Judge a Book by Its Cover: Investigating Multi-Modal LLMs for Multi-Page Handwritten Document Transcription

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Abstract

Handwriting text recognition (HTR) remains a challenging task. Existing approaches require fine-tuning on labeled data, which is impractical to obtain for real-world problems, or rely on zero-shot tools such as OCR engines and multi-modal LLMs (MLLMs). MLLMs have shown promise both as end-to-end transcribers and as OCR post-processors, but to date there is little empirical research evaluating different MLLM prompting strategies for HTR, particularly for the case of *multi-page documents*. Most handwritten documents are multi-page, and share context such as semantic content and handwriting style across pages, yet MLLMs are typically used for transcription at the page level, meaning they throw away this shared context. They are also typically used as either text-only post-processors or image-only OCR alternatives, rather than leveraging multiple modes. This paper investigates a suite of methods combining OCR, LLM post-processing and MLLM end-to-end transcription, for the task of zero-shot multi-page handwritten document transcription. We introduce a benchmark for this task from existing single-page datasets, including a new dataset, `Malvern-Hills`. Finally, we introduce OCR+PAGE1 and OCR+PAGEN, prompting strategies for multi-page transcription that outperform existing methods by sharing content across pages while minimizing prompt complexity.

1 Introduction

A significant proportion of human written material exists only as physical, handwritten documents. Accurate, cost-effective digitization of such documents would benefit many fields by improving information accessibility and ease of processing. Digitized handwriting could also provide a largely-untapped source of training data for future models.

While modern optical character recognition (OCR) software is now adept at transcribing machine-printed text, handwritten text recognition (HTR) remains challenging; handwritten documents are often multiple pages long, extremely noisy, and can vary enormously in handwriting style and document structure. State-of-the-art HTR models (Li et al., 2023; Fujitake, 2024) typically combine pre-trained vision Transformers (Dosovitskiy et al., 2020; Liu et al., 2021; Huang et al., 2022; Xu et al., 2020; Kim et al., 2021) and (small) language models (Devlin, 2018; Liu et al., 2019), and rely on fine-tuning with labeled data to perform well. Unfortunately, labeling this training data, i.e. manually transcribing documents, is usually too expensive and time-consuming to be practical in the real world. For this reason, we are interested in models that can be deployed *zero-shot* — without training/fine-tuning.

There are several zero-shot OCR tools for handwriting, such as Google's Vision API, Amazon's Textract, and Transkribus (Kahle et al., 2017; Nockels et al., 2022). These can perform reasonably well, and are fairly cheap, but still frequently return noisy outputs. Furthermore, they operate at (at most) the page-level. HTR research and benchmarking is primarily focused on the character-, word-, line- or page-level, despite the fact that most real-world handwritten documents are *multi-page*. This means that (after being scanned/photographed) a document is split over multiple images, which are *highly inter-related*: handwriting patterns and quirks, structure and formatting, visual artifacts, and, of course, semantic text content.

All of this shared context goes unused by the models and tools discussed above, as they process documents one page at a time.

Large language models (LLMs; Floridi & Chiriatti (2020); Achiam et al. (2023); Zhao et al. (2023)) show promise for addressing these challenges. One example of this is using LLMs as a *post-processor* for correcting cheap and noisy OCR output; we discuss this in Section 2 and include experimental results in Section 5. Furthermore, by leveraging the long context capabilities of modern LLMs (Chen et al., 2023; Liu et al., 2023a; Kim et al., 2024; Karpinska et al., 2024), this can even be done all-at-once for multi-page documents, theoretically enabling shared inter-page context to inform corrections.

Even more promising are multi-modal LLMs (MLLMs; Wu et al. (2023)), LLMs that can accept both text and images as prompts. Despite being general models and not trained explicitly for HTR, commercial MLLMs such as GPT-4O are *very* good at end-to-end handwriting transcription, often much better than OCR tools designed for the purpose (see Section 5). The main downsides of end-to-end transcription with MLLMs are (i) the risk of hallucination; an OCR engine may produce a noisy, erroneous signal, but it is less likely than an MLLM to corrupt a signal by introducing text that is 'reasonable' but incorrect, and therefore more difficult to identify; and (ii) expense; the best commercial LLMs can be expensive at scale — images consume many more tokens than raw text, and transcription is a task that produces a lot of output tokens, which are typically priced higher than input tokens. Using MLLMs as postprocessors rather than end-to-end can partially mitigate these issues, but without access to images they tend to underperform.

This paper aims to address a lack of empirical research into the comparison and combination of OCR tools and MLLMs for HTR, specifically in the zero-shot, multi-page document setting; the setting most frequently faced by practitioners. The contributions of this paper are three-fold:

We investigate the capabilities of OCR, MLLMs, and combinations of both for *zero-shot, multi-page, handwritten document transcription*, evaluating a suite of methods on documents ranging from 2 to 13 pages in length.

We introduce `Malvern-Hills`, a new multi-page handwritten document dataset derived from previously undigitised archival sources, and complement it with three further multi-page datasets synthesized from existing single-page collections (including `CASIA-5`, a Chinese handwriting dataset), forming a diverse four-task benchmark for multi-page transcription.[1]

We propose OCR+PAGE1 and OCR+PAGEN, simple but effective methods permitting MLLMs to extrapolate information from *a single page image* to improve the transcription accuracy of OCR-generated text, leveraging multi-modality and shared inter-page context to improve transcription accuracy while balancing prompt complexity and token cost.

2 Related work

Handwriting OCR. Most OCR engines, including those that can be run locally like Tesseract, are designed for use with printed text and are nearly useless for handwriting. Several commercial OCR engines, such as Google Cloud Vision, Azure Vision, Amazon Textract and Transkribus (Kahle et al., 2017; Nockels et al., 2022) are designed for use on handwritten text at the page-level scale.

SOTA HTR and OCR models (Fujitake, 2024; Li et al., 2023; Kim et al., 2021; Huang et al., 2022) are typically based on pre-trained vision Transformers (ViT; Vaswani et al. (2017); Dosovitskiy et al. (2020)) and may include recurrent components like LSTMs or CNNs (Breuel et al., 2013; Azawi et al., 2013; Bora et al., 2020; Yang et al., 2019); the commercial handwriting-capable OCR engines mentioned above are likely similar in architecture to the best of these models, leveraging massive, pre-trained ViTs and language models. In general,

[1] Code & datasets: `https://github.com/BenGutteridge/judge-a-book-by-its-cover/`

such models are somewhat effective on HTR tasks zero-shot, and SOTA is reached by fine-tuning on a specific task. This is fine for benchmarks, but for real-world tasks obtaining labeled training data is often prohibitively expensive. Furthermore, most benchmarks are concerned only with recognition at the character- or line-level. This can, of course, be aggregated to return document-level transcriptions, but this neglects the task of text *detection*, and does not consider incidentals that occur in real documents — headings, figures, scribbles, margin notes, imperfections in image quality, distractors, etc. This paper is concerned with transcription over multi-page documents in a holistic manner.

LLMs for OCR post-processing. Several works have investigated improving OCR transcription accuracy with post-processing by a language model (Lund et al., 2011; Schaefer & Neudecker, 2020; Veninga, 2024; Rigaud et al., 2019). LLM-aided OCR is a public tool that uses OCR output with an LLM post-processor to improve OCR transcription accuracy, but the authors do not provide any experimental results demonstrating improvement besides hand-picked examples. Similarly, BetterOCR is a tool that combines results from multiple OCR engines and passes them into an LLM, but only hand-picked examples are provided as experimental results. Furthermore, both tools are only designed for printed text, both operate at the page level (or at the finer-grained 'page chunk' level), and neither process images directly with MLLMs, only using LLMs for post-processing.

Several existing works investigate the use of OCR output, including text and bounding boxes, alongside images as input to MLLMs for document understanding (Wang et al., 2024; Luo et al., 2024; Liao et al., 2025; Wang et al., 2025), but these works also focus on the single page case only, are concerned with tasks like question answering rather than transcription, and do not use handwritten data (with the exception of short mathematical expressions).

Benchmarks. Most OCR benchmarks are for machine-printed text, and only for single pages/images (Liu et al., 2023b), such as receipts (Park et al., 2019; Huang et al., 2019)). Kleister is a pair of multi-page, long-context key entity extraction benchmark tasks, but consists of only machine-printed text (Graliński et al., 2020; Stanisławek et al., 2021).

There are a number of HTR benchmarks, including historical documents, documents not written in English or with Latin characters (Sánchez et al., 2019; Zhang et al., 2019; Causer et al., 2018; Dolfing et al., 2020; Serrano et al., 2010; Wigington et al., 2018; Carbonell et al., 2019; Yu et al., 2021), and transcription of numerical digits or mathematical expressions (Liu et al., 2023b; Yuan et al., 2022; Diem et al., 2014). None are explicitly concerned with multi-page documents, and most are at the line- or word-level.

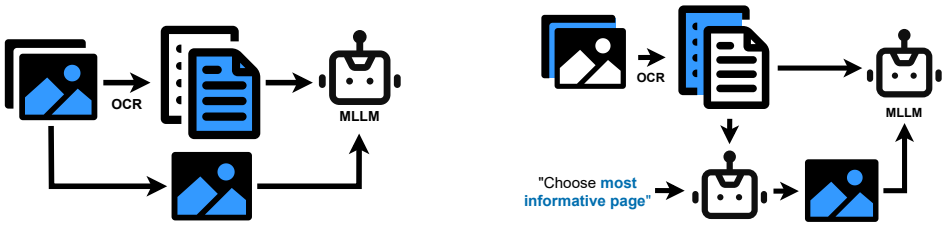
3 OCR+PAGE1 and OCR+PAGEN: correction from a single page

We propose two instances of the following prompting strategy for OCR post-processing of multi-page documents: provide the MLLM with the *OCR output for the entire document* as well as *a single page image*. Figure 1 illustrates the two methods: OCR+PAGE1 and OCR+PAGEN.[2]

OCR+PAGE1 is the simpler strategy: the page image chosen is always the first page of the document. For OCR+PAGEN, a cheap LLM is prompted with the OCR text and asked to *choose* the most promising page image to have access to, which may or may not be the first — it should be clear from the OCR text whether a particular page has more or fewer errors, has a significant amount of reference text or relatively little, etc. OCR+PAGEN adds a small amount of prompt complexity, but can reduce failures caused by unsuitable first pages, such as title pages with limited text. We would expect OCR+PAGEN to perform at least as well as OCR+PAGE1, as OCR+PAGEN can always fall back to OCR+PAGE1 by default.

Motivation. OCR+PAGE1 and OCR+PAGEN (collectively OCR+PAGEX) are based on two assumptions. First, that multi-page documents are likely to be similar in many ways: handwriting is likely consistent for a single document, the semantic content is likely to

[2]We additionally evaluate OCR+PAGER, a variant of OCR+PAGEN that provides a *random* page image rather than one selected by an upstream LLM (see Appendix E).



(a) OCR+PAGE1 (b) OCR+PAGEN

Figure 1: Illustrations of OCR+PAGEX methods. In both, the full OCR text of the document is provided to an MLLM along with a single page image. +PAGE1 always uses the first page; +PAGEN uses the Nth page, where N is chosen by an upstream LLM given the OCR text. The page image/text passed to the MLLM are highlighted. For +PAGEN, in this case $N=2$, but it can be any page.

be highly inter-related, and images of the original documents were likely obtained in a similar fashion (smartphone camera, scanner, etc.) so image artifacts are likely similar across pages as well. We believe this is a reasonable assumption, indeed, a 'multi-page document' without at least some shared traits across pages is better characterized *not* as a multi-page document, but a series of individual documents. The second assumption, which follows from the first, is that OCR errors are likely to be repeated across such similar pages. If a page contains a reasonable amount of text, it likely contains examples of many, if not most, handwriting quirks of the writer; after all, the most common 25 (100) words make up about one third (half) of all written English (Kress & Fry, 2015), there are only 52 letter characters, and character combinations often repeat. Furthermore, more challenging words such as proper nouns (e.g. names, places) are reasonably likely to repeat across pages.

We stress that it is not necessary that *all* OCR errors be present in a single page — difficult names may appear once, an individual page may be damaged, etc. — our methods are based on the idea that **a single page provides more useful information than the second**, which provides more useful information than the third, and so on. A lot of page images means *redundant information*, meaning more tokens, more expense and more prompt complexity.

With these assumptions, we hypothesize that, with OCR+PAGE1 or OCR+PAGEN, an MLLM should be able to pick up on cues, from the provided image, about the relevant part of the noisy OCR input, and use this to improve on the post-processing of the entire text. Furthermore, as the OCR transcription for all pages is provided along with an image, semantic content can be shared between pages. This should provide a reasonable trade-off between useful inter-page information and prompt complexity/cost.

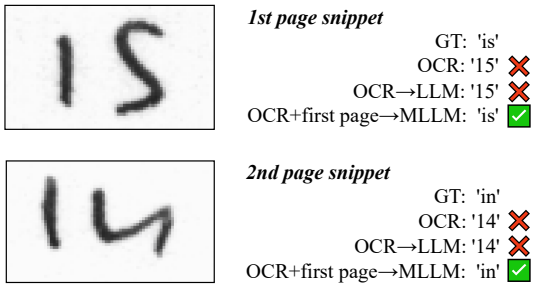


Figure 2: Example of OCR+PAGE1 propagating OCR error corrections across pages. Though the MLLM only has access to the first page image, it can use observed 'i'→1 & word→number errors to correctly transcribe 'in' on the unseen second page.

Figure 2 illustrates a real example of OCR+PAGE1 working in practice on the IAM dataset (see Section 4); see Appendix B (Figures 8–11) for further examples.

We note a loose conceptual parallel to few-shot prompting (Dong et al., 2024), in which one or more examples of expected input and desired output are provided within the prompt. The analogy is not exact, but we believe it aids intuition. The two input modalities for OCR+PAGE1 and OCR+PAGEN, the OCR text and page image, can be thought of as similar to the example input and target. In this case, however, rather than learning in-context to *replicate* the OCR engine's output, the MLLM should (i) exercise its own judgement to identify OCR errors, (ii) identify how the OCR engine's choices should be corrected, and

(iii) extrapolate from this learned image and the corresponding OCR text mapping to the remainder of the OCR output (i.e. the 'unseen' text).

3.1 A comprehensive suite of methods for evaluation

One of the main objectives of this work is to investigate the capabilities of OCR and MLLMs for multi-page transcription by evaluating a comprehensive suite of methods and MLLMs. To our knowledge, no existing works compare and evaluate such a range of methods and prompting strategies for handwriting transcription and OCR post-processing with (M)LLMs. We provide an overview of the methods evaluated in this paper below.

'All-at-once' and 'page-by-page' processing. Although we are interested in multi-page documents, it is an essential part of the task that proper page breaks are maintained in the final transcription; for this reason, in our experiments we evaluate transcription accuracy at the page- rather than document-level, and aggregate. As a result, the methods described below can be classified into 'page-by-page' (PBP), where each page is processed separately, and 'all-at-once' (AAO), where the relevant inputs for all pages are provided, and the MLLM must return output containing a transcription of each page keyed to its given page ID.

For each method below we describe the *input* to the (M)LLM that produces the final transcription. See Figures 1 & 3 for illustrations.

IMAGES (PBP): image per-page; equivalent to using an MLLM for OCR end-to-end.

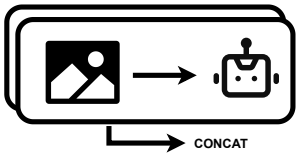
IMAGES-ALL-AT-ONCE (AAO): all images in the document; allows access to context across pages, but increases task difficulty and context length

OCR (PBP): the output from an OCR engine for a given page; LLM has no access to the original image, but has a smaller token burden, and the potentially easier/more surgical task of *correction* rather than full transcription.

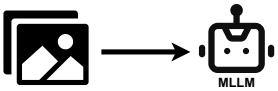
OCR+IMAGES (PBP): the page image *and* the OCR transcription; we might expect this method to perform the best, as it has the most information, but it also consumes the most tokens.

OCR+PAGE1 (AAO): the image of the *first page* of the document, and input of the OCR transcription of every page (see Figure 1a); our hypothesis is that there is sufficient shared context between pages that a single page will permit effective, token-cheap OCR correction.

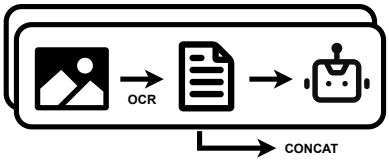
OCR+PAGEN (AAO): the *chosen page* image, and the OCR transcription of every page (see Figure 1b). The chosen page ID is returned by an upstream (cheap) LLM call, asking, 'given the OCR transcription of the full document, which page image would be most beneficial to a downstream LLM?' We might expect +PAGEN to be at least as good as PAGE1.



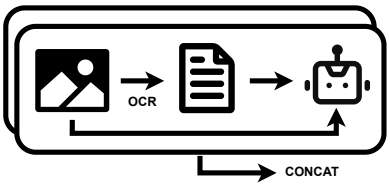
(a) IMAGES → MLLM



(b) IMAGES-ALL-AT-ONCE → MLLM



(c) OCR → LLM



(d) OCR+IMAGES → MLLM

Figure 3: MLLM-based transcription method illustrations.

4 A benchmark for multi-page handwritten document transcription

In Section 5 we evaluate the methods described above on three multi-page handwritten document datasets, including `Malvern-Hills`, a new dataset labeled by the authors and

derived from public domain but not-previously-scanned documents obtained from a charity, the Malvern Hills Trust. See Appendix A for example documents from each dataset.

IAM. The IAM Handwriting Database (Marti & Bunke, 2002) is a handwriting benchmark of single pages, where each page contains a machine-typed passage and a handwritten copy of the same text beneath it, written by one of 657 English-speaking writers. We crop the images to contain only the handwritten part (using provided metadata) and then combine them by writer ID to produce documents with consistent handwriting, and often related content. We use a subset of 242 images to construct 107 multi-page documents, 79 with two pages and 28 with three, and henceforth refer to this multi-page dataset as `IAM`. We note that, though the multi-page documents produced are, in a sense, synthetic, the consistent handwriting means this is suitable for testing the cross-page extrapolation capabilities of our methods. Furthermore, many of the pages in the IAM Database are generated from splitting single text sources anyway (as Figure 5 demonstrates), so many of our multi-page documents do, in fact, flow from page to page and/or share related text content.

Malvern-Hills. This dataset is composed of 161 images taken on a smartphone. From these we construct 70 multi-page documents, 49 with two pages and 21 with three. The documents include meeting minutes, correspondence and legal documents from the public archives of a British charity, the majority being meeting minutes from between 1889 and 1938. They are written in English (with instances of Latin), in multiple hands and styles and often use archaic language and handwriting conventions. As a result, this task is more challenging than `IAM`. The documents are publicly accessible archival materials held by the Malvern Hills Trust, obtained with the explicit permission of the Trust. Ground truth transcriptions were produced by a single annotator, with GPT-4O used as a noisy first-pass tool to accelerate the process; every document was subsequently manually checked and corrected, and every document's transcription differs from GPT-4O's initial output to some degree.

The dataset is included in the linked code repository; see Appendix F for `Malvern-Hills` statistics, and Appendix F.1 for ablations on document properties.

Bentham. The Bentham-R0 dataset consists of 433 images of handwritten notes by the 18th-century philosopher Jeremy Bentham with crowd-sourced transcriptions (Causer & Wallace, 2012; Causer et al., 2018). Each page is identified by source and page number, but there are many gaps and isolated pages, so we create a multi-page version by extracting all groups of consecutive pages (239 total). The resulting multi-page dataset, `Bentham`, is the most challenging of the three, and consists of 52 two-page documents, 21 three-page documents and 18 four-page documents.

CASIA-5. We derive `CASIA-5` from (the test split of) CASIA-HWDB2.1 (Liu et al., 2011), a Chinese handwritten dataset of 300 page images. As with `IAM`, we group pages by author ID to produce 30 *five-page* documents with consistent handwriting. We use Google Cloud Vision as the OCR engine for this dataset, as it supports Chinese. Full results are in Appendix D.

5 Experiments

Full results are detailed in Tables 1 and 2, with the best models trading off cost against transcription accuracy highlighted by Pareto frontier plots in Figure 4.

5.1 Experimental details

The task for each dataset is to produce transcriptions for each page in the given document, from page images, OCR output derived from those images, or some combination of the two. The methods are described in Section 3.1. All MLLM prompts are included in the linked code repository. Prompts for each method were developed over four rounds of

[3]Tarride et al. (2024); an open-source non-MLLM baseline trained on `IAM` (see Appendix H.1.1).

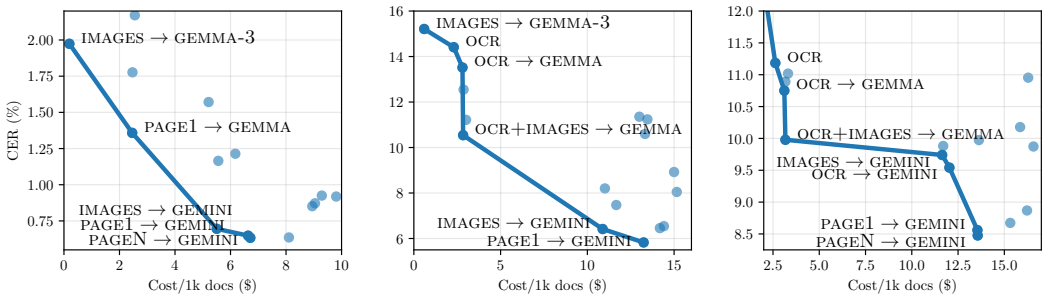


Figure 4: Performance against cost for all methods on `IAM` (left), `Malvern-Hills` (center) and `Bentham` (right). Some outlier points are cut off for clarity. See Tables 1 and 2 for exact values. All Pareto frontier methods are labeled. We see that OCR+PAGE1 and OCR+PAGEN are Pareto frontier methods for all three tasks, and the best-performing overall.

Table 1: Transcription methods on the `IAM` dataset with Azure OCR. 'Minor/Major#Err.' are the average number of trivial/non-trivial errors per document for the given method, as assessed by an LLM; see Section 5.2 for details. Our (OCR+PAGEX) methods are bold. Score emphasis: **1st**, *2nd*, 3rd.

	Input	CER ↓ (%)	Cost ($) /1k docs	Minor#Err.	Major#Err.
—	PYLAIA[3]	6.51	0.00	—	—
—	OCR	3.81	2.26	3.61	5.11
GEMMA -3-27B	OCR	2.93	2.42	3.97	3.17
	IMAGES	2.31	0.19	2.65	4.32
	IMAGES-ALL-AT-ONCE	1.97	0.19	3.45	4.05
	OCR+IMAGES	1.78	2.47	2.78	2.66
	OCR+PAGEN	2.17	2.55	3.44	2.22
	OCR+PAGE1	1.36	2.46	2.41	2.03
GPT-4O	OCR	1.21	6.17	2.81	1.86
	IMAGES	0.92	9.81	2.06	1.79
	IMAGES-ALL-AT-ONCE	0.92	9.29	1.82	1.59
	OCR+IMAGES	0.72	12.69	1.86	1.21
	OCR+PAGEN	0.87	9.04	1.95	1.29
	OCR+PAGE1	0.85	8.94	1.66	1.20
GEMINI -2.5-PRO	OCR	1.57	5.21	1.64	1.22
	IMAGES	1.16	5.56	1.66	1.47
	IMAGES-ALL-AT-ONCE	0.70	5.50	1.77	1.37
	OCR+IMAGES	*0.64*	8.10	1.63	1.32
	OCR+PAGEN	**0.63**	6.71	1.80	*1.04*
	OCR+PAGE1	0.65	6.63	2.51	**1.00**

experimentation on a validation split of 100 multi-page documents from IAM Database images separate from the 242 images used to generate `IAM`.

OCR and MLLMs. We use the Azure Vision OCR engine, as early experimentation comparing Azure Vision, Amazon Textract, Google Cloud Vision and Tesseract revealed Azure to be generally the best-performing OCR engine, as well as the cheapest (see Appendix H).

For MLLMs we use two leading commercial models at time of writing, OpenAI's GPT-4O and Google's GEMINI-2.5-PRO[4], as well as an open-source[5] MLLM, GEMMA-3-27B. For each

[4]We evaluate GPT-4O and GEMINI-2.5-PRO as the respective flagship models of OpenAI and Google at the time our experiments were finalized (mid-2025); our primary goal in evaluating multiple MLLMs is to demonstrate that our methods generalize across model families, rather than to compare model quality directly. Extending evaluation to more recent models (e.g. GPT-5) is a natural direction for future work.

[5]Under Google's 'open' Gemma license.

Table 2: Transcription methods on the `Malvern-Hills` and `Bentham` datasets. OCR engine is Azure Vision. Our methods are bold. Score emphasis: **1st**, *2nd*, 3rd.

(a) `Malvern-Hills` dataset

	Input	CER ↓ (%)	Cost ($) /1k docs
—	OCR	14.41	2.30
GEMMA-3-27B	OCR	13.52	2.80
	IMAGES	27.19	0.66
	IMAGES -ALL-AT-ONCE	15.21	0.60
	OCR+IMAGES	10.54	2.84
	OCR+PAGEN	11.22	3.01
	OCR+PAGE1	12.55	2.87
GPT-4O	OCR	10.60	13.32
	IMAGES	11.24	13.46
	IMAGES -ALL-AT-ONCE	11.35	13.00
	OCR+IMAGES	7.11	17.54
	OCR+PAGEN	8.05	15.15
	OCR+PAGE1	8.92	15.00
GEMINI-2.5-PRO	OCR	7.47	11.67
	IMAGES	*6.42*	10.88
	IMAGES -ALL-AT-ONCE	8.20	11.01
	OCR+IMAGES	6.46	14.18
	OCR+PAGEN	6.54	14.41
	OCR+PAGE1	**5.83**	13.24

(b) `Bentham` dataset

	Input	CER ↓ (%)	Cost ($) /1k docs
—	OCR	11.18	2.63
GEMMA-3-27B	OCR	10.75	3.11
	IMAGES	15.12	0.59
	IMAGES -ALL-AT-ONCE	27.88	0.50
	OCR+IMAGES	9.98	3.17
	OCR+PAGEN	11.02	3.31
	OCR+PAGE1	10.89	3.17
GPT-4O	OCR	9.97	13.63
	IMAGES	9.87	16.58
	IMAGES -ALL-AT-ONCE	10.18	15.85
	OCR+IMAGES	9.35	20.93
	OCR+PAGEN	8.87	16.23
	OCR+PAGE1	10.95	16.29
GEMINI-2.5-PRO	OCR	9.54	12.03
	IMAGES	9.74	11.64
	IMAGES -ALL-AT-ONCE	9.88	11.70
	OCR+IMAGES	8.67	15.32
	OCR+PAGEN	**8.48**	13.56
	OCR+PAGE1	*8.56*	13.55

we use temperature of 0, minimal reasoning (for Gemini) and default parameters otherwise. Details of cost estimates for OCR and MLLMs are included in Appendix G.1, and per-stage token and cost breakdowns are in Appendices H.1, E & D.

We use a single evaluation run per method.[6] Evaluation is at the page level using Character Error Rate (CER; Morris et al. 2004), the most widely-used metric for OCR transcription.[7]

5.2 Semantic evaluation with an LLM

CER measures character-level edit distance and therefore misses semantic quality: a formatting difference counts the same as a corrupted word, while an incorrect initial renders an entire name wrong despite costing only one character. We therefore supplement CER with an LLM-based semantic evaluation on `IAM`, classifying errors as *minor* (formatting or phrasing differences that do not affect meaning) or *major* (missing content, hallucinations, proper noun errors, etc.). Full methodology and error taxonomy are in Appendix C.2.

5.3 Discussion

Surprisingly, *for all three datasets* we find that the best-performing method overall is either OCR+PAGE1 or OCR+PAGEN. Both of these methods have access to *less than half*, and sometimes as little as a quarter, of the original source data, the document images. Yet they outperform methods that have access to all of the images, and those with access to both the OCR text *and* all of the images, despite the fact that *the performance of OCR **alone** is poor for*

[6] A single run keeps costs reasonable, and temperature-zero output is largely, though not perfectly, deterministic. We discuss this, and test it for a subset of methods, in Appendix C.4.

[7] We also experimented with ANLS (Peer et al., 2024) and WER; all three metrics produce very similar relative results.

all three tasks — for IAM it is the worst method outright, and for Malvern-Hills and Bentham it is outperformed by all GEMINI- and GPT-4O-based models.

The performance gap in each case is not large, but our intention is not to propose a SOTA method. It is to demonstrate that MLLMs can leverage common context from limited, expensive image input to improve correction of cheap text input. Put simply, a single image is often as good as the full document. Existing simplistic approaches to transcription based solely on OCR (with traditional OCR engines or MLLMs end-to-end), miss useful context, and methods that use both OCR and all images can overwhelm a model with redundant repeated context that can be found in a single image.

Semantic accuracy. Table 1 includes additional columns with information about document error types; this is described in Section 5.2. Counting MLLM errors semantically, rather than with strict CER, we see that the performance gap between OCR+PAGE1 and OCR+PAGEN and the next best method, OCR+IMAGES→GEMINI-2.5-PRO, is even larger. While all three methods have a similar average number of minor errors per document (semantic and formatting errors that do not affect meaning), our methods have over 20% fewer major errors (genuine mistakes or hallucinations) than the next best method.

Scaling to longer documents. We evaluate the same methods on longer-document variants of our benchmarks: IAM-5 (5 pages, 20 docs), Malvern-Hills-5+ (avg. 5.8 pages, 24 docs) and Malvern-Hills-10+ (avg. 11.5 pages, 10 docs). OCR+PAGE1 remains the top or joint-top method across all three, despite having access to <20% (or even <10%) of document images, and are lower cost than next-best OCR+IMAGES methods (see Appendix E). Even when document pages have both different handwriting and unrelated context (IAM-5-Random; see Appendix E.2), OCR+PAGEX methods remain competitive. Furthermore, ablations on document properties suggest that OCR+PAGEX methods are most beneficial on *more challenging documents*, e.g. those with archaic language (Appendix F.1).

Generalization beyond English-language documents. On CASIA-5, a Chinese handwritten benchmark of 5-page documents (Table 3; full results in Appendix D), our central finding generalizes to non-Latin script: with GEMINI-2.5-PRO, OCR+PAGEX achieves 8.94% CER, nearly matching the more expensive OCR+IMAGES (8.39%) at lower token cost, and significantly improving on OCR alone (12.84%). The result reinforces that a single well-chosen page captures most of the benefit of the full document image set.

Table 3: Transcription methods on CASIA-5, a Chinese handwriting benchmark. OCR engine is Google Cloud Vision. Our (OCR+PAGEX) methods are bold. Score emphasis: **1st**, *2nd*, 3rd. Full results are in Appendix Table 7.

	Input	CER ↓ (%)	Cost ($) /1k docs
—	OCR	12.84	7.50
GPT-4O	OCR	18.32	26.75
	IMAGES	42.40	30.81
	IMAGES-ALL-AT-ONCE	43.64	29.30
	OCR+IMAGES	14.16	41.58
	OCR+PAGEN	12.87	28.68
	OCR+PAGE1	14.48	28.31
GEMINI	OCR	33.17	24.87
	IMAGES	13.55	19.08
	IMAGES-ALL-AT-ONCE	23.07	18.09
	OCR+IMAGES	**8.39**	27.80
	OCR+PAGEN	*8.94*	23.42
	OCR+PAGE1	12.61	23.25

Open-model baselines. We also evaluate PYLAIA (Tarride et al., 2024) on IAM (Table 1), and TROCR (Li et al., 2023) and DOCOWL2 (Hu et al., 2025) on Malvern-Hills-5+ (Appendix E). All perform poorly in our zero-shot, document-level setting: PYLAIA achieves 6.51% CER on

IAM (worse than OCR alone), TROCR achieves 31.4% on Malvern-Hills-5+, and DOCOWL2 is effectively unusable at 92% CER.

6 Limitations and future work

We stated that we would expect OCR+PAGEN to be at least as good as OCR+PAGE1, yet in practice we find that neither method is consistently better than the other across datasets or MLLMs. We hypothesize that this relates to MLLMs' sensitivity to prompt ordering: OCR+PAGE1's prompt keeps the selected page image adjacent to its corresponding OCR text, whereas OCR+PAGEN may select a page far from the start of the prompt, and MLLMs are known to be better at local than long-range context reasoning. We find this effect to be more model- than document-length-dependent: on Malvern-Hills, OCR+PAGEN consistently outperforms OCR+PAGE1 for GPT-4O, and OCR+PAGE1 consistently outperforms OCR+PAGEN for GEMINI-2.5-PRO, holding across all three document-length variants we test (2–3, 5+, and 10+ pages) — suggesting this is a stable property of each model's handling of prompt order, rather than an artifact of any one dataset or document length. We discuss this further, with full results, in Appendix C.3.

Cost and scaling. Although our methods use only a single page, they are sometimes more expensive than methods which use the full set of images. This is due to a combination of high text-density OCR transcriptions, as well as the added cost of OCR transcription itself. One way to address this could be the use of cheaper OCR; we note that some MLLMs, such as GEMMA-3-27B, are significantly cheaper than our chosen OCR engine, and can achieve improved or comparable results over OCR depending on the task. Further experimentation using cheap MLLMs as alternative OCR engines and more powerful MLLMs as post-processors is an area we leave for future work.

Prompt caching (Shi et al., 2024) could further improve cost scaling for OCR+PAGEX methods on long documents, as the shared page image tokens would be cached across per-page chunks; we leave this for future work.

Conclusion. In this work we investigated the transcription of multi-page handwritten documents using various configurations of commercial OCR engines and MLLMs. We provide a set of multi-page transcription benchmarks, including a brand new dataset, Malvern-Hills, which we hope will serve as a useful evaluation tool for the community. We also provide the first known evaluation of the effectiveness of different prompting strategies for the task of zero-shot, multi-page handwriting transcription, on our three benchmark tasks. We propose the OCR+PAGE1 and OCR+PAGEN methods, and empirically demonstrate that they improve transcription accuracy while balancing cost and performance. Notably, they are equally or more effective than end-to-end processing with leading MLLMs, despite not having access to all page images.

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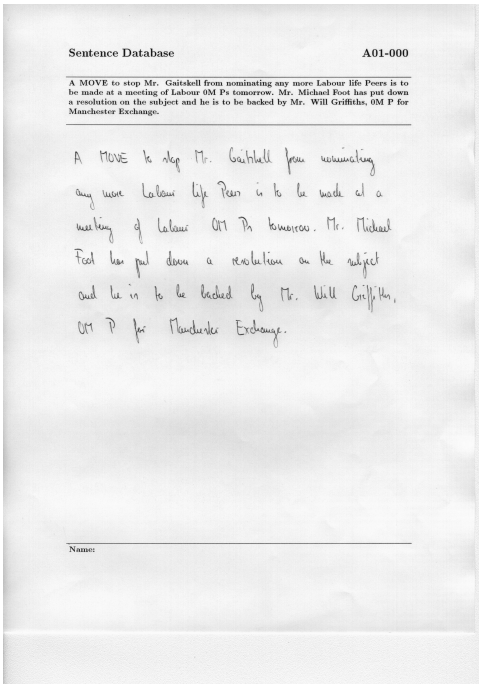
A Example documents from datasets

Figures 5, 6 & 7 show example pages from the `IAM`, `Malvern-Hills` and `Bentham` datasets respectively.



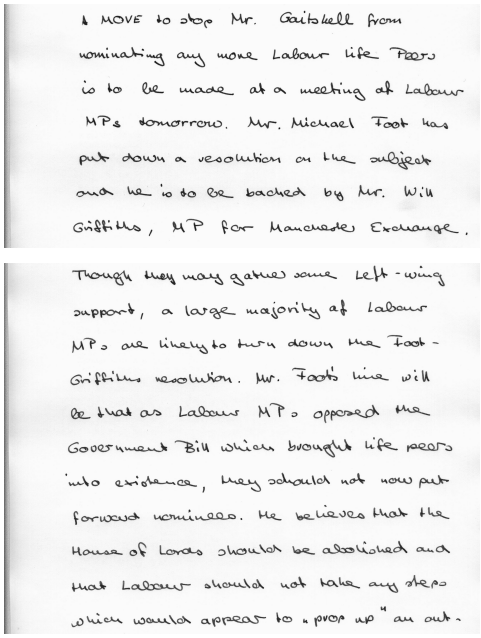
Sentence Database A01-000

A MOVE to stop Mr. Gaitskell from nominating any more Labour life Peers is to be made at a meeting of Labour 0M Ps tomorrow. Mr. Michael Foot has put down a resolution on the subject and he is to be backed by Mr. Will Griffiths, 0M P for Manchester Exchange.

A MOVE to stop Mr. Gaitskell from nominating any more Labour life Peers is to be made at a meeting of Labour 0M Ps tomorrow. Mr. Michael Foot has put down a resolution on the subject and he is to be backed by Mr. Will Griffiths, 0M P for Manchester Exchange.

Name:

(a) An example of a document from the IAM Handwriting Database.

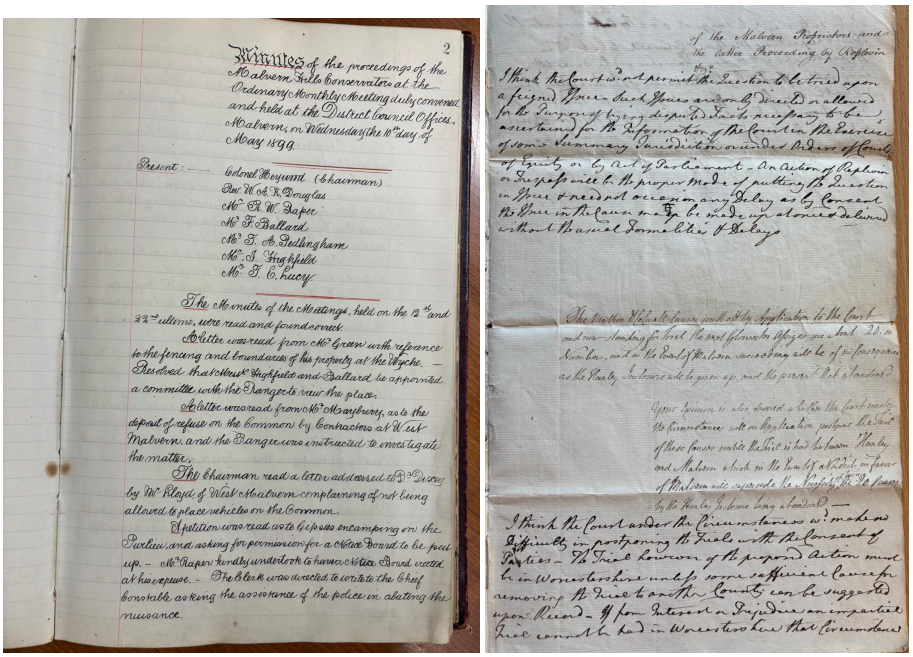


A MOVE to stop Mr. Gaitskell from nominating any more Labour life Peers is to be made at a meeting of Labour MPs tomorrow. Mr. Michael Foot has put down a resolution on the subject and he is to be backed by Mr. Will Griffiths, MP for Manchester Exchange.

Though they may gather some left-wing support, a large majority of Labour MPs are likely to turn down the Foot-Griffiths resolution. Mr. Foot's line will be that as Labour MPs opposed the Government Bill which brought life peers into existence, they should not now put forward nominees. He believes that the House of Lords should be abolished and that Labour should not take any steps which would appear to "prop up" an out-

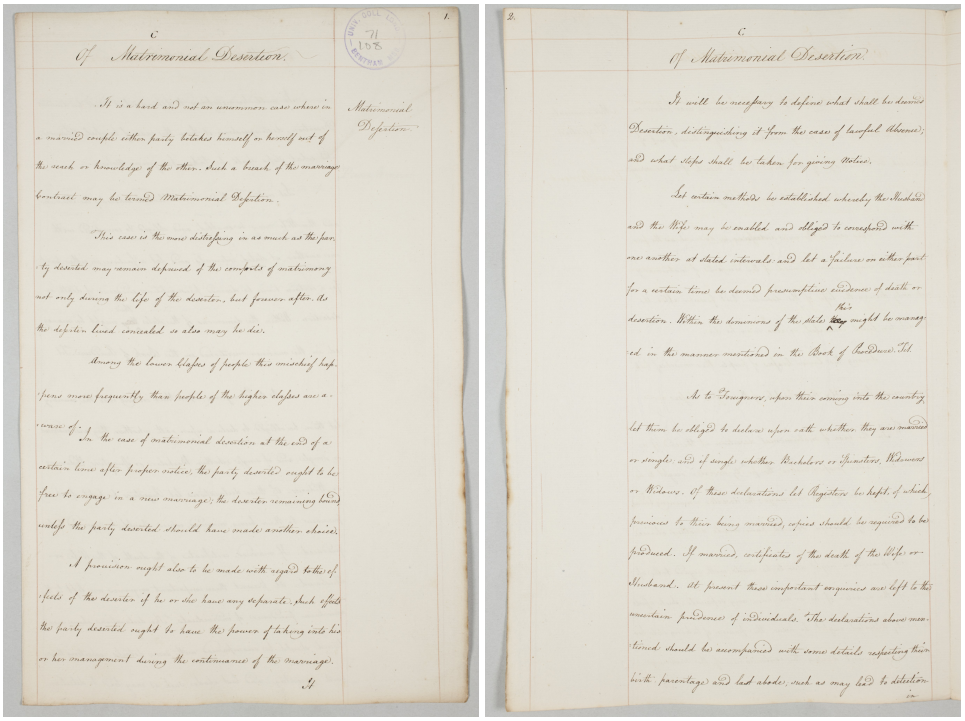
(b) An example of a constructed multi-page `IAM` document, combining two pages from the same writer with the machine-printed text cropped out.

Figure 5: Left: original IAM document. Right: constructed two-page `IAM` document.



(a) (b)

Figure 6: Example pages from the `Malvern-Hills` dataset.

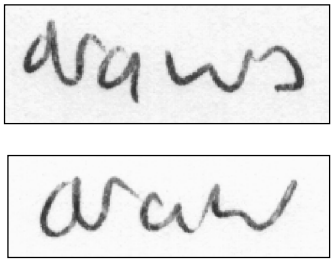


(a) (b)

Figure 7: Example pages from the `Bentham` dataset.

B Examples of OCR+PAGE1 corrections

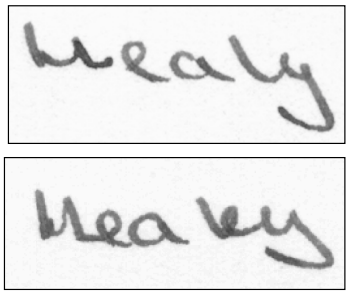
See Figures 8–11. All examples are on IAM, use Google Cloud Vision as the OCR engine and GPT-4O.



1st page snippet
GT: 'draws'
OCR only: 'draws' ✅
OCR→LLM: 'draws' ✅
+first page→MLLM: 'draws' ✅

2nd page snippet
GT: 'draw'
OCR only: 'araw' ❌
OCR→LLM: 'area' ❌
+first page→MLLM: 'draw' ✅

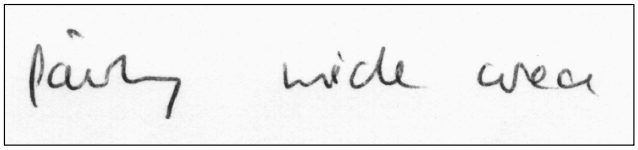
Figure 8: With OCR+PAGE1, the correctly-transcribed occurrence of 'draws' in the first page can be extrapolated to the unseen 'draw' on the second page.



1st page snippet
GT: 'Healy'
OCR only: 'Mealy' ❌
OCR→LLM: 'Mealy' ❌
+first page→MLLM: 'Healy' ✅

2nd page snippet
GT: 'Healy'
OCR only: 'Mealy' ❌
OCR→LLM: 'Mealy' ❌
+first page→MLLM: 'Healy' ✅

Figure 9: With OCR+PAGE1, the correctly-transcribed occurrence of the name 'Mr Healy' in the first page can be extrapolated to the unseen occurrence on the second page.



2nd page snippet
GT: 'fairly wide area'
OCR only: 'Paily miche mide wear' ❌
OCR→LLM: 'fairly large area' ❌
+first page → 'fairly wide area' ✅

Figure 10: OCR+PAGE1 corrects where OCR→LLM gets it wrong, despite *only having access only to the garbled OCR output* and not the image of the word 'wide' shown above. Suggests some degree of reasoning using the seemingly irrelevant first page text — i.e. it can see that 'm's on page 1 look similar to 'w's and reason that 'mide' could be 'wide'.

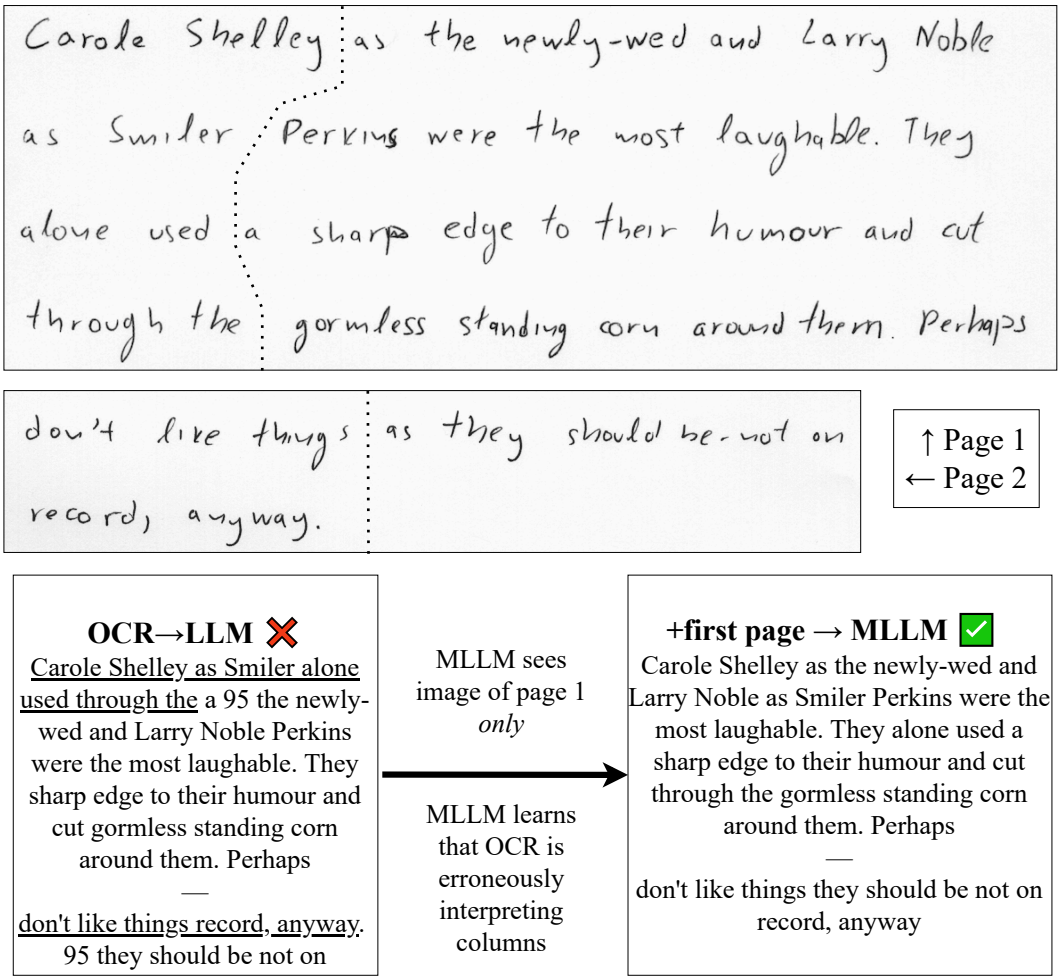


Figure 11: An unusual case where the OCR engine erroneously breaks the text into two columns for both pages. This is shown using the dotted line and underlining of the transcribed text. OCR→LLM preserves this error. OCR+PAGE1 trivially corrects it in the first page — it has access to the image — *but also corrects it in the second page*, even though it has no access to that image. OCR+PAGE1 correctly rearranges the text on page 2 using only context and the inferred formatting from page 1.

C Additional experimental details

C.1 Token counting and image tokenization policy

Tokenization policy for OpenAI models is based on the `tiktoken` Python library. For GEMINI and GEMMA, text token counts are computed using the `count_tokens` method packaged with the Gemini API, and image tokens are counted with a custom script that implements the image tokenization policy described in the Gemini API documentation.

C.2 Semantic evaluation of transcription accuracy with an LLM

For each transcribed page we generate a text diff from the ground-truth using `<ins>...<\ins>` and `<del>...<\del>` tags, and pass it to GEMINI-2.5-FLASH with a prompt asking to return a JSON-structured list of all errors, each classified into one of 7 error types. 'Formatting' and 'semantic' errors (those which do not affect meaning or remove information from the document) are 'minor' errors; 'missing content', 'hallucination', 'proper noun error', 'numeric error' and 'other' are 'major' errors (those which impede understanding or remove information). This method is naturally imperfect, but we found that for a random sample of 5 documents, error classifications were accurate about 95% of the time.

Table 6 shows the full set of error classifications for IAM, as described in Section 5.2 and summarised in Table 1. For conciseness, the table combines the 'proper noun' and 'numerical' error types into one column, and combines the two minor error types, 'formatting' and 'semantic', into the 'minor' error type. The error types are defined in the prompt used to extract them as follows:

```
Error types (choose exactly one per error):
1) missing_content
  - A deletion with no suitable inserted counterpart.
  Example: `<del>word</del>` with no matching `<ins>word</ins>`.
  - Minor missing content, such as single punctuation marks,
  should be `formatting`.
2) hallucination
  - An insertion with no corresponding gt (including numbers
  that appear only in pred).
  - Minor hallucinations, such as single punctuation marks,
  should be `formatting`.
3) mistake_proper_noun
  - gt is a proper noun (possibly multi-word: full or partial
  names, places, institutions, titles) and pred misrenders it
  (letters/wording/order).
  - Pure capitalization changes that don't create a different name
  are semantic.
  - Extended 'proper names', such as full names, should be
  treated in their entirety, e.g. 'A. B. Smith'
4) mistake_numerical
  - Use only when gt contains a number/date/roman numeral/measure
  and pred changes its value or structure or fails to include it.
  - Combine obviously linked components (e.g., an entire date
  like 18 March 1884) into one numerical error.
5) mistake_other
  - Non{proper-noun, non-numeric word/phrase error that affects
  normal reading (e.g., genuine misspelling or wrong lemma/word).
  - Use sparingly, only if none of the other error types are
  appropriate, not as a catch-all
6) semantic
  - Differences that are clearly meaning-preserving or trivial:
    - minor letter/spelling differences where the word couldn't
    reasonably be mistaken for another,
```

```
    - alternative/modernized spellings or contractions with
    the same meaning
    - capitalization-only changes,
7) formatting
  - Minor erroneous punctuation, misplaced or missing newlines,
  misplaced structural content including text that has been moved
  from one place in the transcription to another
  - If a moved block contains internal real mistakes (e.g., a
  wrong year), add separate errors for those internal pieces with
  the appropriate types.
```

C.3 Why isn't OCR+PAGEN always better than OCR+PAGE1?

While OCR+PAGEN often performs better than OCR+PAGE1, this is not consistent over MLLMs or datasets. We attribute this to the added prompt complexity of extrapolating from an arbitrary Nth page rather than the 1st, as this is the only difference between the two methods. There is evidence that MLLMs are sensitive to prompt order (Guan et al., 2025), so it is not unreasonable to suppose that the prompt ordering for OCR+PAGE1, which is 'page 1 image, page 1 OCR text, page 2 OCR text, ...', where the corresponding image and text are adjacent in the prompt, is easier for an MLLM to follow than 'page N image, page 1 OCR text, ..., page N OCR text, ...'. The method relies on learning a mapping from the page N image to the page N OCR, and MLLMs are known to be better at local context reasoning than long-context (Liu et al., 2025). In the case where the first page is approximately as informative as the Nth, the complexity this prompt arrangement introduces may outweigh any marginal benefit from the page ID choice. It is possible that further prompt tuning, such as rearranging the image within the prompt, could mitigate this; we leave it for future work.

This effect appears to be more model-dependent than document-length-dependent: for `Malvern-Hills`, OCR+PAGEN improves on OCR+PAGE1 for GPT-4O and vice versa for GEMINI-2.5-PRO, and this holds across the 2-3-, 5-plus-, and 10-plus-page versions of `Malvern-Hills` (Table 4), where OCR+PAGEN has progressively more page-selection options. We also note that for two-page documents, OCR+PAGEN's upstream page choice is inherently limited, and it defaults to OCR+PAGE1's behavior whenever the first page is selected; the choice can nonetheless be meaningful even here — for example, when the first page is a sparse title page, selecting page 2 can provide substantially more useful handwriting context.

Table 4: OCR+PAGE1 vs. OCR+PAGEN CER (%) on `Malvern-Hills`, by model and document length. Better of each pair is bold. Full results (all methods) are in Table 2a (2–3 pages) and Appendix Tables 10 & 11 (5+, 10+ pages).

	GPT-4O		GEMINI-2.5-PRO	
Document length	OCR+PAGE1	OCR+PAGEN	OCR+PAGE1	OCR+PAGEN
2–3 pages	8.92	**8.05**	**5.83**	6.54
5+ pages	9.12	**7.59**	**5.43**	5.86
10+ pages	21.38	**16.37**	**4.76**	5.41

C.4 Variance across API seeds

To directly test the reviewer concern that single-run, temperature-zero evaluation may be unreliable, we repeated OCR+PAGE1 and OCR+PAGEN (GEMINI-2.5-PRO) across 3 additional API seeds on `IAM` and `Malvern-Hills`, and additionally repeated IMAGES and OCR+IMAGES on `Malvern-Hills` to confirm the comparative ranking is not an artifact of a single run. Table 5 reports per-seed CER, the 4-seed mean (including the original published run as seed 0), and 95% confidence intervals.

On `IAM`, variance is negligible: 95% CI half-widths are $\pm 0.005\%$ (OCR+PAGE1) and $\pm 0.024\%$ (OCR+PAGEN), and the published values sit within 0.02% of the 4-seed mean.

On Malvern-Hills, our most challenging dataset, we observe real run-to-run variance (95% CI half-widths of ±0.09–0.54%, depending on method) — GEMINI-2.5-PRO is not perfectly deterministic at temperature zero on harder inputs. Despite this, the 4-seed mean ranking is unchanged, confirming that our central finding — that a single page image can capture most of the benefit of the full image set — is not an artifact of single-run evaluation.

Table 5: Variance across 4 API seeds for GEMINI-2.5-PRO. CIs are 95%, *t*-distribution, 3 degrees of freedom.

Dataset	**Method**	**seed 0**	**1**	**2**	**3**	**Mean**	**95% CI ±**
IAM (107 docs)	OCR+PAGE1	0.648	0.645	0.642	0.648	0.646	0.005
IAM (107 docs)	OCR+PAGEN	0.633	0.660	0.655	0.668	0.654	0.024
Malvern-Hills (70 docs)	OCR+PAGE1	5.826	5.966	6.609	6.121	6.130	0.543
Malvern-Hills (70 docs)	OCR+PAGEN	6.544	7.343	6.743	6.894	6.881	0.541
Malvern-Hills (70 docs)	IMAGES	6.417	6.545	6.527	6.527	6.504	0.093
Malvern-Hills (70 docs)	OCR+IMAGES	6.456	6.424	6.244	6.390	6.379	0.149

Table 6: IAM error types for all runs in Table 1, evaluated by GEMINI-2.5-FLASH. Each cell contains the average number of occurrences of that type of error in a transcription produced by the given method, and the percentage of total errors in a transcription that are that particular error type. E.g., Azure OCR output alone has an average of 5.1 major errors per transcription for IAM documents, but 41.4% of total errors inn Azure transcription are minor, i.e. semantic or formatting-related only.

	Input	**Major (all)**	**Missing content**	**Halluc -ination**	**Proper noun /Numeric**	**Other error**	**Minor error**
—	OCR	5.1 (58.6%)	0.3 (3.1%)	0.2 (1.9%)	0.8 (9.0%)	3.9 (44.6%)	3.6 (41.4%)
GEMMA-3-27B	OCR	3.2 (47.9%)	0.3 (4.2%)	0.2 (2.4%)	0.6 (8.8%)	2.1 (32.5%)	3.4 (52.1%)
	IMAGES	4.3 (52.1%)	0.2 (2.7%)	0.2 (1.9%)	1.1 (13.0%)	2.9 (34.5%)	4.0 (47.9%)
	IMAGES-ALL-AT-ONCE	4.0 (60.4%)	0.2 (3.3%)	0.1 (1.8%)	0.9 (13.8%)	2.8 (41.4%)	2.7 (39.6%)
	OCR+IMAGES	2.7 (43.6%)	0.2 (3.5%)	0.1 (1.5%)	0.5 (8.2%)	1.9 (30.3%)	3.4 (56.4%)
	OCR+PAGEN	2.2 (44.5%)	0.2 (4.7%)	0.1 (3.0%)	0.5 (9.7%)	1.4 (27.1%)	2.8 (55.5%)
	OCR+PAGE1	2.0 (45.7%)	0.3 (5.7%)	0.1 (3.2%)	0.4 (8.4%)	1.3 (28.4%)	2.4 (54.3%)
GPT-4O	OCR	1.9 (39.8%)	0.2 (4.4%)	**0.0 (1.0%)**	0.5 (10.4%)	1.1 (24.0%)	2.8 (60.2%)
	IMAGES	1.8 (49.6%)	0.2 (5.7%)	0.1 (1.6%)	0.5 (13.2%)	1.1 (29.2%)	1.8 (50.4%)
	IMAGES-ALL-AT-ONCE	1.6 (43.6%)	0.2 (4.9%)	0.1 (1.5%)	0.4 (11.3%)	0.9 (25.9%)	2.1 (56.4%)
	OCR+IMAGES	*1.2 (42.2%)*	0.2 (7.1%)	**0.0 (1.3%)**	0.3 (8.7%)	0.7 (25.0%)	1.7 (57.8%)
	OCR+PAGEN	1.3 (39.8%)	0.2 (5.5%)	**0.0 (0.9%)**	0.3 (7.8%)	0.8 (25.6%)	2.0 (60.2%)
	OCR+PAGE1	*1.2 (39.1%)*	**0.1 (4.9%)**	**0.0 (1.5%)**	0.3 (8.6%)	0.7 (24.2%)	1.9 (60.9%)
GEMINI-2.5-PRO	OCR	*1.2 (32.8%)*	**0.1 (4.0%)**	0.1 (2.8%)	0.2 (6.3%)	0.7 (19.8%)	2.5 (67.2%)
	IMAGES	1.5 (47.1%)	0.2 (6.6%)	0.2 (5.4%)	0.3 (8.1%)	0.8 (27.0%)	**1.6 (52.9%)**
	IMAGES-ALL-AT-ONCE	1.4 (45.2%)	0.2 (7.4%)	0.1 (2.8%)	0.2 (8.0%)	0.8 (27.1%)	1.7 (54.8%)
	OCR+IMAGES	1.3 (42.7%)	0.2 (6.7%)	0.1 (3.9%)	0.2 (6.7%)	0.8 (25.5%)	1.8 (57.3%)
	OCR+PAGEN	**1.0 (38.9%)**	0.2 (7.7%)	0.1 (2.5%)	**0.1 (4.6%)**	**0.6 (24.2%)**	**1.6 (61.1%)**
	OCR+PAGE1	**1.0 (35.7%)**	0.2 (6.7%)	0.1 (2.7%)	**0.1 (5.0%)**	**0.6 (21.3%)**	1.8 (64.3%)

D Chinese handwriting evaluation: CASIA-5

To synthesize CASIA-5, we start with the CASIA-HWDB2.1 test split, which consists of 300 images of multiple lines of handwritten Chinese text. Similar to the process for IAM, we generate multi-page dataset CASIA-5 by randomly grouping pages with the same author ID, such that handwriting, but not semantic content, is consistent. We use a subset of 30 documents of 5 pages each in our experiments. We use Google Cloud Vision as our OCR engine.

See results in Table 7; abridged results are in Table 3 in the main paper.

Table 7: Results on CASIA-5 for all methods described in the main text, plus OCR+PAGER. Our methods, i.e. OCR+PAGEX methods, are bold. Score emphasis: **1st**, *2nd*, 3rd. 'Fails (/doc)' is the average number of retried API calls required per method (all calls eventually succeeded). For GPT-4O, all retries were due to incomplete/truncated response errors. For GEMINI-2.5-PRO, retries were due to invalid JSON output errors.

Method	CER ↓ (%)	Cost ($/1k docs) Total	OCR	In	Out	Tokens (k/doc) Image	In	Out	Time (s/doc)	Fails (/doc)
OCR	12.84	7.50	7.50	0.00	0.00	0	0	0	—	—
GPT-4O										
OCR	18.32	26.75	7.50	6.13	13.12	0.06	2.40	1.31	36.6	0.00
IMAGES	42.40	30.81	0.00	16.91	13.90	5.53	1.18	1.39	84.4	0.03
IMAGES-AAO	43.64	29.30	0.00	14.86	14.44	5.53	0.25	1.44	74.8	0.10
OCR+IMAGES	14.16	41.58	7.50	20.58	13.50	5.58	2.65	1.35	78.5	0.00
OCR+PAGER	13.91	28.41	7.50	7.51	13.40	1.11	1.77	1.34	34.0	0.00
OCR+PAGEN	12.87	28.68	7.50	7.64	13.55	1.11	1.77	1.35	47.7	0.00
OCR+PAGE1	14.48	28.31	7.50	7.45	13.36	1.11	1.74	1.34	44.2	0.00
GEMINI										
OCR	33.17	24.87	7.50	2.81	14.56	0	2.25	1.46	30.7	0.00
IMAGES	13.55	19.08	0.00	6.51	12.58	4.00	1.21	1.26	31.1	0.00
IMAGES-AAO	23.07	18.09	0.00	5.32	12.77	4.00	0.26	1.28	18.8	0.00
OCR+IMAGES	**8.39**	27.80	7.50	8.14	12.16	4.00	2.52	1.22	40.2	0.00
OCR+PAGER	10.13	23.19	7.50	3.08	12.61	0.80	1.66	1.26	18.0	0.00
OCR+PAGEN	*8.94*	23.42	7.50	3.20	12.72	0.80	1.66	1.27	27.5	0.00
OCR+PAGE1	12.61	23.25	7.50	3.05	12.70	0.80	1.64	1.27	48.3	0.07

Discussion. For this challenging Chinese handwriting dataset, we see that the best-performing model overall is OCR+IMAGES, i.e. a model that has access to both OCR prediction and the full set of document images. The OCR engine on its own is already quite effective, indeed, no method involving GPT-4o improves on it, and many significantly worsen it. The only methods that improve on OCR alone are those that use both OCR and at least one image as input to GEMINI. The fact that OCR+PAGEN and OCR+IMAGES provide a similar performance boost over OCR alone supports our findings that a single well-chosen image can provide most of the benefit provided by the full set of images, and at a lower token/overall cost.

E Additional experiments on longer documents

E.1 IAM-5

We generate 5-page documents by the same method we generated IAM; by grouping random individual pages by author ID so handwriting (but not necessarily semantic content) is consistent. We use 100 page images to generate 20 5-page documents.

See results in Table 8.

Table 8: Results on IAM-5 for all methods described in the main text, plus OCR+PAGER. Our methods are bold. Score emphasis: **1st**, *2nd*, 3rd. The single method with failed calls was due to GEMMA 'free resource exhausted' errors.

Method	CER ↓	Cost ($/1k docs)				Tokens (k/doc)			Time (s/doc)	Fails (/doc)
		Total	OCR	In	Out	Image	In	Out		
OCR	3.36	5.00	5.00	0.00	0.00	0	0	0	—	—
GEMMA										
OCR	2.67	5.34	5.00	0.11	0.23	0	1.54	0.47	14.8	0.00
IMAGES	1.54	0.65	0.00	0.40	0.26	4.44	1.21	0.51	20.1	0.00
IMAGES-AAO	1.35	0.59	0.00	0.33	0.26	4.44	0.26	0.53	12.7	0.00
OCR+IMAGES	1.47	5.68	5.00	0.44	0.24	4.44	1.81	0.48	19.5	0.05
OCR+PAGER	2.69	5.40	5.00	0.13	0.27	0.89	0.94	0.54	12.2	0.00
OCR+PAGEN	2.52	5.51	5.00	0.20	0.31	0.87	0.94	0.54	18.3	0.00
OCR+PAGE1	1.22	5.39	5.00	0.12	0.27	0.86	0.91	0.53	12.3	0.00
GPT-4O										
OCR	0.99	13.60	5.00	3.91	4.69	0.06	1.50	0.47	21.6	0.00
IMAGES	0.54	20.68	0.00	15.94	4.75	5.13	1.18	0.47	60.6	0.00
IMAGES-AAO	0.77	18.60	0.00	13.88	4.72	5.13	0.25	0.47	38.2	0.00
OCR+IMAGES	0.58	27.04	5.00	17.38	4.66	5.19	1.76	0.47	62.2	0.00
OCR+PAGER	0.91	14.93	5.00	5.11	4.82	1.02	0.89	0.48	21.9	0.00
OCR+PAGEN	0.83	15.05	5.00	5.19	4.87	1.02	0.89	0.48	26.6	0.00
OCR+PAGE1	0.98	14.82	5.00	5.01	4.81	1.00	0.87	0.48	24.3	0.00
GEMINI										
OCR	1.37	11.51	5.00	1.93	4.58	0	1.54	0.46	11.3	0.00
IMAGES	0.52	11.72	0.00	7.06	4.67	4.44	1.21	0.47	21.4	0.00
IMAGES-AAO	0.54	11.18	0.00	5.87	5.31	4.44	0.26	0.53	7.2	0.00
OCR+IMAGES	**0.47**	17.39	5.00	7.81	4.57	4.44	1.81	0.46	18.1	0.00
OCR+PAGER	0.52	12.48	5.00	2.28	5.20	0.89	0.94	0.52	8.3	0.00
OCR+PAGEN	*0.51*	12.59	5.00	2.34	5.25	0.87	0.94	0.52	13.5	0.00
OCR+PAGE1	**0.47**	12.40	5.00	2.21	5.19	0.86	0.91	0.52	7.9	0.00

Discussion. We see similar results for the longer document case of IAM-5 as we did for IAM. OCR+PAGE1 remains the (joint) top-performing model and all OCR + single-image methods perform approximately as well as the full OCR+IMAGES method, despite lacking access to *80% of images* (and the comparatively poor performance of OCR alone), and correspondingly have lower costs and inference times.

E.2 IAM-5-Random; inconsistent handwriting *and* semantic content ablation

IAM-5-Random is generated in the same way as IAM-5, but we ensure that all 20 generated documents contain pages from 5 different authors.

See results in Table 9.

Discussion. As expected, the benefit of OCR+single-image methods is less pronounced when there is neither consistent handwriting nor semantic content across pages — *but there is still some benefit*. Though OCR+PAGE1 underperforms, +PAGER and +PAGEN are

Table 9: Results on `IAM-5-Random` for all methods described in the main text, plus OCR+PAGER. Our methods are bold. Score emphasis: **1st**, *2nd*, 3rd.

Method	CER ↓	Cost ($/1k docs)				Tokens (k/doc)			Time	Fails
		Total	OCR	In	Out	Image	In	Out	(s/doc)	(/doc)
OCR	3.78	5.00	5.00	—	—	—	—	—	—	—
GEMMA										
OCR	2.88	5.34	5.00	0.11	0.23	0	1.55	0.47	13.8	0.0
IMAGES	2.34	0.67	0.00	0.41	0.26	4.67	1.21	0.51	20.7	0.0
IMAGES-AAO	2.04	0.61	0.00	0.35	0.26	4.67	0.26	0.53	12.6	0.0
OCR+IMAGES	1.75	5.70	5.00	0.45	0.24	4.67	1.82	0.48	17.2	0.0
OCR+PAGER	3.14	5.40	5.00	0.13	0.27	0.91	0.94	0.54	11.8	0.0
OCR+PAGEN	3.10	5.51	5.00	0.20	0.31	0.90	0.94	0.54	18.0	0.0
OCR+PAGE1	1.53	5.39	5.00	0.13	0.27	0.91	0.92	0.53	11.7	0.0
GPT-4O										
OCR	1.09	13.66	5.00	3.92	4.73	0.06	1.51	0.47	21.4	0.0
IMAGES	0.91	21.47	0.00	16.66	4.82	5.46	1.18	0.48	56.8	0.0
IMAGES-AAO	1.20	19.36	0.00	14.60	4.76	5.46	0.25	0.48	35.6	0.0
OCR+IMAGES	0.71	27.83	5.00	18.12	4.71	5.48	1.77	0.47	55.0	0.0
OCR+PAGER	1.01	15.05	5.00	5.21	4.84	1.05	0.90	0.48	20.3	0.0
OCR+PAGEN	0.92	15.18	5.00	5.29	4.90	1.05	0.90	0.49	25.7	0.0
OCR+PAGE1	1.08	15.03	5.00	5.19	4.83	1.07	0.87	0.48	19.8	0.0
GEMINI										
OCR	1.56	11.54	5.00	1.93	4.60	0	1.55	0.46	10.9	0.0
IMAGES	0.76	12.08	0.00	7.35	4.73	4.67	1.21	0.47	21.6	0.0
IMAGES-AAO	0.75	11.43	0.00	6.17	5.27	4.67	0.26	0.53	6.7	0.0
OCR+IMAGES	**0.64**	17.72	5.00	8.11	4.61	4.67	1.82	0.46	18.7	0.0
OCR+PAGER	0.80	12.55	5.00	2.32	5.23	0.91	0.94	0.52	7.6	0.0
OCR+PAGEN	*0.70*	12.66	5.00	2.38	5.28	0.90	0.94	0.52	13.4	0.0
OCR+PAGE1	1.31	12.49	5.00	2.28	5.21	0.91	0.92	0.52	7.0	0.0

perform comparably with methods that include access to all images, at lower cost and faster inference time. These results demonstrate, firstly, that our intuition about the benefit of +PAGEX methods is likely correct; the more similar pages in a document are (in content, writing, etc.) the more performance gain can be achieved with only a single page (and vice versa); secondly, that even in cases where pages are quite different, a single page can still provide performance benefit. This may be a result of other page similarities (e.g. image quality, document type), or an example of multi-modal inputs assisting with reasoning in general as a version of in-context learning.

E.3 `Malvern-Hills-5+`

We group consecutive pages (i.e. pages that are continuous sections from the same book of minutes) from `Malvern-Hills` to produce a dataset of 24 documents from 140 images, each with a minimum of 5 pages: 11 documents have 5 pages, 9 have 6, 1 has 7 and 3 have 8 (average: 5.83 pages/doc).

In addition to the methods from the main text, we evaluate two open-source baselines on this dataset:

- TROCR (Li et al., 2023): specifically `trocr-large-handwritten`, a pre-trained Transformer model fine-tuned on handwritten text. Since our setting is zero-shot, we do not additionally fine-tune TROCR on our datasets. As TROCR is intended for line images, we use the kraken command line tool to generate line sub-images of `Malvern-Hills` pages and concatenate results. We run TROCR on an M1 MacBook Pro, CPU only.

- DOCOWL2 (Hu et al., 2025): an open MLLM specialized for document processing. We use a temperature of zero and a sufficiently high output token limit to ensure no truncation events. We tested two versions: the original (full page images) and DOCOWL2-LINES (cropped line images, identical to TROCR). We run DOCOWL2 on an A10 GPU.[8]

See results in Table 10.

Table 10: Results on `Malvern-Hills-5+` for all methods described in the main text, plus OCR+PAGER, TROCR, DOCOWL2 and DOCOWL2-LINES. Our methods are bold. Score emphasis: **1st**, *2nd*, 3rd. All failed calls (GEMMA only) were caused by API disconnection without a response.

Method	CER ↓	Cost ($/1k docs)				Tokens (k/doc)			Time (s/doc)	Fails (/doc)
		Total	OCR	In	Out	Image	In	Out		
DOCOWL2 -LINES	93.01	0.00	0.00	0.00	0.00	0	0	0	2054	0.00
DOCOWL2	92.08	0.00	0.00	0.00	0.00	0	0	0	234	0.00
TROCR	31.43	0.00	0.00	0.00	0.00	0	0	0	990	0.00
OCR	13.96	5.83	5.83	0.00	0.00	0	0	0	—	0.00
GEMMA										
OCR	12.92	7.10	5.83	0.24	1.03	0	3.36	2.06	44.0	0.00
IMAGES	16.00	1.43	0.00	0.41	1.01	4.52	1.41	2.03	85.4	0.58
IMAGES-AAO	17.64	1.32	0.00	0.33	0.99	4.52	0.26	1.98	92.4	0.75
OCR+IMAGES	9.84	7.40	5.83	0.57	0.99	4.52	3.68	1.99	44.8	0.00
OCR+PAGER	23.65	7.06	5.83	0.24	0.98	0.77	2.70	1.97	79.4	0.58
OCR+PAGEN	24.94	7.22	5.83	0.44	0.95	0.77	2.70	1.81	126	1.12
OCR+PAGE1	21.35	7.03	5.83	0.24	0.95	0.77	2.68	1.90	89.8	0.75
GPT-4O										
OCR	9.42	33.70	5.83	8.35	19.52	0.07	3.27	1.95	47.1	0.00
IMAGES	10.24	33.84	0.00	14.77	19.06	4.46	1.38	1.91	90.8	0.00
IMAGES-AAO	12.38	31.02	0.00	12.25	18.77	4.46	0.25	1.88	80.2	0.00
OCR+IMAGES	6.49	44.21	5.83	20.25	18.13	4.53	3.57	1.81	83.1	0.00
OCR+PAGER	10.17	34.15	5.83	8.61	19.71	0.77	2.53	1.97	46.6	0.00
OCR+PAGEN	7.59	33.90	5.83	8.81	19.26	0.77	2.53	1.92	68.2	0.00
OCR+PAGE1	9.12	33.32	5.83	8.55	18.94	0.77	2.51	1.89	51.8	0.00
GEMINI										
OCR	7.05	29.46	5.83	4.20	19.43	0	3.36	1.94	24.0	0.00
IMAGES	*5.63*	27.37	0.00	7.41	19.96	4.52	1.41	2.00	30.5	0.00
IMAGES-AAO	6.14	27.12	0.00	5.97	21.15	4.52	0.26	2.12	19.2	0.00
OCR+IMAGES	5.69	35.75	5.83	10.24	19.67	4.52	3.68	1.97	27.5	0.00
OCR+PAGER	5.99	31.22	5.83	4.35	21.04	0.77	2.70	2.10	20.9	0.00
OCR+PAGEN	5.86	31.43	5.83	4.55	21.05	0.77	2.70	2.10	31.2	0.00
OCR+PAGE1	**5.43**	31.15	5.83	4.32	21.00	0.77	2.68	2.10	21.4	0.00

Discussion. As with `IAM-5`, even with longer page counts, a PAGEX method remains the best-performing, despite having access to <20% of the raw images per document, along with OCR which has a high error rate on its own. IMAGES alone performs quite well, and is slightly cheaper than OCR+PAGE1 due to the high text density of the `Malvern-Hills` dataset, but it is significantly slower as each image in a multi-page document requires a separate API call.

Unfortunately, our DOCOWL2 and TROCR non-commercial-MLLM baselines perform poorly on this task zero-shot, and are quite slow. TROCR, at least, yields parsable text, but is prone to OCR-like errors such as the misreading of individual words or characters. Conversely,

[8] DOCOWL2 cannot be run on a CPU-only machine as the `flash-attn` python dependency requires CUDA.

DOCOWL2 is occasionally accurate, but is extremely prone to a number of well-known LLM issues that destroy its overall performance: (i) early stopping (or simply outputting a single token), (ii) egregious hallucination often bearing no relation to the actual text, (iii) repetition of words or sentences ad infinitum, (iv) needless addition of code fences or explanatory text (e.g. double quotes, or 'the document reads...'), (v) repeating the prompt, and (vi) ignoring the prompt completely. These behaviors persisted regardless of explicit instructions given against them during prompt iteration.

E.4 `Malvern-Hills-10+`

We use the same generation method as `Malvern-Hills-5+`. We obtain 10 documents in total from 115 images; 2 have 10 pages, 2 have 11, 5 have 12, 1 has 13 (average: 11.5 pages/doc).

See results in Table 11.

Table 11: Results on `Malvern-Hills-10+` for all methods described in the main text, plus OCR+PAGER. Our methods are bold. Score emphasis: **1st**, *2nd*, 3rd. All failed calls (GEMMA only) were a result of incomplete responses (i.e. failure or truncation).

Method	CER ↓	Cost ($/1k docs)				Tokens (k/doc)			Time	Fails
		Total	OCR	In	Out	Image	In	Out	(s/doc)	(/doc)
OCR	12.92	11.50	11.50	0.00	0.00	0	0	0	0.0	0.00
GPT-4O										
OCR	8.48	67.28	11.50	16.65	39.13	0.13	6.53	3.91	93.2	0.00
IMAGES	9.90	67.13	0.00	29.12	38.01	8.80	2.71	3.80	181.1	0.00
IMAGES-AAO	11.64	59.37	0.00	23.45	35.92	8.80	0.25	3.59	100.8	0.20
OCR+IMAGES	6.44	87.86	11.50	40.11	36.26	8.93	7.12	3.63	165.4	0.00
OCR+PAGER	17.11	56.93	11.50	12.22	33.21	0.77	4.70	3.32	103.9	0.30
OCR+PAGEN	16.37	57.09	11.50	12.58	33.01	0.77	4.70	3.30	123.7	0.30
OCR+PAGE1	21.38	56.48	11.50	12.17	32.82	0.77	4.68	3.28	119.1	0.40
GEMINI										
OCR	6.88	59.29	11.50	8.40	39.39	0	6.72	3.94	47.9	0.00
IMAGES	4.87	54.71	0.00	14.61	40.11	8.90	2.78	4.01	60.6	0.00
IMAGES-AAO	6.05	54.46	0.00	11.45	43.00	8.90	0.26	4.30	40.9	0.00
OCR+IMAGES	*4.80*	71.41	11.50	20.30	39.61	8.90	7.34	3.96	54.9	0.00
OCR+PAGER	5.50	61.82	11.50	7.26	43.06	0.77	5.03	4.31	40.1	0.00
OCR+PAGEN	5.41	61.77	11.50	7.62	42.65	0.77	5.03	4.26	63.8	0.00
OCR+PAGE1	**4.76**	61.13	11.50	7.23	42.41	0.77	5.01	4.24	40.6	0.00

Discussion. Even for documents of at least 10 pages in length, OCR+PAGE1 remains the top-performing method, with OCR+IMAGES being the second best, about equivalent in performance, but much slower and more expensive. This suggests that using a single page to improve performance does scale reasonably well, even for quite long documents. This is good news, as it means that, for documents where the average number of text tokens inside each image is less than the average number of tokens produced by tokenizing the image (the case for `CASIA-5`, `Bentham`, `IAM` and many other real-world datasets — `Malvern-Hills` is particularly token-dense), then +PAGEX methods will only be more cost and time effective in comparison to full-image methods as document length increases.

F `Malvern-Hills` dataset metadata and ablations

This section includes information about `Malvern-Hills` at the image level: incidence of challenging OCR features (Table 12) and information about writers (Table 13), time-of-writing (Table 14), and breakdown of pages by primary and secondary content types (Table 15) for each page.

Table 12: `Malvern-Hills` image statistics and prevalence of various OCR challenges. Particularly notable are the reasonably high frequencies of distractor text, tabular data, archaic language and multiple authors.

Word count	219 ± 83
Character count	1260 ± 473
Includes tabular information	19.3%
Includes margin notes	15.7%
Includes distractor text	62.1%
Non-linear structure	0.7%
Archaic language	31.4%
Poor quality image/damaged paper	2.1%
Handwriting from multiple authors	18.6%
Includes crossed-out text	23.6%

Table 13: Unique writers for the `Malvern-Hills` dataset and number of documents containing that writer's handwriting for each. Note that some pages contain multiple hands.

Author ID	Count
0	44
1	23
2	18
3	17
4	16
5	15
6	11
7	6
8	5
9	5
10	2
11	2
12	1
13	1

Table 14: Years of writing for document pages in `Malvern-Hills`. Some documents were written in one year but copied from a document originally written in another year; where known, this table includes both — for example, some documents use archaic 17th century language but were copied by hand in the 19th century.

Year	Original	Written
1631	11	0
1632	17	17
1795	6	6
1899	15	15
1915	17	17
1925	22	22
1932	5	5
1934	20	20
1936	8	8
1938	11	11
Unknown	8	8

Table 15: Breakdown of primary and secondary page types found in `Malvern-Hills`.

Primary Type	# Pages	Secondary Types	# Pages
Historical minutes	98	—	72
		Tabular	26
Historical legal	34	Statute	17
		Memoranda roll	10
		Case memorandum	4
		Memoranda roll, Tabular	1
		Case memorandum, Legal letter	1
		Legal letter	1
Historical inventory/schedule	8	—	8

F.1 `Malvern-Hills-5+` document type and feature ablation

Using primary document types from Table 16 and some choice dataset statistics from Table 12, we ablate document types and features for `Malvern-Hills-5+` in Tables 17–19 (by document type) and Tables 20–22 (by document feature).

Each document of 5 or more pages has a single shared primary type over all individual page images. A document is `tabular`, `archaic` or has `multiiple_hands` if any of its constituent pages has this property.

Table 16: For the individual 5+ page *documents* of `Malvern-Hills-5+` (not individual pages/images), the prevalence of tabular data, archaic language and multiple writers for each document. A document is treated as `tabular/archaic/multiple_hands` if any pages have this feature. In general, only one or two pages per document will have tabular information or multiple hands, whereas archaic language will typically be throughout.

Document type	Num. docs	Num. pages	tabular (%)	archaic (%)	multiple _hands (%)	written_year min | median | max
historical _minutes	17	98	88.2	41.2	82.4	1899 | 1925 | 1938
historical _legal	6	34	16.7	100	33.3	1632 | 1713 | 1884

Table 17: Performance for `historical_minutes`-typed documents only from `Malvern-Hills-5+`. All methods use GEMINI-2.5-PRO as the MLLM.

Method	CER (%)
Azure OCR only	11.8
OCR	5.3
IMAGES-AAO	4.55
OCR+PAGER	3.88
OCR+PAGEN	3.83
OCR+PAGE1	3.8
IMAGES	3.16
OCR+IMAGES	3.11

Discussion. Overall we see that the `historical_legal` documents are much more challenging, with $> 3\times$ the proportion of errors compared to `historical_minutes`. We can likely attribute this to (from examination) the ubiquity of archaic language and florid cursive (a product of the much earlier writing dates, $\sim$ 200 years prior), which is much

Table 18: Performance for historical_legal-typed documents only from Malvern-Hills-5+. All methods use GEMINI-2.5-PRO as the MLLM.

Method	CER (%)
Azure OCR only	20.81
OCR+IMAGES	13.56
IMAGES	13.17
OCR	12.53
OCR+PAGER	12.36
OCR+PAGEN	12.03
IMAGES-AAO	11.11
OCR+PAGE1	10.36

Table 19: Performance for historical_inventory/schedule-typed documents only from Malvern-Hills-5+. All methods use GEMINI-2.5-PRO as the MLLM.

Method	CER (%)
Azure OCR only	9.58
OCR	4.06
OCR+PAGER	3.56
OCR+PAGE1	3.46
OCR+PAGEN	3.41
IMAGES-AAO	3.27
IMAGES	2.42
OCR+IMAGES	2.34

harder to transcribe and much more prone to errors in post-processing/correction. While historical_minutes documents do include some archaic language, these are generally sporadic instances, rather than comprising the overall style of writing.

Comparing the two document types, we can see that OCR+SINGLE-PAGE methods, and especially OCR+PAGE1, are dominant on the *more challenging archaic document type*, while full-image methods IMAGES, OCR+IMAGES struggle. The reverse is true for the overall *easier* historical_minutes document type, where IMAGES, OCR+IMAGES dominate (though OCR+PAGEX methods are still competitive, especially given their comparative image token dearth).

Considering the dominant features of each type of document; it is unsurprising that OCR+PAGE1 is less adept for transcribing documents where a single page includes tabular data, as it is likely that there will not be any on the "seen" page. Conversely, archaic language is likely to be consistent across pages, so single-page extrapolation is more effective in this case.

Overall though, what these results suggest is that OCR+SINGLE-PAGE *methods are most beneficial when the task is more challenging*. We can interpret these results in terms of the tradeoff between prompt complexity and task difficulty. If a task is relatively easier (_minutes), the MLLM is less likely to become overwhelmed by a high-complexity or long prompt; it can leverage the additional detail (e.g. all images and OCR) to achieve incremental performance improvement on an almost-solved task. If a task is more challenging, this additional detail/complexity hurts overall performance, and a more optimal balance is achieved with a multi-modal prompt that reduces redundancy — i.e. OCR with a single page.

Relative importance of document type vs. document features We can see that document type dominates the differences in performance, — i.e. tables for tabular, multiple_writer, non_archaic generally follow historical_minutes (and vice versa for historical_legal).

Table 20: Performance for documents from `Malvern-Hills-5+` split by presence of tabular content. A document is `tabular` if any constituent page includes tabular layout. All methods use GEMINI-2.5-PRO as the MLLM.

(a) `tabular` documents

Method	CER (%)
Azure OCR only	12.18
OCR	5.56
IMAGES-AAO	4.56
OCR+PAGER	4.00
OCR+PAGE1	3.98
OCR+PAGEN	3.97
IMAGES	3.28
OCR+IMAGES	3.20

(b) `non_tabular` documents

Method	CER (%)
Azure OCR only	17.53
OCR+IMAGES	10.68
IMAGES	10.35
OCR	10.05
OCR+PAGER	9.96
OCR+PAGEN	9.63
IMAGES-AAO	9.28
OCR+PAGE1	8.31

Table 21: Performance for documents from `Malvern-Hills-5+` split by presence of archaic language. A document is `archaic` if any constituent page is marked as such. All methods use GEMINI-2.5-PRO as the MLLM.

(a) `archaic` documents

Method	CER (%)
Azure OCR only	16.50
OCR	8.61
OCR+IMAGES	7.96
IMAGES	7.86
OCR+PAGER	7.74
IMAGES-AAO	7.71
OCR+PAGEN	7.58
OCR+PAGE1	6.95

(b) `non_archaic` documents

Method	CER (%)
Azure OCR only	10.96
OCR	5.22
IMAGES-AAO	4.28
OCR+PAGER	3.92
OCR+PAGEN	3.82
OCR+PAGE1	3.63
OCR+IMAGES	3.01
IMAGES	3.00

Table 22: Performance for documents from `Malvern-Hills-5+` split by whether they contain handwriting from multiple authors. A document has `multiple_hands` if any page is written by a different author. All methods use GEMINI-2.5-PRO as the MLLM.

(a) `multiple_hands` documents

Method	CER (%)
Azure OCR only	12.35
OCR	5.73
IMAGES-AAO	5.12
OCR+PAGER	4.79
OCR+PAGEN	4.76
OCR+PAGE1	4.15
IMAGES	3.85
OCR+IMAGES	3.55

(b) `single_hand` documents

Method	CER (%)
Azure OCR only	17.19
OCR+IMAGES	9.97
OCR	9.70
IMAGES	9.20
OCR+PAGER	8.38
IMAGES-AAO	8.17
OCR+PAGEN	8.07
OCR+PAGE1	7.98

G Additional resources

Below are links to several online tools mentioned in this paper:

- Tesseract: https://github.com/tesseract-ocr/tesseract
- LLM-Aided OCR: https://github.com/Dicklesworthstone/llm_aided_ocr
- BetterOCR: https://github.com/junhoyeo/BetterOCR

Figures. We acknowledge the use of (both original and edited) open-licensed SVG vectors from SVG Repo:

- Images clipart by Ionicons: https://www.svgrepo.com/svg/327088/images-sharp
- Robot clipart by Konstantin Filatov https://www.svgrepo.com/svg/521818/robot
- Documents clipart by SVG repo: https://www.svgrepo.com/svg/139884/documents-papers

Malvern-Hills dataset. We are grateful to the Malvern Hills Trust for providing images.

G.1 Commercial tools

Costs of commercial OCR engines and LLMs for estimates used in this paper are given in Tables 23, 24. Most have pricing tiers based on scale, or a limited free allowance; for simplicity we take the lowest (non-batch) cost per run for each engine, and for the OpenAI API.

Costs for each tool were taken from their respective webpages:

- Microsoft Azure: https://azure.microsoft.com/en-gb/pricing/details/cognitive-services/computer-vision/
- Amazon Textract: https://aws.amazon.com/textract/pricing/
- Google Cloud Vision: https://cloud.google.com/vision/pricing
- OpenAI: https://openai.com/api/pricing/
- Google Gemini: https://ai.google.dev/gemini-api/docs/pricing
- Google does not provide pricing information for GEMMA-3-27B, and only provide it for free with usage limits. For this reason we take our estimate of the price of GEMMA-3-27B from https://openrouter.ai/google/gemma-3-27b-it

Table 23: Pricing for OCR Engines

OCR Engine	Cost per 1k Calls ($)
Azure Vision	1.00
Google Cloud Vision	1.50
Amazon Textract	1.50

Table 24: Pricing for LLMs

LLM	Cost per 1M Tokens ($)	
	Input	Output
GEMMA-3-27B	0.07	0.50
GPT-4O	2.50	10.00
GEMINI-2.5-PRO	1.25	10.00

H Additional experiments and extended tables

H.1 Extended tables with token and cost breakdowns

Tables 25, 26 and 27 provide per-stage token and cost breakdowns for the `IAM`, `Malvern-Hills` and `Bentham` experiments reported in the main text, and correspond to Tables 1, 2a & 2b respectively.

H.1.1 `IAM` *with* PYLAIA

Table 25 also includes a row for PYLAIA (Tarride et al., 2024), an open-source baseline. As our problem setting is zero-shot and document-level, PYLAIA poses a problem as it is (i) largely dependent on fine-tuning to achieve reasonable performance on out-of-sample data, and (ii) operates on the line level, rather than the page or document level. We run PYLAIA on an M1 MacBook Pro, CPU only.

We use PYLAIA out-of-the-box with the public `Teklia/pylaia-iam` model, a CNN–BLSTM–CTC recognizer trained on IAM. We enable PYLAIA's lexicon-aware decoding and use the bundled files from the model repository (`tokens.txt`, `lexicon.txt`, `language_model.arpa.gz`). The language model is a 6-gram character LM trained on IAM.

Table 25: Results on `IAM`. Much of this table is reproduced from Table 1; but new columns with token and cost breakdowns have been added, as well as a new row for PYLAIA. See Tables 26 & 27 for similar reproductions of Tables 2a & 2b respectively.

	Method	CER ↓	Cost ($/1k docs)				Tokens (/doc)		
			Total	OCR	In	Out	Image	In	Out
—	PYLAIA	6.51	0.00	0.00	0.00	0.00	0	0	0
—	OCR	3.81	2.26	2.26	0.00	0.00	0	0	0
GEMMA	OCR	2.93	2.42	2.26	0.05	0.11	0	699	211
	IMAGES	2.31	0.31	0.00	0.19	0.12	2,192	547	230
	IMAGES-ALL-AT-ONCE	1.97	0.29	0.00	0.17	0.12	2,192	262	242
	OCR+IMAGES	1.78	2.58	2.26	0.21	0.11	2,192	821	216
	OCR+PAGEN	2.17	2.59	2.26	0.17	0.16	945	648	246
	OCR+PAGE1	1.36	2.50	2.26	0.11	0.12	980	623	243
GPT-4O	OCR	1.21	6.17	2.26	1.77	2.14	26	682	213
	IMAGES	0.92	9.81	0.00	7.63	2.17	2,515	533	217
	IMAGES-ALL-AT-ONCE	0.92	9.29	0.00	7.11	2.18	2,515	252	218
	OCR+IMAGES	0.72	12.69	2.26	8.29	2.13	2,519	797	213
	OCR+PAGEN	0.87	9.04	2.26	4.52	2.26	1,095	613	222
	OCR+PAGE1	0.85	8.94	2.26	4.47	2.21	1,124	589	221
GEMINI	OCR	1.57	5.21	2.26	0.87	2.08	0	699	207
	IMAGES	1.16	5.56	0.00	3.43	2.13	2,192	547	213
	IMAGES-ALL-AT-ONCE	0.70	5.50	0.00	3.07	2.44	2,192	262	243
	OCR+IMAGES	**0.64**	8.10	2.26	3.77	2.08	2,192	821	207
	OCR+PAGEN	**0.63**	6.71	2.26	2.05	2.40	945	648	236
	OCR+PAGE1	*0.65*	6.63	2.26	2.00	2.37	980	623	236

H.1.2 `Malvern-Hills` *and* `Bentham`

See Tables 26 & 27 for extended versions of Tables 2a & 2b respectively, with token and cost breakdowns added.

Table 26: Results on `Malvern-Hills`. Much of this table is reproduced from Table 2a; but new columns with token and cost breakdowns have been added.

	Method	CER ↓	Cost ($/1k docs)				Tokens (/doc)		
			Total	OCR	In	Out	Image	In	Out
—	OCR	14.41	2.30	2.30	0.00	0.00	0	0	0
GEMMA	OCR	13.52	2.80	2.30	0.09	0.41	0	1,331	818
	IMAGES	27.19	0.74	0.00	0.16	0.58	1,791	556	1,152
	IMAGES-ALL-AT-ONCE	15.21	0.66	0.00	0.14	0.52	1,791	262	1,037
	OCR+IMAGES	10.54	2.92	2.30	0.23	0.40	1,791	1,455	791
	OCR+PAGEN	11.22	3.03	2.30	0.25	0.48	781	1,317	879
	OCR+PAGE1	12.55	2.89	2.30	0.14	0.44	781	1,285	888
GPT-4O	OCR	10.60	13.32	2.30	3.31	7.71	25	1,298	771
	IMAGES	11.24	13.46	0.00	5.86	7.60	1,774	542	760
	IMAGES-ALL-AT-ONCE	11.35	12.97	0.00	5.31	7.66	1,774	252	765
	OCR+IMAGES	7.11	17.54	2.30	8.04	7.20	1,799	1,415	720
	OCR+PAGEN	8.05	15.30	2.30	5.35	7.65	774	1,235	761
	OCR+PAGE1	8.92	15.00	2.30	5.16	7.53	774	1,203	753
GEMINI	OCR	7.47	11.67	2.30	1.66	7.70	0	1,331	770
	IMAGES	*6.42*	10.88	0.00	2.93	7.95	1,791	556	794
	IMAGES-ALL-AT-ONCE	8.20	11.01	0.00	2.57	8.45	1,791	262	844
	OCR+IMAGES	6.46	14.18	2.30	4.06	7.82	1,791	1,455	782
	OCR+PAGEN	6.54	14.56	2.30	2.73	9.53	781	1,317	948
	OCR+PAGE1	**5.83**	13.24	2.30	2.58	8.36	781	1,285	835

Table 27: Results on `Bentham`. Much of this table is reproduced from Table 2b; but new columns with token and cost breakdowns have been added.

	Method	CER ↓	Cost ($/1k docs)				Tokens (/doc)		
			Total	OCR	In	Out	Image	In	Out
—	OCR	11.18	2.63	2.63	0.00	0.00	0	0	0
GEMMA	OCR	10.75	3.11	2.63	0.10	0.39	0	1,367	781
	IMAGES	15.60	0.70	0.00	0.20	0.50	2,287	635	990
	IMAGES-ALL-AT-ONCE	25.06	0.55	0.00	0.18	0.37	2,287	262	747
	OCR+IMAGES	9.98	3.28	2.63	0.27	0.39	2,287	1,509	781
	OCR+PAGEN	11.02	3.34	2.63	0.25	0.47	871	1,269	851
	OCR+PAGE1	10.89	3.20	2.63	0.15	0.42	871	1,244	847
GPT-4O	OCR	9.97	13.63	2.63	3.42	7.58	29	1,338	758
	IMAGES	9.87	16.58	0.00	8.88	7.69	2,902	619	769
	IMAGES-ALL-AT-ONCE	10.18	15.80	0.00	8.15	7.65	2,902	252	764
	OCR+IMAGES	9.35	20.93	2.63	11.01	7.30	2,931	1,472	729
	OCR+PAGEN	8.87	16.37	2.63	6.13	7.61	1,105	1,213	757
	OCR+PAGE1	10.95	16.29	2.63	5.97	7.69	1,105	1,189	769
GEMINI	OCR	9.54	12.03	2.63	1.71	7.70	0	1,367	769
	IMAGES	9.74	11.64	0.00	3.65	7.99	2,287	635	798
	IMAGES-ALL-AT-ONCE	9.88	11.70	0.00	3.19	8.51	2,287	262	851
	OCR+IMAGES	8.67	15.32	2.63	4.75	7.95	2,287	1,509	794
	OCR+PAGEN	**8.48**	13.70	2.63	2.77	8.30	871	1,269	825
	OCR+PAGE1	*8.56*	13.55	2.63	2.64	8.28	871	1,244	827

H.2 Early validation experiments

Tables 28, 29 & 30 show results of early experiments with GPT-4O and GPT-4O-MINI for earlier prompt iterations of our methods, on a multi-page validation split derived from the IAM Database. Each table uses a different baseline OCR engine: Azure, Google Cloud Vision and Amazon Textract. As Azure performs the best of the three, and is the cheapest (see Table 23), we use it for final experiments in the main text. We also tested Tesseract, but found

it to be completely incapable of producing any meaningful transcription of handwritten text.

Table 28: IAM: relative performance of transcription methods. Rel(ative) imp(rovement) is against the baseline OCR (Azure), and cost is for processing the entire dataset with the given method.

Method	→ MLLM	CER	Rel. Imp.	Cost ($)
OCR	-	0.036	0.00	0.59
OCR	GPT-4O-MINI	0.032	0.11	0.64
OCR	GPT-4O	0.033	0.08	1.42
OCR-PBP	GPT-4O-MINI	0.025	0.31	0.65
OCR-PBP	GPT-4O	0.029	0.21	1.50
OCR+PAGEN	GPT-4O-MINI	0.029	0.19	2.12
OCR+PAGEN	GPT-4O	0.025	0.29	2.24
VISION	GPT-4O	0.027	0.24	2.32
VISION-PBP	GPT-4O	**0.010**	0.73	2.43
OCR+ALL-PAGES	GPT-4O	0.027	0.24	3.10
OCR+ALL-PAGES-PBP	GPT-4O	0.011	0.68	3.24
ALL-OCR-PBP	GPT-4O-MINI	0.020	0.46	2.48
ALL-OCR-PBP	GPT-4O	0.021	0.43	4.07
OCR+PAGE1	GPT-4O-MINI	*0.015*	0.59	2.10
OCR+PAGE1	GPT-4O	0.027	0.26	2.20

Table 29: Relative performance of MLLMs and prompting strategies compared to the baseline **Google** OCR engine on the IAM dataset.

Method	→ MLLM	CER	Rel. Imp.	Cost ($)
OCR	-	0.095	0.00	0.89
OCR	GPT-4O-MINI	0.074	0.23	0.94
OCR-PBP	GPT-4O-MINI	0.071	0.26	0.95
OCR	GPT-4O	0.064	0.33	1.73
OCR-PBP	GPT-4O	0.064	0.33	1.81
VISION	GPT-4O	0.027	0.71	2.32
OCR+PAGE1	GPT-4O-MINI	0.047	0.51	2.40
OCR+PAGEN	GPT-4O-MINI	0.060	0.37	2.40
VISION-PBP	GPT-4O	**0.010**	0.90	2.43
ALL-OCR-PBP	GPT-4O-MINI	0.020	0.80	2.48
OCR+PAGE1	GPT-4O	0.042	0.56	2.50
OCR+PAGEN	GPT-4O	0.044	0.54	2.53
OCR+ALL-PAGES	GPT-4O	0.035	0.63	3.39
OCR+ALL-PAGES-PBP	GPT-4O	*0.019*	0.80	3.54
ALL-OCR-PBP	GPT-4O	0.021	0.78	4.07

Table 30: Relative performance of MLLMs and prompting strategies compared to the baseline **Textract** OCR engine on the IAM dataset.

Method	→ MLLM	CER	Rel. Imp.	Cost ($)
OCR	-	0.050	0.00	0.89
OCR	GPT-4O-MINI	0.051	-0.03	0.94
OCR-PBP	GPT-4O-MINI	0.045	0.10	0.95
OCR	GPT-4O	0.046	0.08	1.71
OCR-PBP	GPT-4O	0.041	0.18	1.79
VISION	GPT-4O	0.027	0.45	2.32
OCR+PAGE1	GPT-4O-MINI	0.027	0.45	2.40
OCR+PAGEN	GPT-4O-MINI	0.046	0.08	2.41
VISION-PBP	GPT-4O	**0.010**	0.81	2.43
ALL-OCR-PBP	GPT-4O-MINI	0.020	0.61	2.48
OCR+PAGE1	GPT-4O	0.030	0.40	2.50
OCR+PAGEN	GPT-4O	0.027	0.46	2.54
OCR+ALL-PAGES	GPT-4O	0.029	0.42	3.39
OCR+ALL-PAGES-PBP	GPT-4O	*0.011*	0.78	3.54
ALL-OCR-PBP	GPT-4O	0.021	0.59	4.07