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Leveraging Past Data to Support Interactive Automated Feedback in Undergraduate Research Proposals

Moulay Larbi Chalal, Nottingham Trent University, UK
Nacer-Eddine Bezai, Nottingham Trent University, UK
Benachir Medjdoub, Nottingham Trent University, UK
Bhavna Crossley, Nottingham Trent University, UK

Abstract: In academia, educators have been generating substantial amounts of written feedback for many years, yet much of it remains archived and underutilized, limiting its potential to inform and enhance teaching and assessment practices. This study uses past feedback data to develop an interactive, automated feedback tool aimed at addressing feedback inconsistencies during the research proposal stage of an undergraduate research module. To achieve this, we employed a mixed-methods methodology in two phases. First, we developed an automated feedback tool using content analysis of five years' historical feedback data, creating a database of scenarios aligned with research proposal assessment criteria. In phase 2, we applied this tool to provide feedback to 50% of forty-two BSc Architectural Technology students at Nottingham Trent University, United Kingdom, while the remainder received manual feedback. Students' perceptions of feedback relevance and usefulness were assessed via a survey questionnaire across both groups. Mann-Whitney tests were used to analyze the results, comparing the effectiveness of automated versus manual feedback. The analysis of the results suggested that automated feedback from FeedAssist was seen more relevant and useful due to its detailed, contextualized nature with educator personalization. Furthermore, it improved students' key research competencies compared to previous years before its implementation. This study emphasizes that neither approach is inherently superior; rather, each has its own merit and applicability, depending on the specific context and circumstances. FeedAssist effectively balances automation with personalization, offering significant advantages for large cohorts and limited-resource contexts. The study's originality lies in using past feedback data to develop an automated tool that allows educators to guide feedback generation through interactive historical scenarios.

Keywords: *Historical Data, Feedback Automation, Research Modules*

Introduction

Research methodology is a vital component in higher education, offering students a number of benefits. First, incorporating research modules equips students with essential knowledge and skills such as problem identification, methodological design, and planning (Haque and Alagarsamy 2018). Research has shown that engaging students in research projects during their degree enhances their intellectual curiosity, critical thinking, and academic performance (Mathews et al. 2019). Research modules are also proven to have benefits that extend beyond academia to industry. Several studies such as (Mathews et al. 2019; Yaffe et al. 2014) concluded that alumni who participated in a research project as part of their degree were not only more likely to pursue careers aligned with their research interests but also experienced better career progression. However, despite these benefits, delivering engaging research modules can be challenging due to undergraduate students' lack of exposure to research and perception of the subject as dry or irrelevant (Miller et al. 2023). Strategies to address these challenges include early integration of research in courses, balancing theory with practical applications, implementing active learning, and creating supportive environments (Smith et al. 2023; Jonaidi and Nasseri 2022).

This study used the research module in BSc Architectural Technology at Nottingham Trent University, United Kingdom, as a case study. Since 2017, the module has undergone significant enhancements to boost student engagement, satisfaction, and output quality. Key interventions include:

- A shift to applied research tackling real-world problems such as noise pollution. At the end of the academic year, all students must demonstrate a tangible impact of their research project on the design or detailing of their architectural projects, which they develop as part of the design studio module.
- A scaffolding approach breaking down the dissertation process into manageable parts including research proposal, literature review, research poster, research report, and verbal presentation.
- Weekly tutorials offering additional support and feedback.
- Discussions of past work examples with varying quality from lower to higher standards. These examples are utilized to set benchmarks to help students understand what is expected from them across different stages.

These initiatives have led to increased student engagement and satisfaction, averaging 4.42 out of 5 over five years, and enhanced research project quality, with students winning national Chartered Institute of Architectural Technologists (CIAT) research awards in 2021, 2022, and 2024. In 2022 to 2023, the module content was adapted into a flexible five-credit online course for undergraduates across the School of Architecture, Design, and the Built Environment, receiving positive feedback from most students.

Despite improvements, some students raised concerns about feedback consistency, particularly during the research proposal stage. We consulted relevant literature, including (Evans 2013), to identify gaps in our practice and closely examined the flagged feedback. We found issues such as feedback length, use of complex terminology, and relevance influenced by tutors' backgrounds and differing views on research. Although we held additional moderation meetings to address these concerns, the issue persisted.

In seeking solutions, a measure that we have not previously considered in the module, and which is gaining increased research attention, is automated feedback (Cavalcanti et al. 2021). While automated feedback tools can deliver consistent feedback, they are primarily suited for subjects with clear rules and objective answers, such as computer programming and mathematics. Most existing automated tools implemented in subjects relying on academic writing deal with lower-order concerns (e.g. grammar, style, and structure) and have a limited ability to provide nuanced and contextualized feedback (Deeva et al. 2021), which is necessary in research methodology modules to foster critical thinking and analytical skills essential for students' development.

In light of this discussion and to address the ongoing feedback consistency challenges, this study utilized the potential of a comprehensive database of historical moderated feedback issued to students over the past five years to develop an automated feedback tool. This tool aims to provide nuanced feedback on student research proposals while ensuring that educators can guide the process through simple interaction with the system. By leveraging this historical feedback data, we intend to create a more consistent and context-aware feedback mechanism that combines the benefits of automation with the personalized touch of educator involvement.

The development of our automated feedback tool is grounded in an understanding of existing automatic feedback systems and their limitations. To frame our approach and highlight the innovations our tool introduces, it is essential to review the current landscape of automated feedback in educational contexts. The following section (Section "Related Work") examines the evolution of automatic feedback systems, their applications, and the specific challenges they face, particularly in providing quality feedback for complex academic writing tasks such as research proposals. "Different Approaches to Assessment" Section presents different assessment approaches and discusses the authors' standpoint on assessment in this study. The methodology section discusses the general approach used to address the research questions. Furthermore, it details the development of rich feedback scenarios from our historical moderated feedback database. The development process of the automated feedback tool (FeedAssist), the operability of its interface, and the evaluation mechanism for its clarity and usefulness are also covered in this section. The results section analyses and discusses the study findings in relation to relevant literature, while the conclusion provides useful insights into our approach to automated feedback and highlights avenues for future research.

Related Work

Automatic feedback systems have existed since the 1960s, starting with Essay Grade (PEG) (Page 2003) and later systems like E-rater (Burstein 2003). Initially designed to speed up grading for multiple-choice tests and short essays, these systems provided limited detailed feedback. Despite decades of research, recent reviews such as Ramesh and Sanampudi (2022) highlighted persistent limitations: current systems excel at grading multiple-choice questions but struggle to holistically assess essays, considering factors like relevance, cohesion, coherence, and idea development. However, advancements in IT and AI, coupled with a shift from grading to facilitating learning, have led to new tools providing more comprehensive feedback (Stevenson and Phakiti 2019). Recent reviews by Cavalcanti et al. (2021) and Deeva et al. (2021) showed heavy use of automated feedback systems in computer science, programming courses, foreign language learning, and STEM subjects.

The most common technique for generating automatic feedback involves comparing students' answers with pre-determined solutions set by educators. This method has proved effective in disciplines such as computer programming, circuit analysis, and automation, where immediate feedback is crucial (Keuning et al. 2018). For instance, Birch et al. (2016) introduced a rapid model-based fault localization tool to aid novice programmers in identifying and rectifying errors during debugging. They found that their tool could enhance students' programming skills and learning speed. Similarly, Mitrovic et al. (2011) developed Thermo-Tutor, an intelligent tutoring system providing tailored feedback on thermodynamics problems. In a test with twenty-two students over a thirty-seven-minute session, the error rate dropped from 7.5% to 3.5% over nine attempts, showing effective learning. However, their system lacked guidance on how to correct mistakes and improve, which is not aligned with best practices in educational research literature (Maier and Klotz 2022). A common limitation with this type of automated feedback tools is that setting up all possible solutions and knowledge domains in the system can be time-consuming.

Another category of automatic feedback tools relies on Natural Language Processing (NLP) to analyze and manipulate human language. NLP techniques, such as pattern matching, are applied to large text collections to identify writing patterns and develop automated feedback mechanisms. Strobl et al. (2019) examined twenty-eight automatic writing evaluation (AWE) tools and found that most focused on general language writing support, while fewer were dedicated to research papers (22%) and essays (25%). Tools like Pearson WriteToLearn provide micro-level feedback on grammar, punctuation, and vocabulary (Shibani 2023). While studies like Foltz et al. (2011) show that micro-level AWE tools can be effective for native writers, others such as Dikli and Bleyle (2014) and Tetreault and Chodorow (2008) highlighted accuracy concerns for non-native writers, particularly with prepositions, articles, word choice, and word form. For example, Tetreault and Chodorow (2008) found that the Criterion tool identifies only 19% of preposition errors with 84% accuracy, below the (Burstein 2003) minimum threshold. Thus, educators should interpret such feedback cautiously and provide additional input. Unlike micro-level tools, macro-level AWE tools, which are less common, focus on higher-order writing skills such as coherence, relevance, organization, argumentation, and genre, aiming to enhance communication proficiency (Cotos 2023; Strobl et al. 2019). However, research indicates that macro-AWE tools often provide generic feedback that does not adequately adapt to individual writing styles and user groups, making them more suitable for early writing stages and less creative genres like argumentative writing (Geng and Razali 2022; Zhai and Ma 2023).

Several studies have explored AWE tools for research writing. Rapp and Kauf (2018) introduced ThesisWriter (TW) to aid in planning and structuring research proposals and dissertations. TW offers a phrase bank, structuring aids, and feedback templates, helping students with topic identification, research question formulation, and academic writing conventions. Students found TW highly beneficial, especially its tutorial portal and linguistic support. Similarly, Kinnunen et al. (2012) and Turunen (2013) studied the Scientific Writing Assistant (SWAN) developed by Lebrun (2011). SWAN helps students improve core sections of scientific manuscripts, such as abstracts and introductions, by evaluating fluidity and structure using rule-based mechanisms and NLP to analyze text and identify passive voice or judgmental word patterns. While SWAN uses automatic metrics for some analyses, it relies on user input for complex tasks like providing background-related information in abstracts. Both studies found SWAN effective in improving scientific writing quality. However, Turunen (2013) revealed that SWAN required initial training for effective use, and participants found feedback on structure and conclusion evaluation less favorable due to the manual setup process for journal articles.

With the launch of AI tools like ChatGPT in 2022, a new category has emerged in automated feedback provision, relying on generative AI technologies powered by Large Language Models (LLMs). Yan et al. (2024) conducted a systematic review examining 118 journal articles using LLMs in education. Out of the 118 sources, fifty-four journals (approximately 54%) concentrated on resource recommendation and automated feedback provision using GPT-based models in a wide range of domains including data science, programming, mathematics, and essay writing. The advantage of this category over the ones reviewed at an earlier stage is that GPT-based models do not need to be trained on human corpora for particular tasks or genres. Furthermore, they are cost-effective and widely accessible (Steiss et al. 2024). Despite these advantages of GPT models and their reported capacity to provide valuable feedback, there is a consensus in the literature that students generally perceive human-generated feedback as superior in both effectiveness and quality compared to automated feedback produced by GPT models (Steiss et al. 2024; Cao and Zhong 2023; Yan et al. 2024). For example, Cao and Zhong (2023) evaluated the translation outputs of students from Chinese to English supported by three different feedback types—ChatGPT-based feedback, teacher feedback, and self-feedback. Their study concluded that translations guided by teacher feedback and self-feedback were superior to those with ChatGPT feedback. However, ChatGPT's feedback helped students improve word choice and text flow in their translations. Based on that, the authors recommended using ChatGPT as a supplementary tool for complementing traditional feedback methods in translation practice. Similar findings were also reported by (Teng 2024) who evaluated forty-seven students' views on using ChatGPT in their writing process as part of the English as a foreign language course (EFL). Specifically, students perceived ChatGPT feedback as comprehensive. However, they found its overlay formal and less personal when compared to teachers' feedback. Steiss et al. (2024) conducted an interesting study on four hundred students' essays where two hundred received human feedback and the rest obtained feedback using ChatGPT. Their findings advocated that teacher provided higher-quality feedback vis-à-vis feedback accuracy, providing clear direction for improvement, prioritizing essential features, and the use of supportive tone. However, ChatGPT feedback was slightly better in drawing reference to assessment criteria.

To conclude, this section has thoroughly analyzed and highlighted the characteristics, advantages, and limitations of various automated feedback approaches. It is evident that these systems regardless of their type fall short of human-generated feedback in terms of accuracy and personalization, lacking the depth and contextual understanding provided by educators. However, automated feedback does offer benefits in certain contexts, as noted by numerous scholars. Despite their potential, a persistent gap remains: the substantial amounts of written feedback generated by educators over time often remain archived and underutilized, limiting its potential to improve teaching practices and assessment approaches. Educators accumulate a wealth of feedback year after year, yet this resource is rarely leveraged to its fullest. By transforming this archived feedback into an active, accessible tool, through methods such as creating searchable databases and conducting analytics to identify common trends, we can significantly enhance both student development and curriculum design. This would make the feedback process more impactful, future-focused, and aligned with the evolving educational landscape.

Building on these insights, our study proposes a methodology that enables educators to build and customize automated feedback systems by leveraging historical feedback data. By using readily available resources, we developed a comprehensive, context-aware system that balances automation with educator expertise. By utilizing five years of accumulated feedback, our system can draw upon a rich repository of scenarios, discipline-specific language, and evolving academic standards. This historical data allows for pattern recognition in student work and identification of effective feedback strategies, enabling more accurate and targeted responses. By allowing simple interactions for personalization, our tool aims to enhance accessibility for educators with varying technical abilities while maintaining the nuanced, discipline-specific guidance necessary in research methodology modules.

Unlike many automated systems that rely on pre-defined templates, FeedAssist takes a human-centered approach by incorporating a dynamic database of moderated feedback that provides context-aware responses that educators can easily customize. The novelty of this approach lies in its integration of historical feedback with an interactive, educator-driven interface, combining the consistency of automation with the flexibility of human insight.

Different Approaches to Assessment

Assessment serves two purposes: encourage learning and certify attainment against set learning outcomes. In general, there exist three approaches to assessment: Assessment of Learning, Assessment as Learning, and Assessment for Learning (Sambell et al. 2012).

First, "Assessment of Learning" includes traditional mechanisms such as tests and exams, typically conducted at the end of a learning unit, task, or course. Rooted in behaviorist principles, this approach focuses on measurable outcomes and standardization. However, it is widely criticized for promoting passive learning, emphasizing memorization over comprehension and application, and for its inability to measure higher-order skills, such as problem-solving and critical thinking. Nevertheless, it can be beneficial when combined with supportive and timely feedback and used formatively (Carless 2015).

On the other hand, "Assessment as Learning," which aligns with self-regulated learning theory and social constructivism, positions students as active participants by engaging them in self- and peer-evaluation activities, which are typically ungraded and occur during the learning process. This approach fosters metacognition, helping students understand their own learning process, become more independent, handle criticism more effectively, and engage in critical thinking (Thomas et al. 2011).

"Assessment for Learning" shifts the focus from evaluating end results to integrating assessment within the learning process, providing continuous feedback that guides improvement. In this model, both students and educators are learners whereby feedback consists of a dialogue between both parties to improve their learning and teaching (Sambell et al. 2012). At its core, "Assessment for Learning" involves authentic assessment activities that promote reflection on real-world applications, collaboration, and reflection. This strengthens situated learning by immersing students in practical contextualized learning experiences (Carless 2015).

The assessment approach in this study represents an intersection between "Assessment as Learning" and "Assessment for Learning," with minor elements of "Assessment of Learning." FeedAssist was deployed to provide feedback at the research proposal stage in the DESN 30167 module, which is authentic in nature, requiring students to identify an existing problem on their site and tackle it through self-directed research. This process aligns with inquiry-based learning models, which emphasize student-led iterative refinement and exploration.

At the end of the academic year, students must apply their findings to their design projects. The reflective and iterative nature of this process, along with the active engagement of students in self-directed inquiry and peer-evaluation activities, aligns it with "Assessment as Learning." However, this assessment is also summative, albeit with a minimal weighting of 20%. This was designed to serve as a developmental milestone rather than a high-stakes assessment. The greater emphasis on the final report (50%) ensures that students gradually improve their research competencies, such as methodology, critical analysis, and academic writing, throughout the academic year. The strong focus on tutorials and structured peer-review sessions of past student work reinforces "Assessment for Learning," as students receive continuous formative feedback, supporting their development in preparation for their final submissions.

Research Methodology

This study employed a mixed-methods methodology to develop and evaluate an automated feedback tool for assessing BSc Architectural Technology students' research proposals at Nottingham Trent University (NTU) in the Research Project for AT module (DESN 30167). As shown in Figure 1, the research was conducted in three implementation stages.

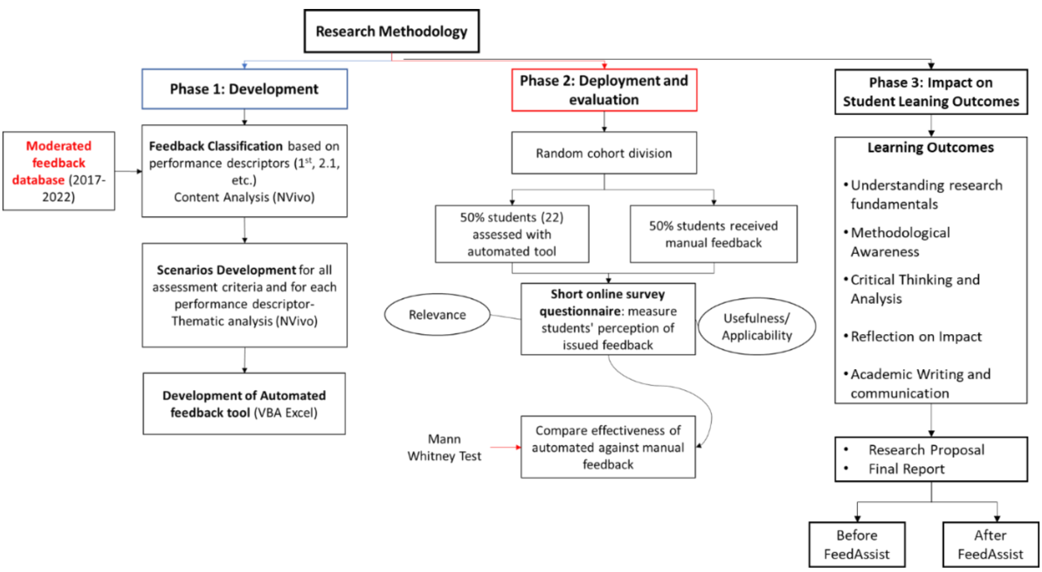

Figure 1: A Methodology Diagram Detailing the Practical Implementations Adopted in This Study

Phase 1: Development of the FeedAssist Tool

To develop a dataset of scenarios, we first conducted a content analysis of moderated written feedback from the past five academic years (2017–2022). Using NVivo software, we systematically coded feedback into categories aligned with the research proposal assessment criteria: introduction, annotated bibliography, methodology, and research feasibility and preliminary results (Figure A1 in the Appendix). As illustrated in Figure 1, within each category, feedback was further stratified by students' performance levels: first-class (1st), upper second-class (2.1), lower second-class (2.2), third-class (3rd), and fail.

For each criterion, various elements were assessed (see Figure A1 in the Appendix). For example, in the annotated bibliography, elements evaluated included the relevance of sources, the quality of critical analysis, and the usefulness of sources for subsequent stages of the student research project. To create consensual scenarios for each element, we conducted a thematic analysis using NVivo, based on the approach outlined by Bezai et al. (2021). We searched for element names with similarity settings on stemmed or synonymous terms to capture variations in educator expressions. For instance, the thematic analysis for the "relevance of annotated bibliography sources" in the upper second-class (2.1) node (see Figure 2) revealed common feedback scenario patterns:

- All three annotated bibliography sources have a very good relevance to the student's research project.
- Two out of the three annotated bibliography sources have a very good relevance to the student's research project.

Following these points, educators can select the scenario the most applicable to the student work.

After creating the consensual scenario database for all assessment criteria, we developed the automated feedback tool, FeedAssist, using Microsoft Excel VBA. As shown in Figure 3, the user interface is designed to be simple, intuitive, and interactive. It features tabs for each section of the evaluated research proposal (e.g., Annotated Bibliography), allowing the educator to navigate easily. In each tab, the marker can access and interact with a wide range of parameters, enabling them to build feedback progressively. Specifically, they can check the elements assessed in that section, such as relevance, track the marking progress using a progress bar (e.g., one out of three elements completed), and specify the estimated student performance for the evaluated section (e.g., 2.1). After that, the marker can select feedback scenarios associated with the student's performance from the previously discussed scenario database. The selected scenario(s) will be incorporated into the section feedback text box (Figure 3). Additionally, the educator has the option to review, amend, or add further feedback using the edit button. As illustrated in Figure 4, the Final Feedback tab consolidates feedback from all sections and allows the educator to check if any elements from any section are pending evaluation using progress bars. Before sending the feedback to students, the educator can review, amend, or add comments in the Final Feedback text box.

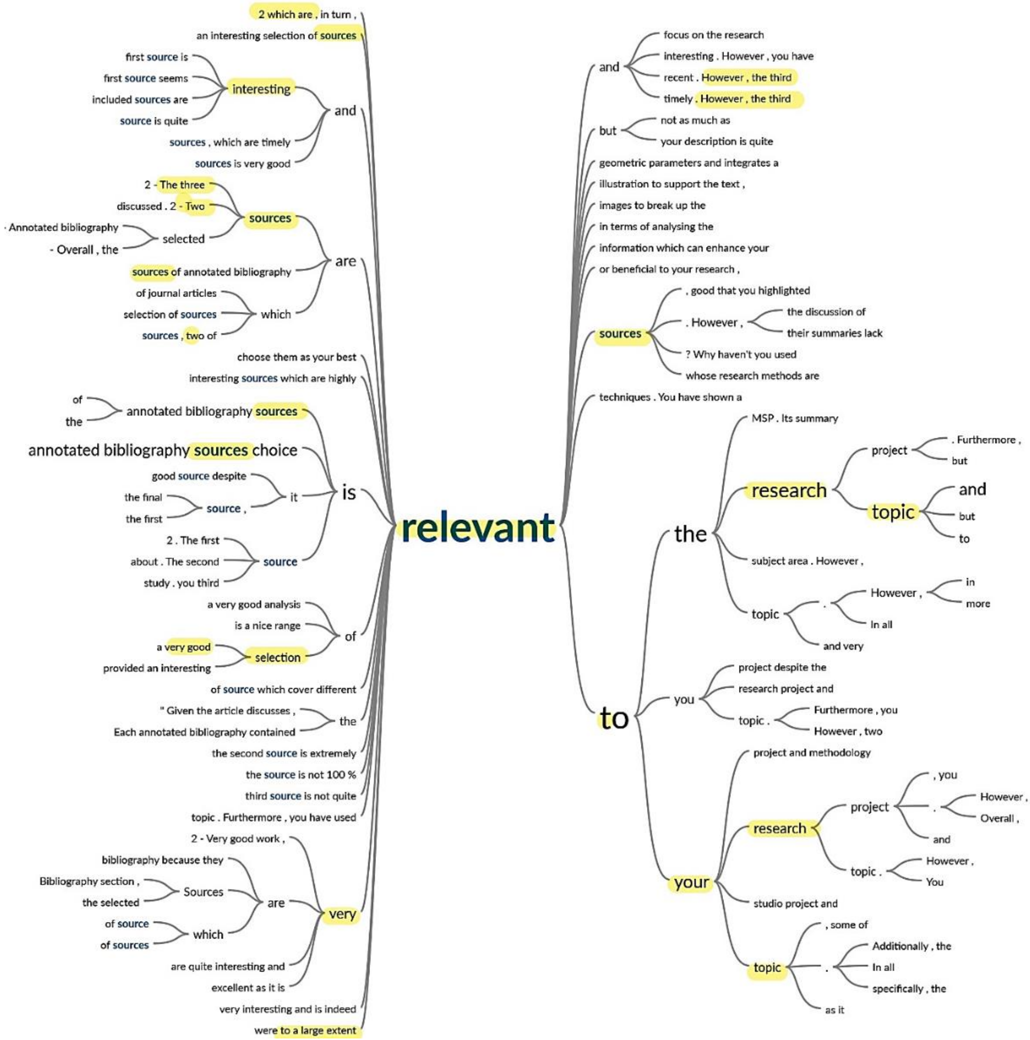

Figure 2: NVivo Word Tree Analysis of Annotated Bibliography Sources' Relevance in the 2.1 Performance Node

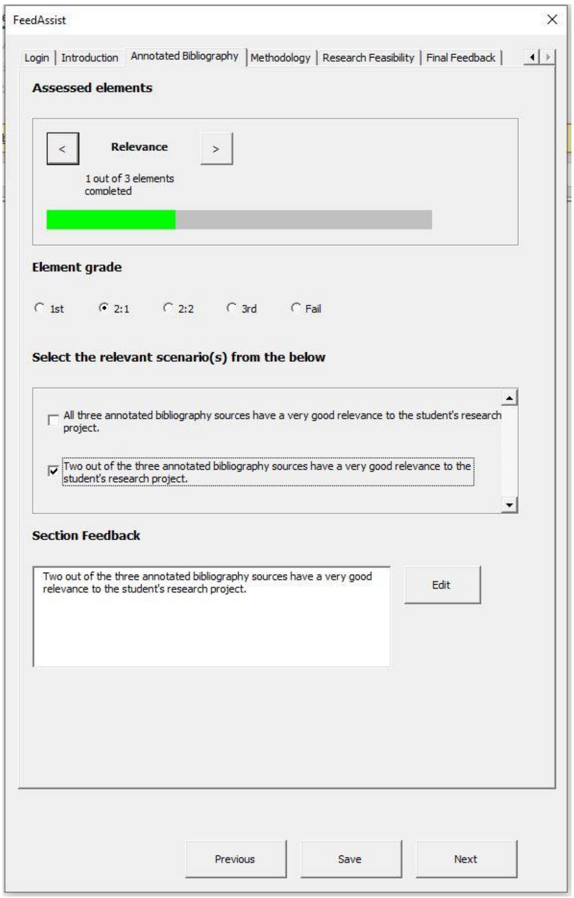

Figure 3: An Example of an Interface Layout of the Proposal Section Tabs in the FeedAssist Tool

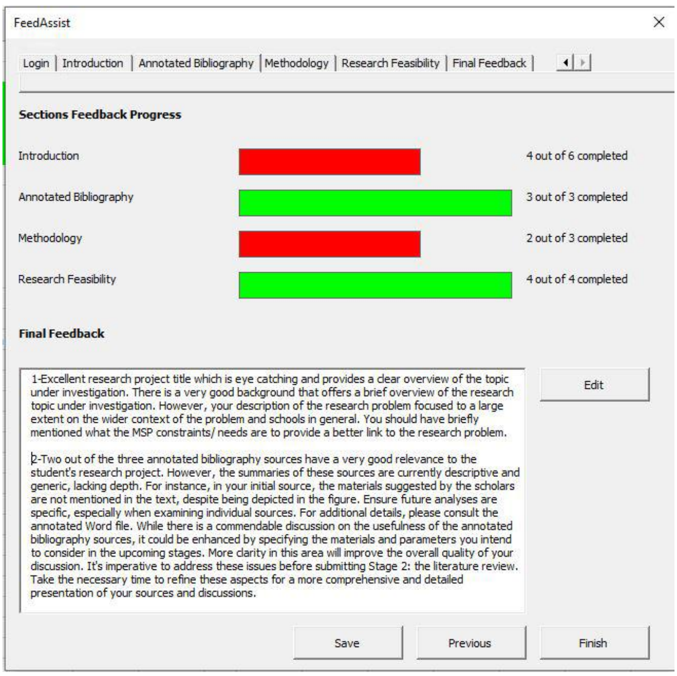

Figure 4: The Layout and Components of the Final Feedback Tab in the FeedAssist Tool Interface

Phase 2: Deployment and Evaluation of the FeedAssist Tool

To evaluate the tool's feedback effectiveness, the cohort was randomly split into two equal groups. Twenty-two students (50% of the cohort) had their research proposals evaluated using FeedAssist, while the remaining students were assessed manually. An online survey questionnaire gathered feedback on two aspects of their research proposal feedback: relevance and usefulness, as outlined by Hattie and Timperley (2007) and Spiller (2009). Responses were collected using Likert scale questions ranging from 1 (strongly disagree) to 5 (strongly agree).

Given the independence of the two groups, the ordinal nature of the dependent variables, and the non-normal distribution of these variables across the groups (refer to Table 1), a Mann-Whitney test was used to assess significant differences in scores between the group receiving manual feedback and the one receiving automated feedback through FeedAssist across the two aspects. The following null hypotheses were tested:

- Null Hypothesis 1 ($H_0 1$): There is no significant difference in the feedback relevance scores between the group receiving automated feedback through FeedAssist and the group receiving manual feedback.
- Null Hypothesis 2 ($H_0 2$): There is no significant difference in the feedback usefulness scores between the group receiving automated feedback through FeedAssist and the group receiving manual feedback.

Table 1: Results of the Shapiro-Wilk Test for Normality for Two Different Dependent Variables

	Group	*Shapiro-Wilk*		
		Statistic	*df*	*Sig.*
Relevance	Manual Feedback	0.841	17	0.008
	Automated Feedback (FeedAssist)	0.785	13	0.005
Usefulness	Manual Feedback	0.809	17	0.003
	Automated Feedback (FeedAssist)	0.706	13	<0.001

Note: All the significance levels (Sig.) are below 0.05, indicating that none of the data sets (relevance and usefulness for both manual and automated feedback groups) follow a normal distribution.

Phase 3: Impact of FeedAssist on Student Learning Outcomes

After evaluating student perceptions of the relevance and usefulness of feedback from FeedAssist in Phase 2, this phase consisted of evaluating the impact of feedback on the student learning outcomes in the research module (DESN 30167). Specifically, our analysis tracked student achievement through a two-tier approach. First, we examined student progress within the 2023 to 2024 academic year, when FeedAssist was introduced, by comparing performance between the Term 1 research proposal and the Term 3 final report. Additionally, we compared the performance between academic year 2023 to 2024 and the four years that preceded the implementation of FeedAssist. The analysis focused on the percentage of students achieving 2:1 (equivalent to 60%) or above in the following competencies:

understanding research fundamentals, methodological awareness, critical thinking and evaluation, academic writing and communication, and reflection on impact. As shown in Figure 5, these competencies were assessed through specific sections in both the research proposal and the final report, including introduction, methodology, expected results, results analysis, and conclusion, except for communication, which was evaluated throughout both documents.

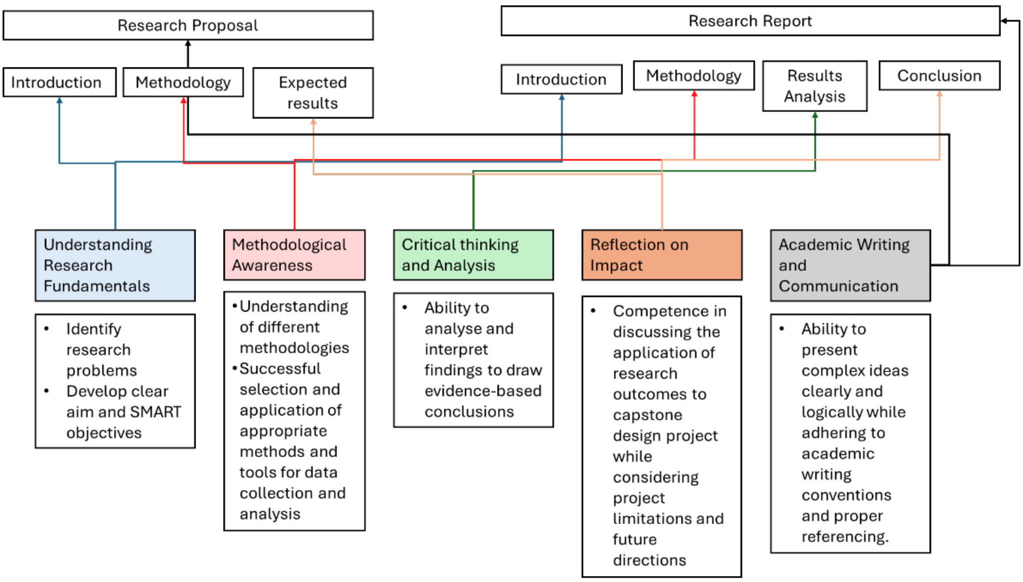

Figure 5: The Learning Outcomes and Their Corresponding Evaluation Section in the Research Proposal and Report

Research Limitations

Although the methodological approach used enabled the objective measurement of student perceptions of FeedAssist's feedback relevance and usefulness, as well as its impact on their learning outcomes following its introduction in 2023 to 2024, several limitations must be acknowledged. First, it is well known that feedback is not the only factor affecting student performance. A key limitation of this study is the influence of external factors such as student engagement and teaching quality (Evans 2013). Improvements in student performance may not be solely due to the introduction of FeedAssist, as other external variables were not controlled. A possible future approach to addressing this limitation is the implementation of longitudinal studies to track individual student progress over several years and isolate the tool's direct impact. Secondly, due to time constraints in this study and the fact that the students concerned had already graduated, the percentage of students achieving a 2.1 or above was used to assess student performance. While this provided a useful measure, it does not fully capture deeper learning outcomes such as critical thinking or independent research skills. In future research, incorporating qualitative methods, such as focus groups or interviews, would provide greater insights into these aspects (Brooks et al. 2019).

Results Analysis and Discussion

Feedback Relevance

Out of forty-two students, thirty participated in the online survey, resulting in a response rate of approximately 71%. Among the respondents, thirteen received automated feedback using FeedAssist, while seventeen received manual feedback. The gender distribution was 70% male and 30% female. Additionally, twenty-nine students were classified as UK home students, and one was an international student. The following sections present the findings from the Mann-Whitney tests comparing the feedback groups.

As shown in Figure 6, the analysis of the mean ranks for relevance ratings revealed that the group receiving automated feedback via FeedAssist perceived their feedback as more relevant (mean rank = 19.50) compared to the group receiving manual feedback (mean rank = 12.44). This was supported by the findings of the Mann-Whitney test in Table 3 ($U = 162.5$, $p = 0.028$ with a medium effect size, $r = 0.42$). Since the p value < 0.05, we reject the null hypothesis that there is no significant difference in the feedback relevance scores between the group receiving feedback from FeedAssist and the group receiving manual feedback.

The perceived relevance of FeedAssist feedback can be attributed to its use of scenarios derived from a large dataset of feedback collected over the past five academic years. These scenarios capture common mistakes and recurring patterns prevalent across all student submissions, making the feedback broadly applicable. Additionally, if a student's submission presents issues not covered by the scenarios, educators can supplement the automated feedback with personalized comments and suggestions for further improvement.

In contrast, the perceived lower relevance of manual feedback may be due to its less contextualized nature, often constrained by time limitations that restrict its depth and comprehensiveness. Discussions with module staff revealed that manual feedback typically focuses on providing broad, holistic insights rather than addressing specific details and limitations of each submission. This aligns with Bloxham et al. (2011), who found that educators prefer holistic assessments for their time-saving benefits, despite the risk of overlooking specific details.

Table 2: Independent Samples Mann-Whitney *U* Test Summary of the Variable Relevance

Total *N*	30
Mann-Whitney *U*	162.5
Wilcoxon *W*	253.5
Test Statistic	162.5
Standard Error	22.554
Standardized Test Statistic	2.306
Asymptotic Sig. (two-sided test)	0.021
Exact Sig. (two-sided test)	0.028

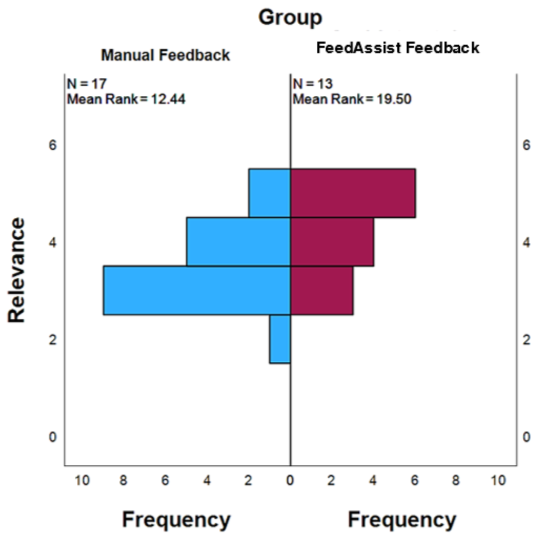

Figure 6: The Mean Ranks for Feedback Relevance Ratings [COMP: Set "U" italic in this figure.]

Feedback Usefulness

As expected, feedback generated by the FeedAssist tool was perceived as significantly more useful (mean rank = 19.19) than manually generated feedback (mean rank = 12.68), as confirmed by the Mann-Whitney test results ($U = 158.5$, $p = 0.043$, $r = 0.39$). With a p value less than 0.05, the null hypothesis of no substantial difference in perceived usefulness between the two feedback modes was rejected (Table 3 and Figure 7). This finding can be explained by the limitations of the predominantly holistic approach taken in manual feedback provision. While holistic feedback has value, its broad nature restricts opportunities for detailed, actionable recommendations tailored to each student's work.

In contrast, the automated tool provided a balanced combination of holistic and granular feedback. Research by Jönsson et al. (2021) suggests holistic approaches better align feedback with assessment criteria, while analytical approaches focus more on justifying students' scores. By integrating both elements, FeedAssist feedback likely enhanced students' understanding of their performance relative to the criteria. Furthermore, studies by Brooks et al. (2019) and Hattie et al. (2021) highlight the effectiveness of balanced feedback in guiding students on tangible "next steps," a factor strongly linked to improved academic outcomes over time.

Table 3: Independent Samples—Mann-Whitney *U* Test Summary of the Variable Usefulness

Total *N*	30
Mann-Whitney *U*	158.5
Wilcoxon *W*	249.5
Test Statistic	158.5
Standard Error	22.345
Standardized Test Statistic	2.148
Asymptotic Sig. (two-sided test)	0.032
Exact Sig. (two-sided test)	0.043

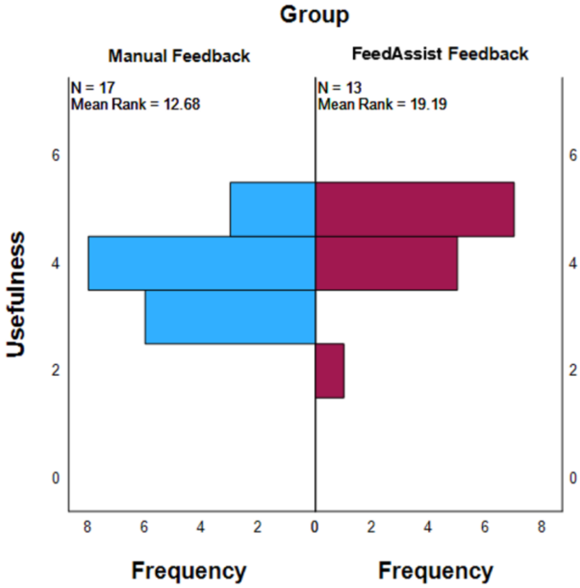

Figure 7: The Mean Ranks for Feedback Usefulness Ratings

Impact on Student Learning Outcomes

Table 4 and Figure 8 depict the student performance in key research competencies in the research proposal and final report before and after the introduction of FeedAssist. Overall, it is evident that every academic year, students demonstrated an improvement in the final report stage across all competencies in comparison to the research proposal stage. This is because the report is submitted at the end of the academic year when students have had plenty of time to develop their research skills through lectures, tutorials, peer-evaluation sessions, and coursework over the academic year. Another factor is that students have received feedback on their research proposal, which allows them to address any weaknesses in preparation for the final report submission.

Before 2023 to 2024, the most notable improvement was seen in academic writing and communication (average increase of 9.8%), followed by reflection on impact (8.4%) and methodological awareness (6.5%). The significant rise in their academic writing and communication standards is a clear indication that students developed an understanding of research writing conventions including referencing, logical structuring of arguments, and critical engagement with academic sources, all of which contribute to better academic writing and communication. In contrast, the improvement in their understanding of research fundamentals was minimal (2.4%). This could be attributed to the heavy emphasis placed on foundational research skills such as problem identification and refining aims/objectives, during Term 1 through sessions and feedback, leaving little room for growth in the final report stage. Also, since the research fundamentals competencies carry out a lower weighting (10%–20%), students may have prioritized addressing feedback in sections with higher weightings, such as methodology.

In the academic year when FeedAssist was introduced (2023–2024), the improvement in all competencies from the research proposal to the final report generally followed a pattern similar to that of previous years. However, except for the competencies related to understanding research fundamentals and methodological awareness, the magnitude of improvement in the remaining competencies was significantly higher than in previous years. For example, in the final report, 70% of students achieved a 2:1 or higher in the critical thinking and analysis competency, which is a 12.4% improvement from last year. Similarly, 83% and 82% of students achieved a 2:1 or above in the reflection on impact and academic writing and communication competencies in their final report submissions, respectively. This represents an increase of 9.6% and 10.8%, respectively, from previous years.

A review of previous feedback revealed a tendency among some tutors (mainly industry-based ones) to place less emphasis on reflection on impact in students' major design projects and on academic writing and communication competencies, unlike other competencies (e.g., methodological awareness). Specifically, their feedback often covered overall performance in relation to these competencies without pinpointing specific areas for improvement. Since FeedAssist has a built-in consensual and comprehensive scenario database for all competencies, we argue that it helped bridge this gap by enhancing the depth and relevance of feedback in these competencies while still offering opportunities for tutors to add personalized input.

Table 4: The Proportion of Students Achieving 2.1 or Above in Key Research Competencies in the Research Proposal and Final Report

	Coursework	*Research Fundamentals (%)*	*Methodological Awareness (%)*	*Critical Analysis (%)*	*Reflection on Impact (%)*	*Academic Writing (%)*
19–20	Proposal	72	61	54	62	60
	Report	73	69	62	69	72
20–21	Proposal	71	65	57	64	58
	Report	73	70	60	69.5	66
21–22	Proposal	76	63	50	67	60
	Report	76	68	57.5	68	69
22–23	Proposal	73.47	59	59	49	63
	Report	80	67	59	69	73
23–24	Proposal	77	67	53	65	61.5
	Report	81	77	70	83	82

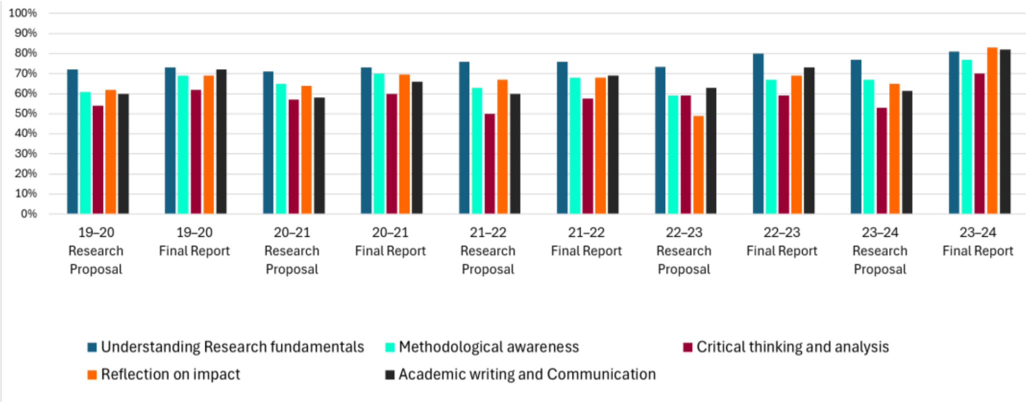

Figure 8: Evaluation of Students' Key Competencies in the Research Proposal and Final Report Before and After the Introduction of FeedAssist

Conclusion

This study introduces FeedAssist, an innovative interactive tool designed to tackle consistency issues in undergraduate research proposal assessments. By drawing on five years of carefully curated and moderated feedback data, FeedAssist provides more relevant, consistent, and actionable insights for students. Our research findings showed that FeedAssist helps educators strike a balance between automation and personal touch, delivering feedback in a progressive way that students find notably more relevant and useful compared to traditional methods. The analysis also demonstrated that the introduction of FeedAssist in academic year 2023 to 2024 led to a greater improvement in key student research learning outcomes including critical thinking analysis, reflection on impact of research findings on their major design project (capstone project), and academic writing compared to previous years. The tool's effectiveness comes from its extensive database of real-world feedback scenarios, which helps identify common student errors and allows educators to easily adjust and fine-tune responses through an intuitive interface. This ensures that feedback is both thorough and tailored to each student's needs, helping standardize feedback quality, reduce inconsistencies in tutor emphasis across all assessment areas, and support students in making more targeted enhancement in their final reports.

As academics, we generate a significant amount of written feedback over the years, much of which remains stored on our computers and underutilized. We argue that automated feedback tools like FeedAssist, which leverage historical data, can help make better use of this wealth of feedback, particularly when we are dealing with large student groups and limited resources. By drawing on historical feedback, FeedAssist enables educators to offer more timely and consistent responses, efficiently addressing recurring issues. However, it is important to recognize that this study is situated within a specific context, and the findings may not apply universally. In the following sections, we present some scenarios showcasing how FeedAssist could be adapted across a wide range of disciplines, including STEM subjects, social sciences, and creative arts, to deliver consistent and tailored feedback.

Integration in STEM Subjects

Laboratory and technical reports are central to STEM students' learning, providing them with a structured way to communicate experimental findings and reflect on their practical work (Parkinson 2017). However, several studies indicated that students usually tend to approach report writing as a checklist exercise, prioritizing the completion of required sections over engaging in critical analysis (Gouvea et al. 2022). Introducing FeedAssist to provide feedback to students about their reports could enhance their critical analysis and technical writing competencies if trained with historical moderated feedback to capture common scenarios aligned with key student competencies. FeedAssist could be also made accessible to students in seminar sessions where they collaboratively analyze a lab/technical report example and use FeedAssist to generate feedback. This would improve their understanding of report requirements and assessment criteria, which encourages deeper critical analysis in their future report submissions.

Integration in Social Sciences Subjects

Argumentation, a reasoning process involving claims, data, and reasoning to form arguments, is essential for discussing sociological issues. However, the literature consistently highlights that students is their early stages of academic journey often struggle with aspects such as constructing coherent arguments, critically analyzing arguments, identifying bias, and recognizing fallacious reasoning (Berkle et al. 2023). If trained with a robust historical database of moderated feedback on argumentation issues, FeedAssist could help students improve their argumentation skills by offering scenario-based guidance on constructing arguments, analyzing arguments, identifying bias, and recognizing fallacious reasoning. It could highlight common issues such as weak evidence for claims, overgeneralization, failure to address counterarguments, false dichotomy, ad hominem, and confirmation bias. Additionally, it could provide examples of well-structured arguments, fallacious reasoning, and balanced arguments, extracted from the historical feedback dataset. To further support critical engagement, the dataset could also be enriched with guiding questions such as "How would people with different ideologies respond to this argument?"

Integration in Art and Design-Related Subjects

Owing to their creative and interpretive nature, feedback in art- and design-related subjects is inherently subjective, influenced by individual perspectives, personal taste, and cultural context (Cheng 2015). This subjectivity can make providing clear and actional feedback to students challenging. FeedAssist could help reduce feedback subjectivity by offering a data-driven standardization approach that prioritizes consistent and objective framework over individual tutor's personal preferences. Specifically, historical feedback data from multiple tutors is analyzed and organized into a wide range of consensual scenarios, reflecting common issues with logical recommendations. While objectivity ensures clarity and consistency of feedback, subjectivity remains important for encouraging creative exploration and develop diverse interpretations (Quill 2023). To balance both, FeedAssist interface could incorporate a dedicated section for subjective or personal comments. This would ensure that students receive both objective and a more personalized interpretive insights from educators.

Despite the promising potential of adapting FeedAssist across various disciplines, it is important to note that automated feedback tools are not a one-size-fits-all solution. In cases where time constraints are less pressing, manual feedback from experienced academics can provide nuanced insights, address unique aspects of student work, and foster stronger personal connections with learners, offering benefits that automation may not fully replicate. This study emphasizes that neither approach is inherently superior; rather, each has its own merit and applicability, depending on the specific context and circumstances. Further research is needed to explore the tool's impact on student learning outcomes in different settings and to fully understand its potential and limitations.

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I acknowledge the use of ChatGPT to improve the English of the article. The prompts used include "Improve the English of the below paragraph" and "Proofread the below paragraph." The outputs generated from these prompts were instrumental in identifying language-related issues, such as grammatical errors, punctuation mistakes, and flow inconsistencies, thereby enabling the authors to refine their sections effectively. While the authors acknowledge the usage of AI, they maintain that they are the sole authors of this article and take full responsibility for the content therein, as outlined in COPE recommendations.

Informed Consent

- The authors have obtained informed consent from all participants.

This study was granted ethical approval by the Schools of Art and Design, Arts and Humanities, and Architecture, Design and the Built Environment Research Ethics Committee (AADH REC) at Nottingham Trent University. Participants were informed of the study's purpose, procedures, potential risks and benefits, and their right to withdraw at any time without penalty. Informed consent was obtained from all participants. The study protocol was approved by the AADH REC

Conflict of Interest

No potential conflict of interest was reported by the author(s).

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Appendix

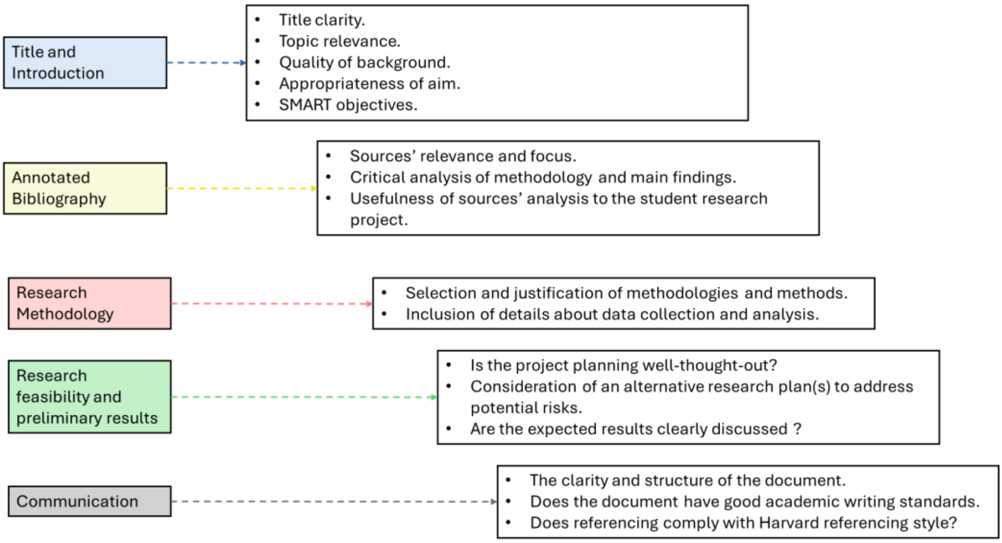

Figure A1: Assessment Criteria of the Research Proposal Submission

ABOUT THE AUTHORS

Moulay Larbi Chalal: Senior Lecturer and Course Leader of the MSc Digital Architecture & Construction, School of Architecture, Design, and the Built Environment, Nottingham Trent University (NTU), Nottingham, United Kingdom.
Corresponding Author's Email: Moulay.chalal@ntu.ac.uk

Nacer-Eddine Bezai: Senior Lecturer and Course Leader of the BSc Architectural Technology, School of Architecture, Design, and the Built Environment, Nottingham Trent University (NTU), Nottingham, United Kingdom.
Email: nacer.bezai@ntu.ac.uk

Benachir Medjdoub: Professor of Digital Architecture, School of Architecture, Design, and the Built Environment, Nottingham Trent University (NTU), Nottingham, United Kingdom.
Email: benachir.medjdoub@ntu.ac.uk

Bhavna Crossley: Principal Lecturer in Architectural Technology, School of Architecture, Design, and the Built Environment, Nottingham Trent University (NTU), Nottingham, United Kingdom.
Email: bhavna.crossley@ntu.ac.uk