharge information is vital for downstream providers—ranging from step-down units to subacute facilities—so they can anticipate patients' needs and align care plans accordingly.

In the United States, the Joint Commission (JC) is a widely recognized, independent, non-profit organization that accredits and certifies healthcare institutions [4]. It sets performance standards aimed at improving healthcare quality and patient safety. Among these standards, *Standard IM.6.10, EP 7* outlines six mandated components for discharge summaries, which also inform best practices in the ICU setting due to their emphasis on clear communication at a high-risk juncture. These components include: **(1) Reason for hospitalization. (2) Significant findings. (3) Procedures and treatment provided. (4) Patient's discharge condition. (5) Patient and family instructions. (6) Attending physician's signature.**

Prior work has investigated the extent to which hospital discharge summaries meet these Joint Commission guidelines. For example, Smith *et al.* [5] analyzed 599 discharge summaries from an academic hospital in the Midwestern United States (2003–2005). Their results showed high overall compliance (88–100%) with five of the six mandated elements. However, "patient's discharge condition" was documented least frequently (79–90%), particularly among stroke patients, potentially compromising post-discharge care planning [6]. Despite these valuable findings, many such studies rely on expert human reviewers, who manually rate DS completeness in relatively small samples. While this approach is precise, it limits scalability and timeliness. Furthermore, large-scale evaluations of ICU discharge summaries—where clinical complexity is greater and documentation demands are higher—have remained understudied.

In parallel, recent developments in *large language models* (LLMs) [7]–[11] offer new opportunities to systematically assess clinical notes, including discharge summaries, on a more expansive scale [12]–[14]. LLMs are trained on vast corpora of text and can exhibit remarkable comprehension of clinical language, enabling them to extract, summarize, and classify information with minimal human intervention. These models have demonstrated promise in tasks ranging from section labeling in electronic health records to automatic generation of coherent summaries for patient handoffs [14], [15]. By leveraging LLMs, it becomes feasible to evaluate thousands of ICU discharge summaries rapidly, thereby detecting gaps and potential biases that might otherwise go unnoticed in smaller, manually reviewed datasets.

In this study, we harness the capabilities of LLMs to examine a large-scale dataset of ICU discharge summaries and assign quality labels based on established clinical documentation criteria. By applying this automated approach, we aim to:

- Assess how well modern ICU discharge summaries conform to the Joint Commission's recommended components;

Figure 4: Inserted PDF

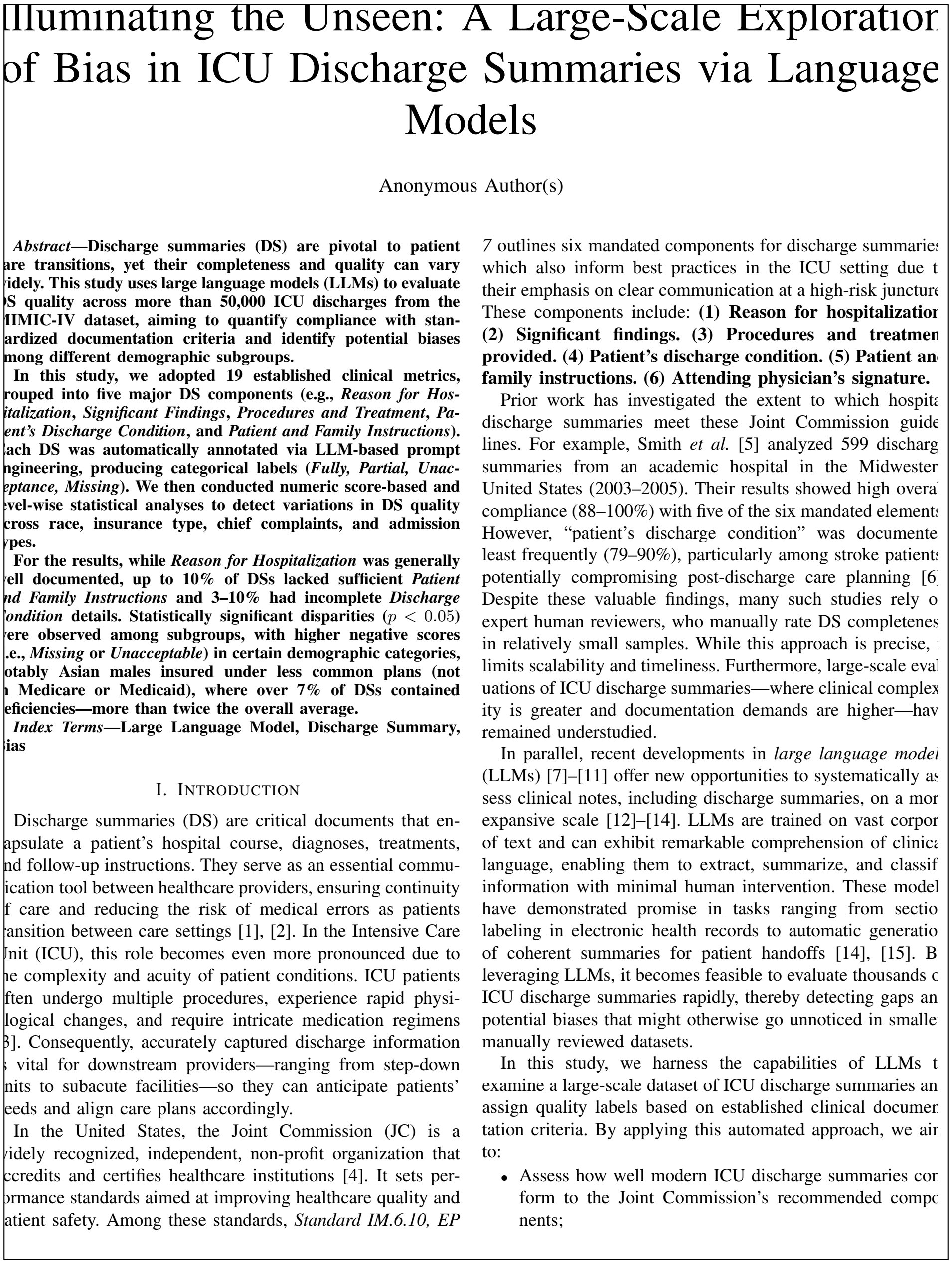
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Figure 5: Trimmed PDF