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Article

Addressing Postgraduate Supervision Bottlenecks Through Automated Structural and Formatting Feedback for Research Proposals

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Abstract: Arguably, the role of a postgraduate supervisor is aligned to support the student to think critically and be able to write academically, but not necessarily as a "proofreader" for checking spelling, grammar, or syntax inconsistencies. This process can be realised as an AI-based tool providing near–real-time automated feedback to students, whilst reducing academic workload pressures. This paper proposes a formal (referring to rules) based proofreading process for information extraction, recognition, and correction of meaningful text chunks, images or figures, and tables (referred to as document tokens) from research proposals. The ultimate objective is custom-fit automated generation of feedback across multiple sections of submitted research proposals for a large number of authors. To this effect, an AI-driven tool was developed to support the proofreading of research proposals by delivering timely, automated feedback at scale, named `RX_Autoproofreader`. The tool's test on eighty (80) publicly available research documents analysed for constituent parts recognition and proofreading in an algorithm programmed in a c# Visual Studio environment, which ran in 182 min, produced an average accuracy of 68%. During the test, the tool extracted and proofread a total of 14,231 document pages into meaningful items of title, author, supervisor, research date, aim, objectives, figures, tables, paragraphs, lists, headings, and page numbers. The recognition and extraction of unstructured texts into meaningful items is a document understanding task necessary for proofreading and feedback generation. It aims to complement existing spell and grammar tools for proofreading academic manuscripts.

Keywords: automated feedback process; proofreading; postgraduate supervision; artificial intelligence; document understanding; academic writing

1. Introduction

Automated, timely feedback on research proposals motivates students. It is an essential means of reducing inefficiencies in the system caused by delayed feedback from often-overloaded supervisors [1]. The arduous task of improving the style, clarity, and academic ideas of research proposals in progress, conferred on a supervisor, would benefit from automated proofreading assistance. The proofreading of a research paper is beyond grammatical and spelling errors; it involves strengthening the academic writing style in structural and formatting clarity for it to communicate as intended [2]. In practice, an academic proofreading task checks whether a manuscript is free of various inconsistencies using the stipulated proposal guidelines or checklist for the subject or academic department.

The role of a supervisor assists the student to think critically and write academically, not as a "proofreader" for checking spelling, grammar, or syntax inconsistencies [3]. There are available off-the-shelf proofreading tools in spell and grammar check applications, useful for any document type for such purposes. The emergence of ChatGPT and large language models (LLMs) in 2022 made it possible to ”prompt” any proofreading feedback of a research proposal. However, these are not ”gold” standard, nor custom fit to the required academic writing guidelines [1]. Supervisors and universities’ writing support program administrators are tasked with rendering support services to students with their proposals, despite the plethora of AI tools available to students. These have other academic portfolios that make it nearly unrealistic to provide one-on-one attention to burgeoning postgraduate students struggling with writing [4]. Important to note is the frequency of corrections on structural and formatting omissions of students’ proposals after submissions, indicating the lack of adherence to the specified guidelines [5].

This study proposes and designs a novel approach to automatically understanding all the contents/items of varied multi-paged research proposal documents and proofreads towards providing timely feedback. This task of proofreading for valid content and style is made into an expert system, an AI tool that supports supervisors and gives automatic feedback to students. Past research detailed the challenges faced by supervisors, and the need for solving with this AI tool [5]. An earlier work describes the understanding of research proposal structure and the analysis of many structures of research proposal documents using formal methods [5].

This research furthers the conquest by the recognition and proofreading of research proposal structure and parts, meaningfully to provide automated feedback using research papers obtained publicly from universities’ repositories. The research is guided by three key research questions: (1) Considering that research proposal documents can have many different structures, how can the AI process understand the varied paginated document’s structure meaningfully? (2) Can a rule-based, machine learning (ML), or large language model (LLM) train effectively on the recognition of the document structure and formatting details of research proposals? and (3) How can we extract the constituent parts? How can we proofread on each of these parts to provide relevant and timely feedback? The paper contributes to knowledge by,

1. designing an AI tool for automated feedback responses on submitted academic research proposal manuscripts,
2. advancing information extraction techniques in formal methods for extracting details of structure and semantics from academic-based large documents (that is, a research proposal document), and
3. meaningful recognition of detailed parts of a research proposal document, which precedes automatic proofreading.

2. Related Studies

Feedback is an essential part of the learning process in academics [6–9]. Automated timely feedback on research proposals may be motivating for students and supervisors as part of many efficient approaches to the supervision of academic writing. In an observation by Murad et al [6], an automated feedback mechanism is a two-pronged approach to achieving efficiency for supervisors and the supervised. In his findings, the revision of two students’ research proposal’s first draft was completed in twenty (20) days. Student submission was made on 1 March 2018 while written feedback was received from their supervisor on 20 March 2018. In another survey, 57% of supervisors’ respondents take over an hour in each round for the review of proposal draft [5]. The revised draft of research proposals containing written comments by the use of digital tools is then emailed to students. Supervisory feedback foci were mainly linguistic based (spelling and grammar errors), followed by content, appropriateness, and organization of ideas [5,6,10].

Linguistic-based and content error proofreading tools, such as Grammarly, are well-researched and available in a variety of open-source, free-ware, or paid software [11]. These are also sometimes freely available at institutional repositories for writing checks which include spelling and grammar, writing auto-complete, similarity or plagiarism checks, and more recently AI-writing detection [12]. We have found no specific tool or software module for checking the structural, format, and syntax consistency of the document contents of academic writing research proposals. The academic feedback mechanism is not only peculiar to university supervisors, it is a necessary tool at the review desk for many journals for initial technical checks at first submission. It may take hours to days for some journals to provide feedback to authors on the manuscript.

2.1. Postgraduate Supervision Challenges and the Need for Intelligent Tools

There are concerns in postgraduate supervision which include timely feedback and adequate supervision support as many supervisors still grapple with challenges of systemic supervisory workload amidst other responsibilities of teaching and academic meetings [13]. The imbalance in the supervisor-to-student ratio is an unresolved dilemma for which there are no quick fixes. The era of Education’s fourth industrial revolution (4IR) alleviates challenging work-life balance for academics by introducing the use of various technological advancements and tools. Academics also expressed concerns about rapidly evolving intelligent tools in teaching and learning space which they often find somewhat difficult and necessary to use [14,15]. Digital skills in 4IR of learners and teachers will undoubtedly shape the future of Education, hence must be embraced despite the appearance of any problem [15,16].

2.2. AI-driven Applications in Education (AIED)

Students may not be aware of imminent errors in the proposals which the human proofreader (e.g. supervisor or writing support administrators) identifies and provides corrections based on some conventional understanding, rules of writing, or stipulated guidelines provided in a document. The human proofreader can provide more detailed feedback, but time is of the essence. Automating the end-to-end process provides time-saving advantages, instant proofreading, and a more personalised feedback outcome [17]. There is a broad array of existing digital tools, including emerging AI-driven applications in education (AIED), that support and enhance the work of scholars and researchers. These tools improve efficiency, facilitate deeper analysis, and enable more sophisticated forms of academic inquiry. In the context of AIED writing-support systems, refs. [1,18] identify three primary categories: Automated Writing Evaluation (AWE), which provides formative feedback on written text; Intelligent Writing Prompting (IWP), which elicits learner input and offers pedagogical scaffolding without analysing that input; and Intelligent Tutoring Systems (ITS), which deliver strategy-oriented writing guidance. With the advancement of large language models (LLMs), a fourth category—Automated Writing Generation (AWG)—has emerged, extending and complementing the existing groups of AWE, ITS, and IWP.

2.3. Automated Writing Evaluation Feedback (AWE/AWF)

Automating feedback on the structure and formatting of research proposals, including proofreading functions, constitutes an AWE task, as AWE systems are designed to generate immediate feedback on written texts—typically student essays—by providing evaluative reports or visual annotations on the submitted work [4]. Groundwork in AWE follows a rule-based approach, with predefined rules and statistical heuristics for identifying errors and suggesting feedback from a list of corrections [2]. It is still relevant, popular, and used in the conceptual design of this work for describing the syntactic structure of a research proposal document. Over the past decade, advancements in AWE technology have increasingly incorporated machine learning (ML) methodologies and, more recently, large language model (LLM) approaches [4]. These techniques offer greater flexibility and accuracy by leveraging large, labelled text corpora. Although these three approaches share a common goal, each presents distinct strengths and limitations.

AI is reshaping education in teaching, learning, assessment, and administrative processes, whilst raising important pedagogical, ethical, and policy considerations. AI in education towards automated evaluations in writing has been widely implemented as an automated essay scoring system [19], personalised assessments having real-time feedback to teachers that will see where the student is struggling [20], and more recently as integrated AI that assists students directly in writing [21]. Ref. [1] developed an AI-based tool that delivers immediate feedback on reference accuracy and grammatical correctness on academic writings before final submission.

2.4. Formal Grammar, Used as an AWE Rule-Based Approach

Conventional machine-learning and deep-learning approaches require adequate data and extracted key features of the document for a generalised model in tackling text-based error detection and correction [22]. Artificial learning approaches are sufficient for document classification (for example, classifying if a document is a research proposal or not) or error checking based on large corpora of text (for example, spell-check of words based on large corpora of text). However, it is an inefficient process when there is a dearth of data for a corpus of all possible document format types, or syntax and structure consistency types, such as in academic writing. Context-free grammars (CFGs) have been applied in current research areas for synthesising and providing automated feedback in documents such as legal contracts [23], clinical notes [24], regulatory documents [25], academic writings which include research proposals [1,4,7], and others.

2.5. The Gap

Feedback as scores, text comments, or at face-to-face meetings is very crucial for academic development [10,26]. Digital tools exist to make the feedback process seamless and create a more innovative learning environment, especially since the advent of COVID. Undeniably, Universities have investments in some generalised feedback tools like Grammarly and Turnitin, which are important in the academic writing review process. Similarly, a research proposal proofreading feedback tool can improve service quality and reduce the manual hours of academics on the first draft review process of a research proposal. In literature and practice, pockets of AI tools are being developed to assist in academic writing evaluation before final submission. Ref. [7] developed a tool for generating automated feedback on students' project reports. There also exists automated feedback on complex structures of programming exercises [27]. For research proposal documents, there are literatures of tools developed providing automated feedback on (1) references [1], (2) higher-order concerns such as methodological soundness driven by LLMs [28], (3) content organisation [28,29], (4) automated scoring or assessment of different sections [4], and (5) English foreign language (EFL) learner support [29]. However, none is focused on the content organisation and valid structure of a research proposal, as far as checked, considering that it is very complex and several students' submissions will have a varied number of pages in a research proposal.

3. Methodology

Once a student submits a proposal manuscript to a given submission link or email, the AI tool extracts the document structure and different constituents of the document, such as the title, author, supervisor, abstract, research problem, research objectives, and so on. Each constituent part/section is checked for validity (i.e. proofread) against rules conforming to submission guidelines. The document structure is also checked against acceptable formatting styles. The extraction of meaningful constituents of a research proposal, such as the research aim, objectives, chapter key points, contributions, and other details of a proposal, like author, title, and supervision, is yet to be achieved in any research. The research follows an experimental approach in assessment and provides feedback on Information Systems research proposals. The artefact tool designed as an independent tool, can be integrated as a software application program (or function) interface (API) into Learning Management Systems (LMS) such as Canvas, Moodle, or Blackboard.

3.1. Meaningful Text Chunks Referred To As Document Tokens

Given a research proposal, P, which contains constituent parts of $P = \{S_p, S_c, S_a, S_r\}$ where S_p is the preliminary section, S_c is the chapters section, S_a is the appendix section, and S_r is the reference section. All constituent section parts and details are from a universal set containing all possible document elements (referred to as document tokens) of a proposal parts. The "universal set" given as U is defined as $U = \{u_t, u_a, u_s, u_{tp}, u_d, u_{st}, u_p, u_n, u_f, u_{ta}, u_ap, u_r\}$. The symbols u_t, u_a, u_s, u_{tp}, u_d, u_{st}, u_p, u_n, u_f, u_{ta}, u_ap, and u_r are text strings symbols for (1) proposal_title, (2) author, (3) supervisor, (4) title_paragraph, (5) proposal_date, (6) section_title, (7) paragraphs, (8) page_number, (9) figure_label, (10) table_label, (11) appendix_label, and (12) proposal reference-item respectively. Table 1 presents the decomposition of the research proposal document's parts into document tokens of meaningful text chunks (that is, a collection of text that ensures a single idea), an image or figure, or a table item. The research proposal document is considered structurally correct if all parsed document tokens are accepted by the language acceptor [5].

Table 1. Document Parts Definition By Document Tokens.

Document Parts	Contains (Document Tokens)
t_p (Title page)	$u_t u_a u_s u_{tp}^{1,2} u_d$
d_p (Declaration page)	$u_{st} u_p^+ u_n$
a_p (Acknowlegment page)	$u_{st} u_p^+ u_n$
c_p (Contents page)	$u_{st} u_{ta} u_n$
l_f (List of Figures page)	$u_{st}(u_i \| u_{ta}) u_n$
l_t (List of Tables page)	$u_{st}(u_i \| u_{ta}) u_n$
a_{bp} (Abstract page)	$u_{st} u_p^+ u_n$
c_{intro} (Introduction chapter)	$u_{st}((u_p \| u_{sst} \| u_f \| u_i \| u_{ta})^+ u_n)^+$
c_{lit} (Literature chapter)	$u_{st}((u_p \| u_{sst} \| u_f \| u_i \| u_{ta})^+ u_n)^+$
c_{method} (Methodology chapter)	$u_{st}((u_p \| e_{sst} \| u_f \| u_i \| u_{ta})^+ u_n)^+$
c_{contr} (Contribution chapter)	$u_{st}((u_p \| u_{sst} \| u_f \| u_i \| u_{ta})^+ u_n)^+$
c_{plan} (Plan Chapter)	$u_{st}((u_p \| u_{sst} \| u_f \| u_i \| u_{ta})^+ u_n)^+$
c_{concl} (Conclusion chapter)	$u_{st}((u_p \| u_{sst} \| u_f \| u_i \| u_{ta})^+ u_n)^+$
p_a (Appendix)	$u_{st} u_f^+ u_n$
p_r (Reference)	$u_{st} u_r^+ u_n$

3.2. Tool's Development

The tool, named `RX Autoproofreader`, is designed as an intelligent system for extracting meaningful, relevant information from research proposals (unstructured documents), recognising, and providing proofreading feedback. It takes the research proposal document, slices it into text lines and extracts document tokens categorised by chapters and document sections. The tool's lexical analyser part performs the proofreading by checking the correctness of all document tokens recognised in it. For instance, a paragraph in the research proposal document represented by a document token (u_p) can be recognised and identified by an analyser as "research aim", "research problems", "research objectives", "limitations", "conclusion paragraph" and so on. The tool also performs a syntax analysis of the structure of the input proposal document to proofread if the document arrangement is valid as a research proposal document. The tool, `RX Autoproofreader`, is integrated into a seamless process for which a student may receive feedback automatically. Figure 1 shows a process flow of the end-to-end automated feedback process.

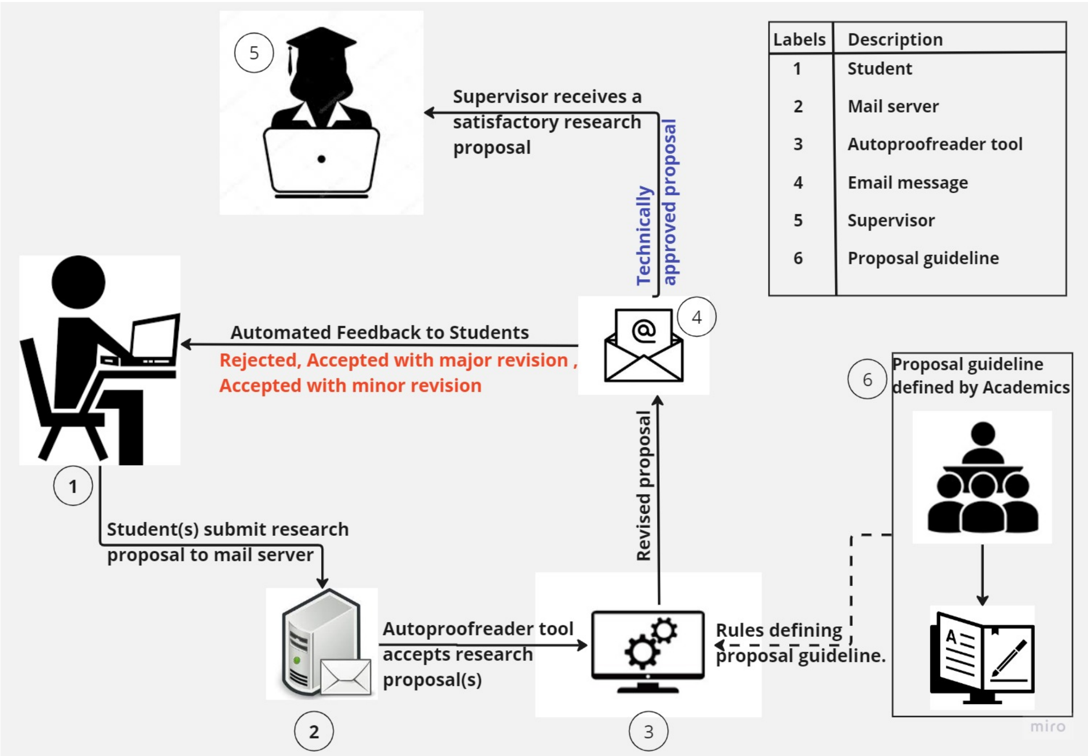

Figure 1. Conceptual Framework of Automated Feedback Generation on Research Proposals.

3.3. Automated Feedback Steps and RX_Autoproofreader Pseudocode

The following are the steps for achieving automated feedback generation on proposals.

1. receive students' research proposal submission to a designated (collector) email address,
2. proofread research proposals in the mail server using `RX_Autoproofreader`,
3. the `RX_Autoproofreader` tool performs information recognition, extraction, and interpretation of document consistency based on formal methods of rules defined in Table 1 indicating a proposal writing guideline. `RX_Autoproofreader` receives research proposal document (S_{doc}) as input whilst it outputs a revision feedback document. The pseudocode for implementing the tool's algorithm is highlighted in the steps below:
   - Step 1: Parse the proposal (S_{doc}) into structured document parts.
   - Step 2: Check if parsed parts are structurally valid and if any format error. If ValidParse(DocumentParts) is false, then structural error has occurred.
   - Step 3: Use regular expression (REGEX) match to confirm that all document tokens and elements are free of formatting issues. If FormatParse(DocumentToken) is false, then formatting error has occurred.
   - Step 4: Highlight structural and formatting errors in the proposal or copy into a feedback document
   - Step 5: Output the highlighted proposal or feedback document
4. sends a revised proposal or proposal feedback (pdf attachment) to the student via email,
5. alternatively, sends a revised proposal (pdf attachment) to supervisor if the proposal feedback is devoid of any error or inconsistencies.

3.4. Experimental Analysis

The tool was developed using C# development platform and API dependencies: (1) iTextsharp, (2) inspire.PDF, and (3) IronPython. The steps for summarising and proofreading the proposals are implemented as program function modules receiving parameters and providing output. The details of structure and format checks by the tool in a proposal document are in Table 2. To demonstrate how the tool was useful for a research paper proofreading, the study provides an AI-generated research proposal's title page as shown in Figure 2.

Table 2. Some Proofread Checks of a Research Proposal.

Aspects	**Autoproofreader Checks**
General outlay	Number of words, Number of characters, Number of pages, General font type, General line spacing, General font size, General use of italics
Missing content	Headings with missing text, Table title with missing table, Figure title with missing image, Paragraph text with less than 2 sentences
Research proposal parts	Title, Author, Supervisor, Title-paragraph, Title-date, Abstract, Objectives, Research Questions, Introduction, Literature review, Methodology, Expected results, Work plan, Conclusion.
Format consistency	Text alignment, Table alignment, Figure alignment, Headings alignment, Page numbering.


Managing Information Systems in Organizations: An Empirical Study of Governance, Security, and Outsourcing

By: Thakiso Ogero

Supervisor: Fisher Price

Research Proposal Submitted in Partial Fulfilment of the Requirements for the Degree of Master of Science in Information Systems, University of Colorado

March 2023

Figure 2. Sample of a ChatGPT Generated Research Proposal Title Page.

3.5. Tests on Varying Research Proposals

Eighty (80) selected research proposals from various universities' online institutional repositories were used for the testing of the `RX_Autoproofreader` tool which generates the automated feedback. The tool generates into a folder the image files of all extracted figures and the feedback summary of the entire document pages as a separate document in the same folder for every research proposal document. The details of the folders are available here. The understanding and proofreading of selected components such as figures, tables, research proposal title, research abstract, research aim, research objectives, chapter headings, sub-headings, lists, paragraphs, and page numbers detection, were checked to determine the performance of the tool to generate feedback on each research proposal document.

It is aimed that the feedback on research proposal submissions will be generated in near real time and communicated to authors via email. Proposals with feedback categories of rejection, minor corrections, or major corrections will be sent back to the student's email with an appropriate auto-generated mail subject for review or rewrite. The process is seamless and reduces the painstaking review process of a proposal's first draft manually.

4. Discussion of Results and Evaluation

4.1. Summary of Results

The tool successfully performed the task of document understanding for every proposal. The process required an end-to-end, detailed analysis of every text in the multiple pages of a document. The entire content of a research proposal document is well understood in the algorithm by first extracting the entire document into readlines of texts, then into meaningful text chunks, or figures, or table components; referred to as document tokens. The tool automates the check for correctness on recognised document tokens, document's general layout, missing content (such as figures with missing images), missing parts (such as the absence of an abstract in a research proposal document), and format consistency (such as consistent paragraph or heading alignment). See sample-generated feedback in Figure 3. The overall accuracy of the tool was based on proofreading and feedback on content or parts of the document and general format consistency. The tool performed well in providing recognition and feedback on figures, tables, and the structure or organisation of content contained in the research proposal document. The recognition and feedback of meaningful constituent parts, such as abstract, research aim, research objectives, and research questions, form a large chunk of research documents, which have a lot of variability, hence the inability of the tool to detect them efficiently. See result summary and evaluation details of generated proposals in Tables 3 and 4 respectively.

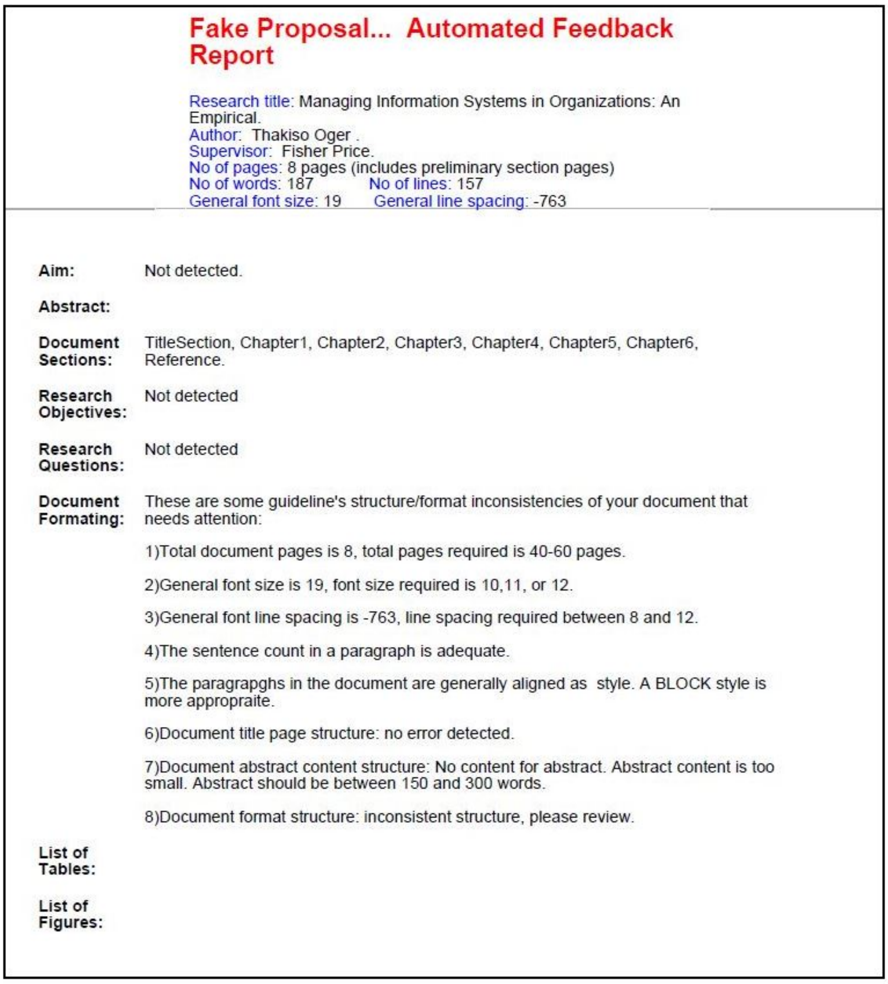

Figure 3. Feedback of a ChatGPT Generated Research Proposal.

Table 3. RX_Autoproofreader Document Content Recognition and Proofread.

	Figures	Tables	Chapter Structure	Abstract	Research Aim	Research Obj/Questions	Formatting	Pages
P1	TP	TP	TP	TP	TP	TP	TP	136
P2	TP	TN	TP	FN	FN	TP	TP	93
P3	TP	FN	TP	FN	FN	FN	TP	136
P4	TP	TN	TP	TP	FN	FN	TP	137
P5	TP	FN	TP	TP	FN	FN	TP	114
P6	TN	TP	TP	TP	TP	TN	TP	22
P7	TP	TP	TP	FN	FN	FN	TP	82
P8	TP	TP	TP	TP	FN	FN	TP	79
P9	TP	TP	TP	TP	FN	FN	TP	247
P10	TP	TP	TP	FN	FN	FN	TP	234
P11	TP	TP	TP	FN	FN	FN	TP	201
P12	TP	TP	TP	TP	FN	TP	TP	235
P13	TP	TP	TP	FN	FN	FN	TP	104
P14	TP	TP	TP	TP	FN	FN	TP	112
P15	TP	TP	TP	TP	FN	FN	TP	206
P16	TP	TP	TP	TP	FN	FN	TP	132
P17	TP	TP	TP	FN	FN	FN	TP	231
P18	TP	FN	TP	FN	FN	FN	TP	234
P19	TP	TP	TP	TP	TP	TP	TP	173
P20	TP	TP	TP	FN	FN	FN	TP	231
P21	TP	TP	TP	TP	FN	FN	TP	84
P22	TP	TN	TP	FN	FN	TP	TP	47
P23	TP	TP	TP	TP	FN	TP	TP	221
P24	TN	TP	TP	TP	TP	TN	TP	85
P25	TP	TP	TP	FN	FN	FN	TP	105
P26	TP	TP	TP	FN	FN	TP	TP	230
P27	TP	TP	TP	FN	FN	FN	TP	183
P28	TP	FN	TP	TP	TP	FN	TP	118
P29	TP	FN	TP	TP	FN	FN	TP	231
P30	TP	TN	TP	FN	FN	FN	TP	269
P31	TP	TN	TP	TP	FN	FN	TP	363
P32	TN	TN	TP	TN	TP	TP	TP	18
P33	TN	FN	TP	FN	TP	TP	TP	10
P34	TN	TP	TP	TN	TP	TP	TP	39
P35	TP	TP	TP	FN	FN	FN	TP	340
P36	TP	TP	TP	TP	TP	FN	TP	157
P37	TP	FN	TP	TP	FN	FN	TP	117
P38	TP	TP	TP	TP	FN	FN	TP	150
P39	TP	TP	TP	FN	FN	FN	TP	167
P40	TP	TP	TP	TP	FN	FN	TP	190
P41	TP	TP	TP	FN	FN	FN	TP	143
P42	TP	TP	TP	FN	FN	FN	TP	244
P43	TP	TP	TP	TP	FN	FN	TP	112
P44	TP	TP	TP	FN	FN	FN	TP	331
P45	TP	TP	TP	FN	FN	FN	TP	165
P46	TP	TP	TP	FN	FN	TP	TP	119
P47	TP	TP	TP	TP	FN	FN	TP	121
P48	TP	TP	TP	FN	FN	FN	TP	121
P49	TP	TP	TP	FN	FN	TP	TP	253
P50	TP	TP	TP	FN	FN	FN	TP	249
P51	TP	TP	TP	FN	FN	FN	TP	120
P52	TP	TP	TP	TP	FN	FN	TP	259
P53	TP	TP	TP	FN	FN	FN	TP	126
P54	TP	TP	TP	FN	FN	FN	TP	251
P55	TP	TP	TP	FN	FN	FN	TP	130
P56	TP	TP	TP	TP	FN	FN	TP	197
P57	TP	TP	TP	TP	FN	FN	TP	248
P58	TP	TP	TP	FN	FN	TP	TP	165
P59	TP	TP	TP	FN	FN	FN	TP	209
P60	TP	TP	TP	FN	FN	FN	TP	189
P61	TP	TP	TP	FN	FN	FN	TP	271
P62	TP	TP	TP	FN	FN	FN	TP	259
P63	TP	TP	TP	FN	FN	FN	TP	201
P64	TP	TP	TP	FN	FN	FN	TP	325
P65	TP	TP	TP	FN	FN	FN	TP	292
P66	TP	TP	TP	TP	FN	FN	TP	203
P67	TP	TP	TP	TP	FN	FN	TP	319
P68	TP	TP	TP	TP	FN	FN	TP	230
P69	TP	TP	TP	FN	FN	FN	TP	104
P70	TP	TP	TP	FN	FN	TP	TP	187
P71	TP	TP	TP	TP	FN	FN	TP	48
P72	TP	TP	TP	TP	FN	FN	TP	120
P73	TP	TP	TP	TP	FN	FN	TP	119
P74	TP	TP	TP	FN	FN	FN	TP	182
P75	TP	TP	TP	FN	FN	FN	TP	182
P76	TP	TP	TP	TP	FN	FN	TP	274
P77	TP	TP	TP	FN	FN	TP	TP	220
P78	TP	TP	TP	TP	TP	TP	TP	283
P79	TP	TP	TP	FN	FN	FN	TP	124
P80	TP	TP	TP	TP	FN	FN	TP	273
								14231

Table 4. Performance and Evaluation.

	Figures	Tables	Chapter Structure	Abstract	Research Aim	Research Objectives/Questions	Formatting (Headings, List, Paragraphs, ...)
Available and detected (TP)	75	67	80	35	10	16	80
Not Available and not detected (TN)	5	6	0	2	0	2	0
Available but not detected (FN)	0	7	0	43	70	62	0
Not available but detected a false result (FP)	0	0	0	0	0	0	0
Accuracy (TP + TN)/Total	1.00	0.91	1.00	0.46	0.13	0.23	1.00

4.2. Evaluation and Performance

The research proposal documents were mainly of computer science or information technology background. The tool spanned a total of 14,231 document pages of eighty (80) research proposals. The performance of the tool on proofreading and automated feedback of eighty (80) research proposals are given in Table 4 while the details of the performance of the tool on format and structure of the documents are expressed in Table 3. The tool, auto-generated files and folders, evaluation worksheet are available here. The performance measurement is based on a confusion matrix of details given as:

1. Available and detected (True Positive): The document contains a given component and the tool is able to detect and proofread it. For example, a document contains a figure and the tool is able to detect the figure and image representing the figure.
2. Not available and not detected (True Negative): The given component is missing or unavailable in the required format, and not detected by the tool. For example, research objectives contained in the research proposal document as text paragraphs and not as list items were not detected nor proofread by the tool.
3. Available but not detected (False Negative): The document contains a given component, but the tool did not detect nor proofread it. For example, the document contains a research abstract but the tool could not detect nor proofread the abstract for having more than the required number of words.
4. Not available but detected a false output that is non-existent (False Positive): The given component is missing or unavailable in the required format; however, it is detected by the tool as a valid component. For example, a figure label within a paragraph is detected as a figure with a missing image. This is a rare occurrence.

The measured overall accuracy of the tool given in the performance evaluation in Table 4 is a mean of 1.00, 0.91, 1.00, 0.46, 0.13, 0.23, and 1.00 given as 68%

4.3. Failure Mode Analysis Observations in `RX_Autoproofreader`

The tool has a focus on research proposals of the "Information Systems" discipline - narrow intelligence. It requires a more general learning intelligence to build a global software for as many cases of research proposal disciplines as possible. This is possible and may have some trade-offs on the tool's overall accuracy; however, it is not the focus of the paper. The tool is custom-built for specific guidelines and research proposals submissions bound by it. During the evaluation process, some observable conditions under which the AutoProofreader may generate inaccurate or suboptimal feedback were noted and steps taken to identify and mitigate possible recurrence. See Table 5 for observed failure modes in the tool.

Table 5. Observed Failure Modes and Analysis.

S/N	Observed Failures	Possible Reasons	Mitigation
1.	The tool incorrectly identifies proposal sections	Non-standard proposal structures. Inability of students' submissions to follow through on provided guideline	Proposal submissions should follow through standards, or else they should be flagged whether missing or not
2.	Document tokens (Abstract, Research Aim, and Research Objectives) flagged as "missing" when present. A case of False Negatives (FN)	Inconsistent headings across institutions although same discipline. For example P35 contained an image before the Abstract keyword, whilst P39 contained inconsistent section header and textual details aside the keyword "Abstract"	Extend rules for handling more complex scenarios hence improving accuracy and reliability of the tool
3.	The tool under-represents or over represents sections due missing word anchor or identification tags	Predefined grammar rules embeds broad range of tags for identifying certain sections. Sometimes, the tool may not find any predefined tags for identifying a given section due to a broad range of writing styles. For example, a research objective may not have an anchor of "…this study aims to…"	Automatically curate and include new tags in checkup list of tags
4.	Flags discipline-accepted jargons or passive voice usage	Not a common occurence since the tool treat all text as plain text	Create an exclusion list of special words jargons of discipline specific field
5.	Hallucinating - the tool detects a non-existent text, image or table as present in the document. Thisis a rare occurrence with the tool, but observed as possible during the test stage. A case of the tool an image or table as present in a document, based on automatic detection of false indications such as the anchor tag word and expanded line spacing in the document	Automatic detection may be subject to detecting noise and representing has genuieiue	The tool was improved to prune noise

4.4. *Comparism of* `RX_Autoproofreader` *with Similar Tools*

This research tool represents a novel contribution, purpose-built for research proposals that focus on automated structural and formatting feedback aligned with postgraduate proposal requirements. Rather than functioning as a general-purpose AWE system, the tool positions itself as a pre-supervisory screening and formative support mechanism, providing actionable feedback before proposals reach supervisors. Embedding writing guidelines and institutional proposal templates into the feedback logic. It offers context-aware and rubric-driven feedback to enhance proposal quality, thus reducing repetitive supervisory workload. Table 6 compares the tool with other existing similar tools to underscore its distinctiveness as a useful AI tool for higher education.

Table 6. Comparison of Tools.

S/N	Tool	Description	Focus Area	Approach
1.	AcaWriter [4]	A parser automated feedback on research proposals	Paragraph style summarised feedback on different sections of a research writing	Rule-based
2.	Feedback-fruits Automated Tool [1]	A tool that generates summarised feedback to improve academic writing before final submission	Proofreads references and grammar	Rule-based and Machine-learning based
3.	Insta-reviewer [7]	An automated instant textual feedback on students' project reports	Paragraph style feedback and suggestions on project reports	Machine-learning based
3.	Criterion [29]	An automated feedback software anticipated to assist English foreign language (EFL) learners to improve writing skills through feedback	Paragraph style feedback and suggestions to help improve essay writing in terms of content (planning ideas) and organisation	Machine-learning based
5.	GPTs [28]	LLM like ChatGPT used as feedback assistant for long-format academic writing tasks	It provides in-depth feedback, including feedback relating to higher-order concerns such as methodological soundness, critical thinking, logic and originality; but lacks precision on domain-specific documents	LLM
6.	RX Autoproofreader	An automated structural and formatting feedback tool	It provides detailed structural automated proofreading, recognising all sections, including heading paragraphs in a research proposal document. It checks that all parts are properly arranged and	Rule-based

5. Conclusions

This paper demonstrates the design and application of an intelligent tool named `RX_Autoproofreader` in Education pedagogy for automated feedback generation to students on their research proposals' manuscript initial reviews. The tool is integrated into a feedback process that receives the input proposal from students and aims to send back feedback to students. This tool acts as an assistant to human reviewers or postgraduate supervisors who are busy professionals and can focus on idea content review (or more salient review areas) of technically approved proposals. It is not a replacement for spelling and grammar checks, plagiarism checks, or other general AWE tools for proposals; it introduces another check phase that may be integrated with these tools to have a more satisfactory proofread research proposal document.

5.1. Limitations and Assumptions

The tool embeds the workings of various natural language processing techniques in generalizing the patterns in the written research proposal documents. However, some of these rules are assumptions that may vary in some unique cases. The following highlights some limitations and assumptions for which the tool is based upon -

1. All research proposal titles are placed as the first line of text on the title page.
2. Figures are extracted as images but picture quality cannot be proofread.
3. Tables in research proposals are detected with some limitations. The rows and columns of tables are recognized, however, the texts contained in the tables could not be detected as contained in table cells but as lines of text.
4. Research aim detection is a sentence extracted from the research abstract automatically selected based on containing one or many of the words in the keywords collection given as (paper, research, aim, explain, study, describe, explore, explain, purpose, work, design, report, suggest, and propose).
5. Page numbering of research proposal's preliminary section given as Roman numerals are detected but not proofread as page numbering.

5.2. Future Work

Some considerations for near future work are to recognize and extract cell boundaries of text in tables for more accurate proofreading of research proposals. Also, embed API for proofreading figure/image picture quality.

Author Contributions

O.I.: conceptualization, methodology, software, data curation and writing—original draft preparation; A.A.: supervision, software validation and writing—review. Please turn to the CRediT taxonomy for the term explanation. All authors have read and agreed to the published version of the manuscript.

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Processed data supporting the findings of this study are available from the corresponding author upon reasonable request. No personal, confidential, or ethically restricted data were used.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the author(s) used ChatGPT to improve the grammar in sentences. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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