To What Extent Can Users Contribute to the Adaptive Feedback Process to Improve Cognitive Behaviour?

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Abstract—Concept mapping is a promising research area, particularly for learning and education. They provide visual representations of information about a topic and the relationships between such information. Previous research has shown significant improvements in cognitive behaviours when concept maps are used, which is emphasised when feedback is used. Adaptive feedback systems have been widely incorporated into concept mapping, but there has been limited research on how a user can contribute to the feedback system and the potential impacts this has on cognitive behaviour. Therefore, this research investigates the effects user contribution to an adaptive feedback system has on cognitive behaviours in concept mapping. A tool was made where a user could build a concept map and receive adaptive feedback based on their concepts. Users could specify their feedback preferences and the feedback system adapted to them using various thresholds. Overall, there was no significant difference in cognitive behaviour between users who contributed to the feedback system and those who did not. Therefore, we conclude that user contribution to an adaptive feedback system does not improve cognitive behaviours in concept mapping. This paper provides a new and previously unexplored way of allowing users to contribute to an adaptive feedback system.

Index Terms—concept learning, intelligent tutoring systems, interactive systems, language parsing and understanding

1 Introduction

COGNITIVE overload is a major issue for people of all ages, caused by copious amounts of information above a person's ability to process it. In the case of children, methods have been created to overcome this overload. Specifically, Novak developed concept maps to understand how children's cognitive behaviour was impacted when large amounts of information were summarized into smaller visual aids [1]. Concept maps are a visual representation of ideas, with a focus, and the relationships between them. The purpose of a concept map is to structurally organise thoughts about a subject area and understand how they relate to one another. From this, concept maps have become increasingly popular in education. Consequently, they are a useful tool for enhancing the quality of teaching and encouraging positive cognitive behaviours [2], [3].

Concept maps promote reflection of a learner's understanding of concepts and their relationships, allowing for meaningful learning [4]. This is an important research area as it is rarely used purposefully and is more effective in improving knowledge retention than other traditional learning activities [5].

Within education, concept maps are used to enhance the learning of a subject. The way a person learns and understands concepts can be shown through the comparative strategies they exhibit, which include how a person navigates content, identifies key concepts and establishes relationships between them [6]. The comparative strategies performed can give a larger indication of learning when compared to the final concept maps created. Therefore, it is important to measure comparative strategies to gain a more detailed perception of a person's cognitive behaviour.

Concept maps can be used to provide information about the nature of a student's misunderstanding, by seeing the gaps in knowledge and misinterpretations [7]. This gives experts of the map's subject area an insight into a learner's difficulties in the mapping process, which can allow for feedback to be given. Such feedback can instigate positive behavioural changes in the learner, resulting in more meaningful learning.

Feedback is considered one of the most important stimuli to assist a learner's understanding [8]. Thus, it has a high influence on a person's cognitive behaviour. As a result, different areas of feedback have been developed and the forefront of research suggests adaptive feedback is the most beneficial to meaningful learning. Adaptive feedback systems take into account any learner's characteristics, such as their prior knowledge and the nature of the learning task, and return feedback specific to the learner. Often adaptive feedback is given verbally to a learner, but it has become increasingly popular to include adaptive feedback in concept mapping software. This helps the learner understand the overall hierarchy of the content and the relationships between concepts, which is a common difficulty encountered when concept mapping. Subsequently, there is less opportunity for the user to experience cognitive overload, thus strengthening performance and engagement.

The paper aims to determine if user input to an adaptive feedback system has a positive impact on a user's cognitive behaviour and if so, the extent to which the user's input does this. Therefore, the research question for this paper is *"To what extent can users contribute to the adaptive feedback process to improve cognitive behaviour?"*

The objectives of this paper are described below.

Basic objectives:

- Create an app where a user can create concept maps.
- Create an adaptive feedback system that gives feedback whilst the user creates a concept map.
- Embed the learning content within the app, so the user can navigate content and build a map at the same time.

Intermediate Objectives:

- Expand the adaptive feedback system to take into account user input.
- Evaluate a user's learning and behaviours shown during mapping.

Advanced Objectives:

- Create thresholds that change the amount of impact a user has on the adaptive feedback system.
- Create a system to measure a user's comparative strategies whilst they build their concept map.

This study aims to extend the current research regarding the support adaptive feedback provides to cognitive behaviours. Previous studies have limited exploration of the effects different levels of user contribution have on an adaptive feedback system and consequently, the potential positive behavioural changes exhibited during the concept mapping process. A study with 9 undergraduate students was held to measure cognitive behaviours exhibited during concept mapping. During this, an adaptive feedback system was used and a proportion of participants had a direct influence on the feedback that was given. We studied the learning of participants and conducted an in-depth analysis of the comparative strategies exhibited. We found that the user influence on the adaptive feedback system did not improve cognitive behaviours.

The paper is structured as follows. In section 2 related work regarding the research question is explored. In section 3, the methodology of the research is explained. In section 4, the result of the research is analysed. Then, in section 5 an evaluation of the research is made and a conclusion is reached in section 6.

2 Related Work

Concept mapping is a developing research area due to much of the learning coming from the process that a learner employs rather than the final maps they create. Also, the structure of a concept map is said to reflect a learner's cognitive structure, so a lot can be learnt about the cognitive behaviours and strategies used [9].

2.1 Concept Maps as a Learning Tool

Concept maps are used as a learning resource in many different areas, for example, education and business. They can have specific objectives or can be used generally, for example, a website that helps users create a concept map could also be targeted at users with a specific learning type. Leading research papers emphasise the importance of concept mapping, including how such a technique enhances critical thinking skills, creating an empowering learning environment. The paper written by Lee *et al.* [10] conclusively shows the high development of learning and improvement of inference and deduction as a result of the longitudinal effect of concept mapping. The main weakness of this study comes from the probable selection bias as a result of the non-random convenience sampling used. It may be the case that the data is subsequently skewed so using the data should be avoided. However, the final conclusion strongly suggests the use of concept maps will encourage positive cognitive behaviours.

Previous studies have focused only on the benefits of concept mapping and not the possible cognitive overload that can occur from the use of concept maps. Concept maps quickly become complex, making it harder to sustain an organized structure. Therefore, a learner must not be overloaded with information and approaches should be taken to reduce this. Krieglstein *et al.* [11] explore how the design and complexity of concept maps influence cognitive learning processes. Their data-driven study shows how the structure of a concept map can lead to disorientation and cognitive overload. Therefore, it can be inferred that the structure of a concept map plays an important role in the meaningful learning of a concept mapper. Conversely, the researchers fail to find any other significant results that express how complexity influences cognitive learning. The existing research provides evidence that concept mapping supports cognitive behaviours but should be monitored and structured so that cognitive overload is reduced.

These papers show the progression of understanding of the impact concept mapping has had since Novak [12] first introduced them. This research confirms the importance of concept mapping as a learning tool and future research should concentrate on the specific features that can be used to improve concept mapping techniques.

2.2 Computer-based Concept Mapping Tools

Concept maps were first developed in 1972 by Novak [12], but the development of technology, particularly user interfaces and touch screen technologies, and the increased use of websites have led to more modern approaches to concept mapping. This includes the development of popular websites, such as CmapTools and Miro [13], [14].

Several issues have been discovered as a result of traditional concept mapping being used. Not only does constructing a concept map using the traditional pen and paper techniques make it hard to restructure the concepts already written, but also it is harder to adapt and manipulate existing concepts and the presentation of concept maps. Reader and Hammond found that college students struggle to construct and revise concept maps on pen and paper [15]. Thus, they propose the need for computer-based concept mapping tools and argue the advantage of computer-based concept mapping compared to traditional note-taking. This is a dated study, so all statistics used to support their argument are outdated and do not take into account the recent developments in concept mapping or the advancements in computing. However, all the sources are valid and the conclusion that computer-based concept mapping tools should be used to promote meaningful learning is supported. Therefore, the results should be accepted and further research should be carried out. From this, Anderson-Inman and Horney [16] support the idea that computer-based tools are beneficial as they indicate the "practical advantages of constructing concept maps electronically are . . . an ease of construction, an ease of revisions and the ability to customise maps." Their argument sufficiently explains the advantages and disadvantages of both computer-based and traditional methods and there is no obvious bias towards either method. As a result, the paper is very clear and concise, so we argue that there is a need for computer-based concept mapping tools. Further evidence to support computer-based concept mapping tools includes the rise of concept mapping tools created since the release of both papers. We argue that computer-based tools are needed to help with concept mapping and they should be explored further.

Whilst many pieces of software aid the creation of a concept map, there are not many that specifically target the support for cognitive behaviour. Michigan State University [17] developed software that allows students to build concept maps and receive immediate feedback based on automatic scoring systems. The system is based on predefined concepts and their relationships, leaving an opportunity for further development. This is a good opening to collect data regarding the learning of concepts, although there is no such data to suggest the software is adapted to different cognitive behaviours and learning styles. This software could be adapted to broaden the support for different cognitive behaviours. Similarly, Chung *et al.* [18] explored software which also scores user-built concept maps based on predefined concepts and linking terms. Their scoring system is not intelligent and leaves little space for further development. Both systems mentioned above have been evaluated as having high thresholds, meaning it takes some time to learn how to use the software. This could be intimidating to a user and lead to cognitive overload, so the designs of these apps are not recommended. On the other hand, CmapTools [13] is a low-threshold environment, taking only a few minutes to understand how to use the system. This software has no restrictions on the concepts or the relationships you can add, making it more flexible and available to a wider range of people. However, CmapTools does not have a scoring system, so a user cannot grasp the quality of their map. From this, a learner may not understand if the behaviours they are using to build a concept map are correct or not, creating doubts and disbelief.

Based on this research, it is evident there is not one piece of software that combines intelligent scoring and freedom to create a concept map with no prerequisite concepts. Therefore, we suggest such a piece of software should be further explored and researched.

2.3 Feedback in Concept Mapping

It is easy for a newcomer to create basic concept maps, but it is more difficult to create a high-quality concept map [9]. Hence, there is a lot of research into the ways software can be used to develop concept mapping skills. Feedback discussions have dominated concept mapping research in recent years. It is used to support the learner in their map-building techniques and provide help with the content they write. Feedback is regarded as one of the most critical influences in learning and as a result, it is a widely researched area within concept mapping.

The two types of feedback that can be given are adaptive and conclusive feedback. Adaptive feedback will encourage behavioural changes during the mapping phase, by recommending concepts and areas of the map to improve. Conclusive feedback is used to assess the quality of a concept map once it has been fully developed. Both types aim to improve a learner's cognitive behaviours as a better performance of such behaviours will contribute to optimal learning and reduce cognitive overload. Several research works have provided sufficient evidence to suggest that delayed (conclusive) feedback is less effective than immediate (adaptive) feedback. Specifically, Opitz *et al.* [19] found a significant increase in learning for people receiving immediate feedback, compared to delayed feedback. Their data was solidified by a complementary analysis to confirm this. Hence, their research provided encouraging evidence towards adaptive feedback. Therefore, the focus of this research will be on adaptive feedback in the hopes of optimising a person's meaningful learning.

Awais [20] proposed an adaptive feedback system based on collaborative behaviour. The system gave a user adaptive feedback whilst they built a concept map. This feedback depended upon their performance from a pre-test questionnaire and also depended upon the user's incentive that motivates them, for example, if they preferred earning points or looking at their position on a leaderboard. This meant the user had an implicit contribution to the feedback they received. The study had a justifiable number of participants, of which they were randomly selected so little bias was introduced. There was a notable performance increase in learning for students who used the adaptive feedback system, as shown by the higher grades received and the more time spent on concept mapping. Therefore, we argue that adaptive feedback will be useful for improving cognitive behaviours. A limiting factor within this paper was the extent to which users can contribute to the feedback system. The users are given no explicit information that allows them to change the format feedback is given in. Therefore, this could be researched further. The conclusions reached by Awais are further supported by Wang and Walker [21] who, through their thorough examination of concept map comprehension, focus on providing adaptive feedback during the creation of a concept map. Adaptive feedback was given to users based on the way they built their concept map. This was compared to the feedback given when the user had completed the mapping process. Similarly to Awais, an intelligent model was used to generate the feedback, which observed not only the concepts and relationships (not) included, but also the positive and negative cognitive behaviours observed. This model provided an accurate measure of learning and cognitive development and the overall research provided a promising start to support the use of adaptive feedback. The approach taken by Wang and Walker used ten actions to determine the type of process or content-based feedback they would be shown and the feedback shown was one of ten different sentences. The results concluded that providing adaptive feedback to a user does not necessarily improve learning, but more research needs to be conducted to reach any strong conclusions. This is not a sufficient conclusion and more concrete deductions could have been made if data was analysed further. However, this study provided the concrete evidence needed to combine adaptive feedback systems and concept mapping into a single application. In terms of the methodology, the study had several flaws; not only were different learning styles not acknowledged, but also, by restricting the feedback given to 10 sentences, the user could become unmotivated. Therefore, further research based on this study should use a wider range of feedback and a different method of data analysis. Therefore, we acknowledge the support adaptive feedback systems can potentially provide and will avoid using the methodology explained in this paper. Furthermore, Kroeze *et al.* [22] use a similar methodology to Wang and Walker, but with exhaustive feedback prompts and a more reliable, systemic approach. Kroeze *et al.* designed an expert concept map as a basis for feedback and allowed for individual deviations from this, including concepts with alternative wording or spelling mistakes. The feedback given is suggestive prompts that encourage a user to rethink misconstrued concepts. The paper reveals the limitations of the feedback system and explains the ways to overcome them. Contrary to expectations, there was no conclusion reached about the effect feedback has on the quality of concept maps produced. As a whole, the feedback system given is robust and if the limitations are overcome, the feedback system could provide valuable data to confirm how cognitive behaviours affect concept mapping. This is the most advanced system explored so far, by providing options to fix spelling mistakes and add synonyms the system becomes more sustainable and improves over time. No other system has had such a feature. Based on this research, there is conclusive evidence to suggest adaptive feedback improves the learning of the mapper and supports cognitive behaviours. Moreover, the feedback motivates the learner to continue expanding their concept map and consolidates their learning.

Most studies regarding adaptive feedback have had a limited explanation of the structure of the feedback system. In contrast to this, a study written by Gouli *et al.* proposes an adaptive feedback system with an in-depth explanation of the feedback components involved and the data needed [23]. The system is designed to guide and support a learner towards a specific target, in this case, to support positive cognitive behaviours. It also focuses on providing personalised feedback based on an identified error within a user's concept map. In particular, the paper sets out four distinct layers of feedback that are given to a user based on the conditions found at the previous layer. The final two layers of the adaptive feedback system have components that can be influenced by users. However, the authors do not explain the extent to which a user can do this. Whilst the paper fails to define the thresholds upon which a user should contribute to the adaptive feedback system, they mention the importance of the user contributing in some way and specify examples in which the user can specify their preferences. This is a weak area and further research should be done to investigate the full potential user contribution can have to support cognitive behaviours. Within the paper, the adaptive feedback system is incorporated into a popular concept mapping software called COMPASS [24]. The system encompasses a Knowledge Reconstruction and Refinement (KR+R) process that, while preliminary, underlines the important features needed to encourage users to review their concept map and reconsider their misinterpreted results. The results were taken from a small sample, so the results may be potentially biased. However, these findings add to our understanding of how adaptive feedback can be used to support cognitive behaviours. A considerable amount of literature has been published about this particular adaptive feedback system and it has been used by well-regarded researchers. One paper took the adaptive feedback framework in COMPASS and compared it with nineteen other feedback systems, specifically in computer-based learning environments [25]. This existing research fails to define an optimal system, but from the comparative analysis, the COMPASS system unquestionably meets all the aims of an efficient feedback system, including having a target, strategy and goal. Therefore, the adaptive feedback system for this research paper will be based on the adaptive feedback system explained by Gouli *et al.* [23].

COMPASS is an adaptive concept mapping environment that supports learning and aims to assess students' understanding of concepts. A further study investigated user opinions and preferences for the COMPASS system [26]. The analysis from this showed that the majority of users in the study preferred receiving feedback on the content of their maps and found it was more helpful than other forms of feedback, such as a score of their overall performance. Due to this, the feedback used in this research should focus on qualitative analysis of users' concepts.

The papers to date provide evidence that adaptive feedback systems can support cognitive behaviours and result in efficient behavioural changes. Such approaches, however, have failed to show any changes in cognitive behaviour based on user contribution to the feedback system so more exploration is needed to address this.

2.4 Assessing Concept Maps

To provide sufficient feedback to a user, there must be a way of evaluating their current activity and assessing the overall quality of the concept map they have created. In terms of adaptive feedback, this assessment must be done dynamically and concurrently to provide the best response.

MindDot is an interactive concept mapping environment, created by Wang *et al.* [27], integrated with a digital textbook. The app is designed to support cognitive behaviours and they are measured through the actions performed by a user. A study was conducted to determine how the features included in their app affect learning. To measure this a 12-question pre-test and post-test were carried out by each participant and an ANOVA test was conducted to determine if the features improve learning. Comparative strategies were measured and modelled, including back navigation, cross-links and context switches performed by participants to assess the concept maps made. Context switches involve the switch in attention between the learning content and the concept map. Cross-links signify the relations between concepts and show the cognitive connections a learner has. Back navigation is the backwards progression in the learning content after reading new material. It denotes the act of making connections between different concepts within the learning material. Each behaviour was counted and a generalized linear model was created to reflect any potential effects of the features on a learner's comparative strategies. A diagram was used to show a learner's navigation path, including the comparative strategies used and the concepts they have added during the concept mapping process. This gave an idea of the cognitive behaviours exhibited by students and the learning as a result of this. This approach provides a strong contribution to concept mapping research by presenting a modern approach to measuring comparative strategies that illustrate a learner's cognitive behaviours. The data from the study indicate the importance of measuring comparative strategies to measure cognitive behaviours and is a strong method for future research in this area. Also, it is a simple process to measure the comparative strategies, so a short amount of time would be needed to implement this. However, this paper mentions several factors that potentially caused bias in their results, including the environment the study was conducted in. A research lab was used instead of a classroom, so the validity of the results may have been negatively affected. However, the data and conclusions can be used for investigating the effects on learning in general, rather than specifically in a classroom. A review session was also performed, where learners were given time to read over their concept map. Yet, the influence of this session was not measured so the learning effects may be higher than without this session. For that reason, any future work should either measure the influence this has or the session should not be included in the study.

In contrast to MindDot, Kroeze *et al.* [22] take a more statistical approach to assess a concept map. They focus on measuring the quality of the concept map via several factors, including the density of concepts and relationships, that are based on graph theory. However, these measures did not indicate the quality of the qualitative content of the maps, so they had experts rank the maps on their comprehensiveness and correctness. This assessment process is very time-consuming and measuring the quality of the concept map did not have a significant impact on the quality of the final concept map. Therefore, the results suggest using quality as a measure for assessing a concept map will have no benefits in the learning of a user. As a consequence, we do not recommend measuring the quality of the concept map for this research question and offer the process used by MindDot as a suitable process for assessing a concept map.

3 METHODOLOGY

3.1 Problem

Concept mapping exploring the effects users can have on an adaptive feedback system and the learning from this has limited research. Studies suggest that users have the potential to directly influence an adaptive feedback system using their preferences and personal needs. However, there is significantly little evidence of how much influence the user should have on the adaptive feedback system or the impact the user contribution has on cognitive behaviours.

3.1.1 Research Hypotheses

We hypothesise that meaningful learning of a subject requires not only knowledge of the content but also an awareness of how comparative strategies affect cognitive behaviours. Without the essential knowledge of content, participants may struggle to apply comparative strategies in practice, which limits their cognitive behaviour development. Also, without the awareness of comparative strategies participants may be unfamiliar with the skills needed to construct an adequate concept map. In general, learning the content and using comparative strategies both contribute to the improvement of a learner's cognitive behaviours in concept mapping. In consequence, we propose two hypotheses to provide a comprehensive investigation into the extent to which users can contribute to an adaptive feedback system to improve cognitive behaviour.

Hypothesis:

H_1: Does user contribution to the adaptive feedback system improve learning?

H_2: Does user contribution to the adaptive feedback system improve comparative strategies?

3.2 Proposed Solution

We propose an interactive tool that will collect data about users' behaviour when building a concept map and it will also provide an appropriate application for the user to learn about the subject area. This tool will allow us to collect the information needed to measure the effects user contribution to an adaptive feedback system has on a learner's cognitive behaviour. Also, the tool will be adaptable so that the extent to which the user contributes can be changed by the admin.

This solution is based on the current state-of-the-art features used by concept mapping applications. The solution will strengthen the concept mapping field by providing an interpretation for an unexplored area and potentially introduce a new feature that can be helpful in concept mapping applications that use adaptive feedback.

The basis of this tool consisted of an Apple iOS application. The tools used to build the iOS app included the Integrated Development Environment (IDE) Xcode which provided a piece of software to write and build code for the app and debug and test the app. Xcode was used as it is designed specifically for iOS app development and provides an array of tools to aid this. The app was built using the framework SwiftUI which encompasses the programming language Swift. This framework enables the use of simulators, so app interfaces can be previewed and tested without having to compile and run the application on a physical device. All the code was stored in a private repository on GitHub for ease of access and version control. Also, Excel was used to visualise participant data and helped us to conclude the research question through visual analysis.

The method proposed is adequate as it is feasible and can be completed in the time available. Also, this solution meets the needs of a user wanting to learn by building a concept map. Moreover, the solution addresses the research question and will facilitate the appropriate outcome using the data that is collected.

3.3 System Design

An interactive app was designed as a tool for concept mapping. This was then used in a study to collect data for the research problem. The app and study were both designed so that sufficient data could be collected to test the hypotheses.

3.3.1 App Design

The concept mapping tool was designed so the user can easily build a concept map, using circular nodes and define relationships between them using lines. Other basic functionalities were integrated into a menu bar, including buttons for adding a node, adding a relationship and deleting nodes and relationships. The menu bar and concept mapping area are shown in Figure 1. The user can also move a node around the concept mapping area and add text to a node. When a node is moved, the relationships automatically adjust accordingly. The concept mapping area is a large interactive part of the app that has pinch-to-zoom features allowing the user to see a full overview of the map they have built or to zoom into specific sections to see more detail. The concept nodes are designed specifically to fit three lines of text within them. This is sufficient enough space to type all the information a user should need because the user should not overload a node with too much information as it is not optimal for learning.

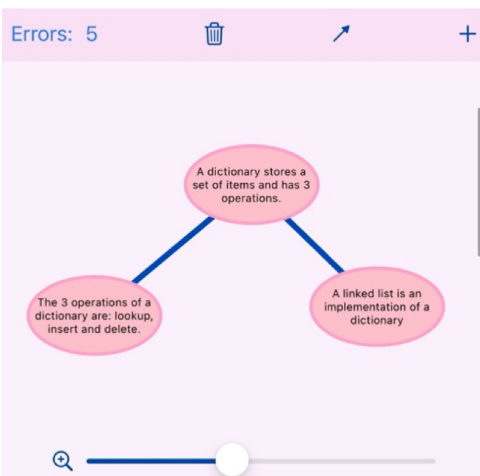


Fig. 1: A close-up view of an example concept map created using the built-in features of the app.

The information the user bases their concept map upon is called the learning content. This was included within the app as a PDF. There is a button to toggle the learning content in and out of view. This ensures the user can easily see the learning content and also has the maximum amount of space to build the concept map. Functionality was added such that the user can zoom in and out of the content and scroll through the pages. For this paper, the learning content was taken from a lecture about *Hashing* in the *Design of Algorithms and Data Structures* Module taught by T. Friedetzky [28] at Durham University. The tool was designed with the idea that the learning content and concept map should be shown to the user on the same page as this will ease the collection of user data. This means the user can see the information used to build the concept map at the same time as building the concept map. Figure 2 shows how we visually integrated this. From this, we were also able to determine the patterns users performed when building their concept map. We collected several pieces of information to determine this, including: when a user scrolls to a new page, when the user adds a node and the timings between each of these actions.

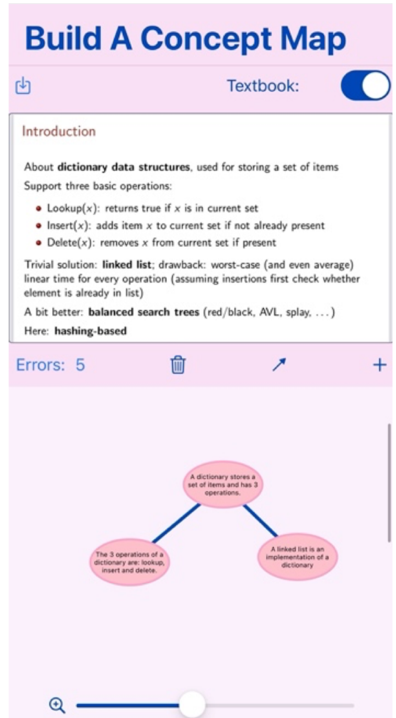


Fig. 2: A screenshot of the concept mapping app with the learning content positioned in the top half of the page and the concept mapping area positioned in the bottom half.

Feedback is introduced when a user adds a new concept. Once they have finished typing their concept, a feedback prompt pops up and this is where the adaptive feedback system commences. The user is shown feedback about the concept they have just added and further feedback is shown based on the buttons the user selects. The feedback always appears in a pop-up box as shown in Figure 3.

The app is designed to work with a set of preconfigured expert concepts. As a result, this tool is only suitable for use with the specific learning content mentioned above. New expert concepts and information would need to be collected to manipulate the adaptive feedback system for a different subject area. However, this is not an issue as all the data needed to investigate the research question is contained within this app.

The app was designed to optimise the visual area available for concept mapping, so the user could view as much of their concept map as possible at one time. This meant the functionality was minimised so only the essential features needed to build a concept map were included. This facilitated an optimal user experience for the user as there was no complex understanding needed to use the app.

There is a balance between the portability, adaptability and accuracy of an adaptive feedback system. The accuracy

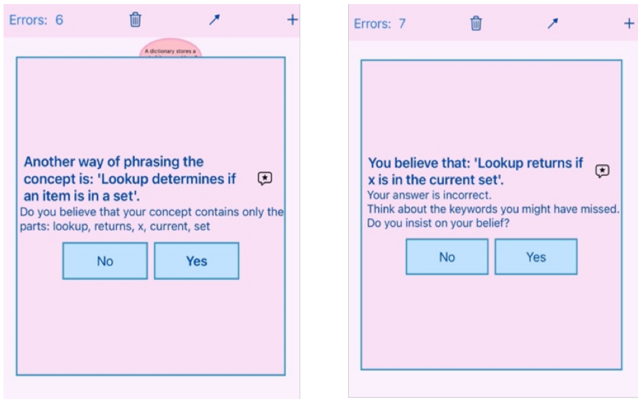


Fig. 3: Screenshots of exemplar feedback that is shown to a user after they have added the concept: 'Lookup returns if x is in the current set'.

will depend on how much the feedback system can reflect an expert's judgement and the adaptability is the freedom to which a user can utilise the app in the most suitable way for them. Portability is how a tool can be used in different domains. This app is designed to collect the data needed to test the hypotheses, so the app is designed to have higher accuracy and adaptability and not be very portable for alternate uses. This influences the design by focusing only on the visual appearance of the app on an iPhone 14 Pro. The application was designed for iPhone 14 Pros due to the availability of this device at the time of the study. However, it works suitably on other devices, including iPads, making it portable. To optimise usability and adaptability several Human Interface guidelines were followed, some of which were designed specifically for iOS apps [29]. This created an accessible, intuitive application that would be suitable for users and data collection.

3.3.2 Adaptive Feedback System

The adaptive feedback system was based on a popular paper used by several other researchers [23]. It includes four different layers of feedback, each of which is shown based on conditions met in the previous layer. The first layer is shown as soon as the user has finished typing their concept and their concept is categorised based on the keywords identified in their concept. The categories are separated into the following types:

- InComplete: missing at least one keyword
- InAccurate: contains all keywords and a keyword from another expert concept
- InAccurate-Superfluous: contains extra keywords from other expert concepts
- Missing: contains no keywords
- InComplete-InAccurate: missing keywords and contains keywords from other expert concepts
- Complete-Accurate: contains all the keywords
- Not Applicable: cannot infer a safe conclusion

All the expert concepts have keywords and the user's keywords are extracted from their concept. The user's concept is then matched with the expert concept with the same keywords. This provides a comparison concept so the user's concept can be categorised.

These categories have been interpreted from the information given in the original adaptive feedback system paper. In this context, the Missing category has not been included as there is no expectation that the user will complete their concept map so there will always be missing concepts and relations. Therefore, it is not included to avoid confusion for the user and reduce the overload of information being given to them.

Different amounts of feedback are shown based on the categorisation of the user's concept. The feedback aims to guide the learner to the correct answer by giving hints and examples.

An overview of the different layers of the adaptive feedback system is shown in the flow chart in Figure 4. The first layer of the feedback system contains the Belief Prompt-Rethink Write component which asks a user to confirm that they believe what they have written is true and correct. If the user's concept is incorrect they are also told so, which is included in the Correctness-Incorrectness of Response component.

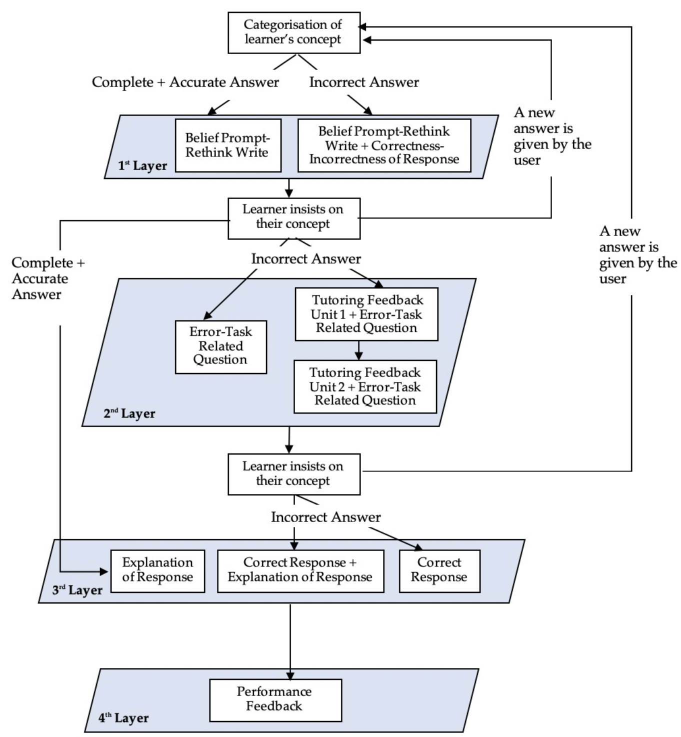


Fig. 4: A flowchart to show the algorithm that executes when a user adds a new concept in the app.

If the user insists on their belief and their concept is not correct, they are progressed to the second layer of the feedback system. If they insist on their belief and they are correct, they are taken straight to the third layer. Within the second layer, there are two types of feedback shown depending on the user's knowledge level. If the user has a low knowledge level, they will be provided with Tutoring Feedback Units and the Error-Task Related Question. Else, the user is only shown the Error-Task Related Question. This question changes based on the categorisation of the concept, but all the questions aim to redirect the learner to the correct concept by giving them a hint. If the user is also provided with the Tutoring Feedback Units they are shown two pieces of feedback. This feedback can be in several forms, including real-world examples, images, keywords and definitions. The Tutoring Feedback Units aim to teach learners the correct concept by showing them relevant learning material.

The second layer of the feedback system will adapt specifically to the user's preferences. This is where different levels of user contribution will come into effect. User contribution is implemented using thresholds. The type of feedback shown in the Tutoring Feedback Unit is determined by randomly generating a number between 0 and 100 and if the number is below the user contribution threshold, then the user's preferred feedback type is shown. In all other instances, the type of feedback shown is randomly selected. To ensure the second layer was observed, the number of times the user reached this layer was counted. All participants read and used layer two at least 10 times. As there is no previous precedent for how many times a user should receive the preferred feedback, we propose that 10 times is sufficient for the user to understand the feedback they are receiving and observe their preferred feedback choices.

The third layer shows different information based on whether the user's concept is correct. If correct, the user is shown the Explanation of Response component. If they are incorrect, the learner is shown different amounts of feedback based on their knowledge level. If they have low knowledge, they are shown the Correct Response component and the Explanation of Response component. Else, the user is only shown the Correct Response component. The Correct Response component simply states the correct concept. The Explanation of Response component tells the learner why what they have written is either correct or incorrect.

After all the feedback is given, the user is always shown the 4th layer. This is the performance feedback component, where the user is asked if they want to change their preferences and they can see how many errors they have made. The preferences are collected through three multiple-choice questions, where the user can select the type of feedback they prefer for specific scenarios. An example of this is: 'When learning do you prefer images and examples of definitions and keywords?' This feedback is then used to influence the second layer.

To summarise, the adaptive feedback system works by taking a user's concept and categorising it, displaying different types of feedback based on the current layer and then confirming the user's feedback preferences.

3.3.2.1 Expert Concepts: An expert concept map was created as a comparison to the concepts users added during the concept mapping exercise. This map also provided a basis of information for the feedback system. A comparison of a user concept map to an expert concept map is a method used in many papers and is one of the recommended practices for valid results [30].

Each expert concept had several other pieces of information to aid the feedback system. These include a photo visualising the concept, an alternate phrasing of the concept, an example of the concept in real-life situations and the keywords for that concept. This provided each layer of the feedback system with enough information to guide the learner to the error they had made so they could correct it.

Due to the time limit given to produce this research and the large amount of time taken to gather the information for the expert concepts, the expert map was limited in size and only the lecture slides with the most important information were included. All other redundant slides were removed. In total, there were 78 expert concepts included in the application.

3.3.2.2 Learner Model: A learner model was designed and incorporated into the feedback system as a way of adapting the feedback to a specific user.

This model included a knowledge level that updates over time based on how many Complete-Accurate concepts the user creates. The initial knowledge level is calculated from a pre-test completed before the concept mapping exercise. There are three knowledge levels: low, mediocre and high. The initial level is set to low or mediocre; it is never set too high as the questions asked in the pre-test are limited in number and do not necessarily demonstrate the full knowledge needed to understand the expert concepts. The knowledge level boundaries increase when the learner has added 10 and 15 Complete-Accurate concepts. Whilst there is limited data that suggest appropriate values for such a component, it is plausible to suggest that the values chosen are rational and will provide adequate results for this research. As the knowledge level changes the feedback shown changes, including the type of feedback and how much feedback is given at each layer. In particular, if a learner has a low knowledge level, they are given more feedback from the Tutoring Feedback Units.

The learner model also stores and updates the number and types of errors made during the concept mapping process. This does not influence the feedback given but is used to see how often the feedback system was used and it also shown in the performance feedback. One of the most important parts of the learner model is the learner's preferences, which consist of three questions, each with two options. These preferences directly impact the feedback shown as they will potentially change the type of feedback given by the Tutoring Feedback Units. With no user contribution, the components are chosen randomly, but with the low and high thresholds, the learner's preferences have a higher influence on the feedback system.

3.3.2.3 User Contribution: To measure the extent to which a user influenced the adaptive feedback system, two thresholds were created: a low contribution and a high contribution. In terms of how this was implemented, a percentage of 30% and 60% for the low and high thresholds were used. Random values were then generated and if they were below the thresholds, the user's preference for feedback was used in the second layer; else the feedback type was randomly selected. These values were tested to ensure there was a significant difference in the feedback shown to the user between the low and high thresholds. On average, where there is a high contribution, user-preferred feedback is shown 40% more often than with a low contribution, assuming the user reaches the second layer each time. A control threshold of 0% was also used, where the user had no contribution to the adaptive feedback system. This allowed for a comparison to the original feedback system with no user influence.

3.3.3 Data to be Collected

The data collected was used to determine if the research hypotheses should be rejected. All data was quantitative and no free-input data was collected.

A pre and post-test questionnaire were used within the study to determine if the participant learns the information from the learning content. The questions were based on the main learning points of the lecture and 4 multiple-choice answers were given for each question. The answers to the questionnaires were collected to determine if there has been a difference in learning for individuals who received different levels of personalised feedback.

Within the app, a count was kept that tracked the numbers and types of errors made by a user in their concepts. This data was collected to monitor how many times a user was receiving feedback from the personalised layer and the count was embedded in the interface of the app so users could see the type and number of errors they were making as part of their performance feedback.

The comparative strategies were measured using data collected about user actions. The data collected for this included when a user created a relationship between two concepts, when they navigated backwards to different pages in the learning content and when they switched between the learning content and the concept mapping area. A navigation map of the user's actions was used to visualise the comparative behaviours and help determine if the user has positive cognitive behaviours. These graphs were used in previous studies and helped to analyse the behaviours of learners [27]. To create a navigation map the timings of a user changing pages of the learning content and the timings of a user adding new concepts were stored.

The app automated data collection to ensure the quality and accuracy of data was not liable to human error. As a result, the menu buttons had automated timings that were stored when pressed by the user and the time was stored when a user changed the page of the learning content. All data were kept confidential to ensure the validity and reliability of the research findings.

3.3.4 Testing

To guarantee a user-friendly, reliable app several testing phases took place. Firstly, functional testing was carried out on a simulator and an iPhone 14 Pro device. This ensured all expected features of the app worked as intended. Then, compatibility testing was carried out to confirm that the app can be run on different devices, including iPhones and iPads. After this, two individuals were invited to test the app; one had knowledge of app development and the design processes involved and the other did not know about app development. This process resulted in feedback that detailed the efficiency and effectiveness of the app. The feedback was examined and refinements were made to the layout of the app to optimise the flow of building a concept map. The individuals then explored the app further and it was deemed to be user-friendly and seamless.

3.4 Study

3.4.1 Study Aims

The primary aims of the study were to:

- Invite at least 3 participants for each context of the study.
- Gather accurate and reliable data.
- Find evidence that either supports or contests the hypotheses.

A participant was not expected to complete the concept map as this would require them to add all the concepts from the expert map. However, a large number of expert concepts were created so users would not be limited in their learning. Also, there was not enough time for the user to add all of the expert concepts within the study time frame.

All aims set for the study were achieved and so the results were valid and we can be confident in our findings.

3.4.2 Study Method

Ethical approval was received before the completion of the study. This was a requirement made by Durham University and ensured there were no unethical occurrences. Also, consent was collected by all participants once they were told about the content of the study and all data was kept anonymous to ensure confidentiality.

The study was targeted at university undergraduate students with a knowledge of computer science. This meant all participants had previously studied computer science at some level. In total, 9 participants took part in the study, meaning there were 3 participants available for each contribution threshold.

Some predetermined issues we expected to encounter throughout this research included the short amount of time we had to complete the research. Also, the complexity of the adaptive feedback system meant large amounts of data and time were needed to implement it. Therefore, the study was targeted at students with a previous experience in computer science and the learning content was based on a computer science lecture taught in the third year at Durham University. This was put into effect because the specific feedback system that we implemented works best for procedural information which this lecture contained [28]. This ensured the expert concepts were focused on a specific subject area so the participants could go into as much depth as they liked about that area, rather than using a broader, less detailed approach. This is more optimal for meaningful learning. By anticipating these issues, the risk of degradation of tool quality and study validity were reduced.

A study was conducted that tested the hypotheses against the controlled condition. The study was partitioned into 4 parts:

- The pre-test questionnaire
- An introduction to the app
- The concept mapping exercise
- The post-test questionnaire.

The pre-test questionnaire was designed to investigate the learner's current knowledge level and provide the basis for the user's learner model. A participant was then introduced to the concept mapping app, so they could understand all the features of the app and this also allowed them to learn how to build a basic concept map before the official exercise. The concept mapping exercise was the focus of the study where the participant built a concept map based on the learning content given and manipulated their map based on the feedback given. This is where the main data collection takes place. The post-test questionnaire consolidated the participant's learning and allowed for a comparison to the participant's pre-test answers. In total, the participant had 45 minutes to complete the study, with the pre and post-test questionnaires taking 5 minutes each, the app introduction taking 5 minutes and 30 minutes being given to the participant to complete the concept mapping exercise. This measure of 30 minutes was found to be sufficient for the typical student to build a concept map of at least 20 concepts, which is sufficient to ascertain a user's cognitive behaviours and learning [30].

Convenience sampling was used to gather respondents for the study due to the time limits and the limited number of potential participants. As such, 9 students took part in the study and they were randomly assigned the threshold from which their preferences influenced the adaptive feedback system. This random selection reduced the chance of there being sampling bias, helping to keep the results valid and reliable. The participants were not made aware of the threshold that was used for their personalised adaptive feedback system, so they were all asked the same questions about their preferences. All participants partook in the study in an at-home environment where they would usually study. This was done to create an environment of learning where the participant felt comfortable and in a learning mindset.

Prior to the execution of the study, the data collection procedure was established whereby convenience sampling was to be used and all data would be collected and stored automatically within the app. This reduced the chance of issues occurring in the data collection. The way the data would be analysed was also predetermined to ensure all the data needed was collected and processed consistently.

3.4.3 Study Measures

Several measures were used from the data collected to investigate the research question. These measures were used to determine if there was an improvement in comparative strategies and thus the cognitive behaviours of participants.

The learning is measured through the pre and post-test questionnaires. There were 15 questions in the questionnaires, 13 of which were included in the learning content and the other 2 were not included. The other 2 questions are used as a control to determine a participant's ability to guess the correct answers. All questions were multiple choice and the same questions were given in both the pre and post-test questionnaires to establish a means for comparison.

Comparative strategies were also measured to develop a comprehension of cognitive behaviours. Comparative strategies 'refer to behaviours and activities that contribute to the comparison of different concepts and the construction of a coherent knowledge structure' [27]. They measure different user actions and are used to determine positive and negative behaviours. These behaviours were determined through three comparative strategies: back navigation, cross-links and context switches. The back navigation represents a user making connections between parts of the learning content. Cross-links indicate a person's knowledge structure by showing the inferences a person makes between the concepts they have created. Context switches convey the changes in attention between the learning content and concept map, which should be happening frequently whilst building a concept map. All three of these comparative strategies are deemed as positive and the more they are employed the higher a person's learning will be.

Navigation diagrams were created from the comparative strategy data and timing data collected. This gave a visual measure of comparative strategies and from this an indication of positive or negative cognitive behaviours performed. The graph allowed us to visually acquire the timings of concepts and relationships being added and the switches between the learning content and the concept map. In general, a high-learning participant has frequent references between the two areas of the app, with concepts being added regularly. These results were confirmed in a previous study and we extend them by adding the cross-links made to the graph to further analyse users' actions [27]. The diagrams do not necessarily show the development of comparative strategies but will confirm whether the learner has advantageous cognitive behaviours, which helped supports the research hypotheses.

The measures used within the study were chosen because they were objective and appropriately sensitive so they can be detected and measured easily. This will reduce the chance of bias being introduced to the results.

3.4.4 Validation

The main causes of error in concept mapping include variations in concept mapping competence, variations in content knowledge and the consistency of concept map evaluation [30]. Therefore, to maintain the reliability of the research outcomes all concept maps were evaluated using the same process and all participants had little to no knowledge of concept mapping. Also, all participants had previously been taught computer science but were not knowledgeable about the specific topic chosen in the learning content. This ensured the participants had no exposure to this specific content, but were able to understand the content.

To help maintain the validity of the results, participants were given an introduction about building concept maps and how they should lay out their concepts. This was beneficial as it reduced the complexities involved with building a concept map, reducing the likelihood of cognitive overload.

These methods ensured all data collected was valid and reliable, minimising any possible errors.

3.4.5 Testing

A mock test was carried out with 2 individuals who followed the proposed structure of the study. This was done to test the feasibility and improve the efficiency of the study. No data collected here was used in the analysis of the research question. This process allowed us to gauge the smoothest transition between parts of the study and also confirmed the usability of the app and the operation of the built-in data collection. Also, this test helped identify any potential sources of bias and refined the procedure before the official study.

TABLE 1: Pre and Posttest Scores for the Concept Mapping Session.

Contribution	Pretest		Postest	
	Main Questions	Control Questions	Main Questions	Control Questions
I. None	5.0 (2.0)	0.67 (1.2)	8.3 (3.2)	1.0 (1.0)
II. Low	3.0 (1.7)	0.67 (0.58)	9.7 (2.5)	0.67 (0.58)
III. High	5.7 (2.5)	0.67 (1.2)	9.3 (0.58)	0.67 (1.2)

4 RESULTS

4.1 Data Analysis

4.1.1 H_1: Does user contribution to the adaptive feedback system improve learning?

The questionnaire scores were calculated and the average and standard deviation for the pre and post-tests are shown in Table 1 The control questions were scored separately from the main questions to determine if students' guesses had an impact on the results found.

At first glance, there does not appear to be a major difference in the post-test scores. However, this does not take into account the large standard deviations that suggest a variation in learning between participants. Therefore, further analysis was performed using a Kruskal-Wallis H test to determine if there is any significant difference in post-test scores. At a 5% significance level, there was a non-significant difference in the post-test scores between the different groups (χ^2 = 0.71, p = 0.700). This shows that there is no statistically significant evidence to show that the user contribution threshold had different effects on learning, but the overall test scores improved showing that the feedback system as a whole does improve learning.

When comparing the pre and post-test scores, the mean and standard deviation for the control questions do not change for the low and high contributions and the change for no contribution is very small. This implies that the results found for the main questions were not impacted by a participant's ability to guess the correct answer. To validate this assumption a two-tailed Mann-Whitney U test was conducted and the results confirmed that there was no significant difference in the test control scores (U = 37, p = 0.77). Therefore, we assume all results discussed are not affected by participants guessing the answers.

This analysis does not take into account the covariate pre-test scores, so the percentage improvement in test scores was calculated and the average for each threshold is shown in Table 2. This took into account both pre and post-test scores. A Kruskal-Wallis H test was then performed on the percentage gain and the test indicated that there was a non-significant difference in the learning improvement between the user contribution thresholds (χ^2 = 3.65, p = 0.161). This means we do not accept H_1 and infer that user contribution to the adaptive feedback system does not improve learning.

4.1.2 H_2: Does user contribution to the adaptive feedback system improve comparative strategies?

The average count and standard deviation of the comparative strategies were calculated and summarised in Table 3.

TABLE 2: The Improvement in Test Scores Before and After the Concept Mapping Session.

Contribution	Increase in Learning (%)			Average Learning Increase (%)
I. None	2.0	0.20	0.00	0.73 (1.1)
II. Low	5.0	1.0	2.5	2.8 (2.0)
III. High	0.50	0.25	2.0	0.92 (0.95)

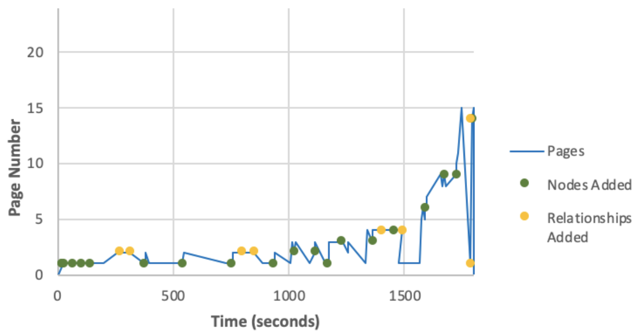
TABLE 3: The Average Number of Comparative Strategies Used for each Contribution Threshold.

Contribution	Back Navigation	Cross-link	Content Switch	Average Total
I. None	19 (4.0)	11 (2.5)	23 (7.6)	18 (4.4)
II. Low	22 (4.0)	13 (4.9)	23 (11)	19 (5.3)
III. High	22 (5.2)	12 (8.1)	21 (6.2)	18 (5.6)

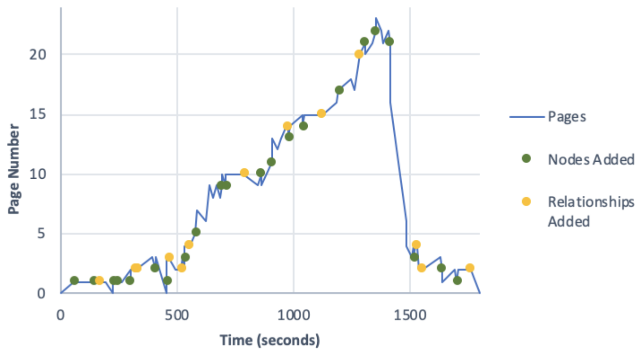
Upon initial examination, there is no remarkable contrast in the number of comparative strategies shown from the different user contribution thresholds. At a high level, there is no obvious threshold with a higher number of comparative strategies used overall. To verify this a Kruskall-Wallis H test was carried out on the mean total number of comparative strategies used. The difference in the mean ranks of the groups was not big enough to be statistically significant, so we assume there is no significant difference between the comparative strategy used at different contribution thresholds (χ^2 = 0.620, p = 0.733).

There is a large difference in the standard deviation for the cross-links and content switches. This could indicate potential outliers within some of the data, but to reinforce this, further research needs to be done with a larger sample size. Due to the limited sample size, potential outliers were kept in the data when performing further statistical analysis. To further support the argument that user contribution to the adaptive feedback system does not improve comparative strategies several Kruskal-Wallis H tests were performed to determine if there are any significant differences in the cross-links and content switches made between the thresholds. The test performed on the counts of cross-links revealed that there was a non-significant difference in the number of cross-links added by a participant at different thresholds (χ^2 = 0.690, p = 0.707). When the test was conducted for the content switch strategy, there was a non-significant difference from the user contribution thresholds (χ^2 = 0.16 p = 0.925). A Kruskal-Wallis H test was also conducted with the number of back navigation actions used for each participant at each threshold. The statistics indicate that at a 5% significance level, there is a non-significant difference in the numbers of back navigations made by learners with different contribution thresholds (χ^2 = 1.08, p = 0.584). This suggests that user contribution to the adaptive feedback system does not improve comparative strategies, no matter how much influence the user contribution has on the feedback system. Therefore, we do not have sufficient evidence to accept that user contribution to the adaptive feedback system improves comparative strategies, so we do not accept the initial H_2.

The evidence thus far suggests there is no substantial impact on comparative strategies when the user contribu-



(a) The Navigation Path of a Learner with Poor Cognitive Behaviours.



(b) The Navigation Path of a Learner with Favorable Cognitive Behaviours.

Fig. 5: The Navigation Paths of Two Participants from the Concept Mapping Session.

tion thresholds are changed. To carry out a more exhaustive investigation, we analyse the navigation paths of the participants. These diagrams visualise the concept mapping process, allowing for an in-depth analysis of the cognitive behaviours performed by learners. The visual representation combines the comparative strategies performed, the concepts added and the timings of all these actions to provide an understanding of how these cognitive behaviours are used in sequence. Figure 5 shows the prototypical examples of the navigation paths for a learner with favourable cognitive behaviours and a learner with poor cognitive behaviours. These diagrams were taken from two participants in the study with some of the corresponding highest and lowest comparative strategy counts. The x-axis represents the time during the concept mapping exercise and the y-axis represents the page number of the learning content shown in the application. The blue line represents the reading path of the user, with the line increasing in height the further the user reaches in the learning content. The green dots represent a new concept being added to the concept map and the yellow dots represent a new relationship (cross-link) being added between two concepts in the map.

From the navigation diagrams, we can compare three additional strategies: the horizontal coverage of concepts added, the vertical coverage of concepts added and the zigzag of the reading line. A high horizontal coverage would be where the green dots (concepts added) are more spread-out horizontally. This depicts how often a learner is

TABLE 4: The Points Awarded for the Participant's Navigation Paths.

Contribution	Zigzag	Horizontal Coverage	Vertical Coverage	Total
I. None	1	2	2	5
II. Low	2	3	1	6
III. High	1	2	1	4

adding concepts to their map; ideally, the concepts added should cover more than half of the timestamps. A high vertical coverage would be where the green dots are more spread-out vertically. This illustrates how many pages the user is adding concepts from; ideally, concepts should have been added from more than half of the pages. A point system was employed where a value of 1 was given for each map showing high horizontal coverage and high vertical coverage. Then another point was awarded for the zigzag component where the reading line resembled a gradual increase in page number over time, with consistent peaks and valleys. Table 4 shows the points awarded in total for the navigation paths created for each contribution threshold.

There is a clear difference between the learners with favourable and poor cognitive behaviours. More precisely, the reading path of Figure 5b has a gradual increase in page number over time. Throughout this, there are constant zigzags, representing consistent referrals to previous parts of the learning content. The steep descent at around 1400 seconds may account for a cognitive relation made by the user to a section at the start of the learning content. Conversely, the other participant, shown in 5a, has a more linear reading line with a sudden spike in the pages read at the end of the exercise. The horizontal coverage of both learners is similar, but the learner from Figure 5b was more consistent when adding relationships after adding a concept. Also, the learner in Figure 5b has high vertical coverage, with the concepts and relationships added spanning almost all of the page numbers. On the other hand, the learner in Figure 5a has low vertical coverage, with concepts and relationships narrowly covering half the page numbers. In terms of the number of comparative strategies used, the learner from Figure 5b has 23 back navigations, 14 cross-links and 31 content switches. The learner from Figure 5a has 16 back navigations, 8 cross-links and 19 content switches. When comparing the two learners in isolation, the learner from Figure 5b has better use of comparative strategies, with a higher-scoring navigation diagram. In terms of contribution, the learner from Figure 5b had no contribution to the adaptive feedback system and the learner from Figure 5a had a high contribution. A shallow assumption from this is that a high user contribution to the adaptive feedback system has negative connotations on a learner's comparative strategies. However, when considering all the learner's navigation paths this idea is not supported and further analysis is required.

A closer look at the data from the point system shows there is no clear trend in cognitive behaviours and user contribution to the adaptive feedback system. All contribution thresholds scored similarly in all three areas and there are no obvious trends between individual factors and user contribution. The data shows a weak indication of a trend in vertical coverage; as the user contribution increases from zero, the vertical coverage decreases. However, further research is needed to confirm this as more variation in user contribution would perhaps suggest a more detailed pattern and a larger sample would provide further analysis of this.

In summary, there is insufficient evidence to suggest that user contribution to the adaptive feedback system improves cognitive behaviours. Therefore, we do not accept H_2 and we claim that user contribution to a feedback system, at any level, will not improve a learner's comparative strategies.

5 Evaluation

In this paper, a concept mapping tool was created that contained an adaptive feedback system that could be influenced by user preferences. The extent of user contribution was defined into a low and high threshold, which adapted the feedback shown to a user depending on their preferred types of feedback. These thresholds, alongside a control threshold, were compared in a study with 9 undergraduate students. Data analysis revealed that any user contribution to the adaptive feedback process does not improve learning (H_1) or the use of comparative strategies (H_2). From this, we can infer that cognitive behaviours are not improved from user contribution to the adaptive feedback system.

The concept mapping app created was user-friendly and had a low threshold for understanding, so it did not take long to understand how to use it. However, the practicality of building a large concept map on a small phone screen can be awkward. Therefore, study participants were given the option to use their own larger device if desired. Despite this, all participants used the iPhone 14 Pro device to complete the study. This meant there was limited space where the user could build their concept map because of the small screen. Accordingly, we introduced the zoom feature to mitigate the effects of this, but alternative features could be applied that further reduce the crowding. This could have resulted in concept maps taking longer to build, but we do not believe this had significant effects on the data collected as a reasonable time limit was given and all participants created a concept map with at least 10 correct concepts. Alternate studies have separated the learning content and concept mapping area into two different views, but these applications do not facilitate the use of comparative strategies and their analysis regarding cognitive behaviours is limited as a result. Hence, we did not take this approach. Alternatively, in the future, a system could be put in place to optimise the available space to avoid crowding and messy concept maps, which can reduce the effect of cognitive overload. Such features are mentioned by Anderson-Inman and Horney [16] and include child layers of smaller subsections of the concept map that are visible on request by the learner. These features were not implemented within this app due to strict time limits.

Whilst we acknowledge our solution may not be beneficial in other contexts, it allowed us to collect all the data needed to determine an answer to the research question. Also, the app was created in such a way that it can be extrapolated to other contexts if the learning content and expert concepts are predefined. However, the feedback system is limited in how advanced it can become. This is due to the feedback system not making use of advanced natural language processing, meaning different tenses and synonyms could not be used in a user's concept, so user interpretation of concepts was restricted. Whilst this controlled the vocabulary that could be used, it was still possible to use the adaptive feedback system to tutor correct concepts. To reduce the potential bias of this and frustration within the user, the participant was told to phrase their concept in the same way as shown in the learning content. We acknowledge that the extent of learning may be limited because of this, but this did not appear in the results as all participants improved from the pre-test to the post-test. A future improvement would involve the use of stemming, which transforms a word into its root form. This would eliminate the need for the user to write concepts in the same tense as the lecture slides. The use of artificial intelligence could also have significant impacts on the natural language processing performed, allowing for synonyms and similar phrases to be recognised and categorised as having the same underlying concept.

Within the study, there is a potential sampling bias with the sampling method used. This is because the small number of participants could not be representative of the student population. As a result, there may be outliers and skewed data in the results. However, bias was mitigated to the best of our ability by using the largest sample size available and using random sampling to determine the threshold of a participant. It is also important to highlight that the primary aims of the study were all reached and the rejection of both hypotheses is supported by several pieces of valid and reliable data. The data that would be needed for this was pre-determined, which allowed for a variety of data to be collected and ensured there was no redundant or important missing data. On the other hand, one of the largest problems faced during data analysis was the lack of data due to the small number of participants in the study. This restricted the statistical analysis that could be performed for several reasons. Tests such as ANOVA require the variance of the dependent variable to be approximately equal and all the data must follow a normal distribution. However, when checked the data did not follow a normal distribution. Also, the sample size was too small for tests such as the repeated measures ANOVA test, so determining significant differences in data was hindered. The small sample size also meant averages and standard deviations were highly influenced by outliers, which can lead to biased results. To overcome all this, the Kruskal-Wallis H test was used to analyse data as the data does not have to follow a normal distribution and when compared to ANOVA, it is less sensitive to unequal variances, so the bias is reduced. Also, the Kruskal-Wallis H test is particularly useful for data with small sample sizes where the distribution is unknown. It is worth noting if a significant difference in data is found from the Kruskal-Wallis test, posthoc tests should be performed to determine which groups have statistically different values. However, this was not the case for the data collected so no further analysis was required.

A consideration we must take is the way in which context switches are measured as a comparative strategy.

This measurement is limited in the sense that it can only be detected by interactions the user makes with the app. If a user simply switches their attention from the concept mapping area to the learning content with no touch actions this will not be detected. However, due to the interactivity required to do the concept mapping exercise the effects of this are very small and we are confident that this limitation did not have a significant impact on the data collected or the findings of the research.

One further assessment that should be made is the subjectiveness of the navigation diagrams included in the results section. It can be argued that the metrics zigzag, vertical coverage and horizontal coverage are all subjective to a person's opinion, which introduces the potential for confirmation bias. To help mitigate this the general rule was introduced that if the green dots did not cover at least 50% of an axis, either horizontally or vertically, it could not be awarded a point. Also, Figure 5 was introduced as a comparison of the ideal and flawed navigation paths. As these diagrams and the point system were used to support other data, and not used to make another independent analysis, the potential bias introduced does not significantly affect the conclusions made.

These disadvantages did not negatively impact the research as the app was designed with the main focus being data collection and this data was collected successfully. Therefore, the findings are not undermined, but the potential bias introduced should be considered when applying the results in other contexts. Overall, this research completed all the basic, intermediate and advanced objectives, resulting in a successful research investigation. This meant we were able to find a sufficient conclusion to the hypotheses proposed and thus the research question, contributing to the existing feedback domain in the concept mapping field.

Given more time to complete the research, a larger number of participants would be invited to take part in the study. This would give a wider range of results and help reduce any bias shown in the data. From this, more powerful statistical measures could be used to support any conclusions made. Also, further natural language processing features would be introduced to advance the current categorisation process.

6 Conclusion

In this paper, we presented an app that provides an area for users to build concept maps and receive feedback on the concepts they created. The app also included an area containing the learning content, which the user based their concepts on. The adaptive feedback system could be influenced by user preferences and this was implemented using a low and high contribution threshold. Our study showed that the different user contribution thresholds, on the adaptive feedback system, did not have an impact on learning or comparative strategies. Therefore, we conclude that cognitive behaviours are not improved as a result of user contribution to the adaptive feedback system.

This research provides a new perspective on learning using concept mapping by integrating concept mapping software with the learning content, as most current-day concept mapping software is used independently to the learning content. Also, the findings of this research provide a deeper understanding of how users can contribute to an adaptive feedback system and the effect this has on their cognitive behaviours. This area has received limited attention in previous studies and although the research question was disproved, it is an important contribution to the concept mapping field as it provides a starting point for further investigation into the relationship between users and adaptive feedback systems in concept mapping.

The concept mapping tool could be used as a revision tool for students learning about the subject area the expert concepts were made for. Also, the app created can be extended to fit other learning domains and includes sufficient portability for use in other contexts, provided that the expert concepts are created. The results from the research would suggest that incorporating user preferences into an adaptive feedback system will not significantly improve a learner's cognitive behaviours, so for this context, it would not be worthwhile to implement this. However, further research with more data and fewer limitations may find benefits to user contribution in an adaptive feedback system for concept mapping so this should be considered.

6.1 Future Work

Further work can be carried out to validate our data and strengthen the findings. This includes a new study with a significantly larger sample size. This will overcome the statistical limitations we experienced and will rule out any unforeseen bias in the data.

From our findings, we recommend further investigation into the effects alternate phrasing of concepts has upon a person's learning, instead of using the same phrasing from the learning content. This could impact the way feedback is given as further emphasis may need to be placed on taking a concept and interpreting it in the learner's way.

Although this is not specific to adaptive feedback systems, in the future a system could be put in place to optimise the available space for concept mapping, to avoid crowding and messy concept maps. The effect this has on cognitive behaviours as a result of reduced cognitive overload may be statistically significant, which would impact the way concept mapping software targeted at learning is developed in the future.

One measurement not made during this research was the long-term development of cognitive behaviours as a result of user contribution to the feedback system. We recommend that this be explored further as any different effects on longer-term learning and comparative strategies would significantly improve cognitive behaviours.

REFERENCES

[1] "What is a concept map," 2017. [Online]. Available: https://www.lucidchart.com/pages/concept-map

[2] D. Hay, I. Kinchin, and S. Lygo-Baker, "Making learning visible: the role of concept mapping in higher education," *Studies in Higher Education*, vol. 33, no. 3, pp. 295–311, 2008. [Online]. Available: https://doi.org/10.1080/03075070802049251

[3] K. Jablokow, J. DeFranco, S. Richmond, M. Piovoso, and S. Bilén, "Cognitive style and concept mapping performance," *Journal of Engineering Education*, vol. 104, pp. 303–325, 07 2015.

[4] J. D. Novak and A. J. Cañas, "The theory underlying concept maps and how to construct them," Technical Report IHMC CmapTools, Tech. Rep. 2006-01, 2006. [Online]. Available: http://cmap.ihmc.us/Publications/ResearchPapers/TheoryCmaps/TheoryUnderlyingConceptMaps.htm

[5] J. C. Nesbit and O. O. Adesope, "Learning with concept and knowledge maps: A meta-analysis," *Review of Educational Research*, vol. 76, no. 3, pp. 413–448, 2006. [Online]. Available: https://doi.org/10.3102/00346543076003413

[6] N. B. Afini Normadhi, L. Shuib, H. N. Md Nasir, A. Bimba, N. Idris, and V. Balakrishnan, "Identification of personal traits in adaptive learning environment: Systematic literature review," *Computers Education*, vol. 130, pp. 168–190, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360131518303026

[7] J. R. Surber and P. L. Smith, "Testing for misunderstanding," *Educational Psychologist*, vol. 16, no. 3, pp. 165–174, 1981. [Online]. Available: https://doi.org/10.1080/00461528109529238

[8] B. Mason and R. Bruning, "Providing feedback in computer-based instruction: What the research tells us," *Center for Instructional Innovation*, vol. 15, 01 2001.

[9] W. Wei and K.-B. Yue, "Concept mapping in computer science education," *J. Comput. Sci. Coll.*, vol. 32, no. 4, p. 13–20, apr 2017.

[10] W. Lee, C.-H. Chiang, I.-C. Liao, M.-L. Lee, S.-L. Chen, and T. Liang, "The longitudinal effect of concept map teaching on critical thinking of nursing students," *Nurse Education Today*, vol. 33, no. 10, pp. 1219–1223, 2013. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0260691712001992

[11] F. Krieglstein, S. Schneider, M. Beege, and G. D. Rey, "How the design and complexity of concept maps influence cognitive learning processes," *Educational technology research and development*, vol. 70, no. 1, p. 99–118, 2022.

[12] J. Novak and A. Cañas, "The origins of the concept mapping tool and the continuing evolution of the tool," *Information Visualization*, vol. 5, pp. 175–184, 09 2006.

[13] A. J. Cañas, G. Hill, R. Carff, N. Suri, J. Lott, G. Gómez, T. C. Eskridge, M. Arroyo, and R. Carvajal, "Cmaptools: A knowledge modeling and sharing environment," 2004.

[14] "Create a concept map: Miro," 2023. [Online]. Available: https://miro.com/concept-map/

[15] W. Reader and N. Hammond, "Computer-based tools to support learning from hypertext: Concept mapping tools and beyond," *Computers Education*, vol. 22, no. 1, pp. 99–106, 1994. [Online]. Available: https://www.sciencedirect.com/science/article/pii/0360131594900787

[16] L. Anderson-Inman and M. Horney, "Computer-based concept mapping: Enhancing literacy with tools for visual thinking," *Journal of Adolescent Adult Literacy*, vol. 40, no. 4, pp. 302–306, 1996. [Online]. Available: http://www.jstor.org/stable/40013436

[17] A. Cañas, J. Coffey, M. Carnot, P. J. Feltovich, R. Hoffman, J. Feltovich, and J. Novak, "A summary of literature pertaining to the use of concept mapping techniques and technologies for education and performance support," pp. 54–62, 01 2003.

[18] G. K. W. K. Chung, E. L. Baker, and A. M. Cheak, 2002.

[19] B. Opitz, N. Ferdinand, and A. Mecklinger, "Timing matters: The impact of immediate and delayed feedback on artificial language learning," *Frontiers in Human Neuroscience*, vol. 5, 2011. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnhum.2011.00008

[20] M. Awais Hassan, U. Habiba, H. Khalid, M. Shoaib, and S. Arshad, "An adaptive feedback system to improve student performance based on collaborative behavior," *IEEE Access*, vol. 7, pp. 107 171–107 178, 2019.

[21] S. Wang and E. Walker, "Providing adaptive feedback in concept mapping to improve reading comprehension," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, ser. CHI '21. New York, NY, USA: Association for Computing Machinery, 2021. [Online]. Available: https://doi.org/10.1145/3411764.3445554

[22] K. A. Kroeze, S. M. van den Berg, B. P. Veldkamp, and T. de Jong, "Automated assessment of and feedback on concept maps during inquiry learning," *IEEE Transactions on Learning Technologies*, vol. 14, no. 4, pp. 460–473, 2021.

[23] E. Gouli, A. Gogoulou, K. A. Papanikolaou, and M. Grigoriadou, *Designing an Adaptive Feedback Scheme to Support Reflection in Concept Mapping*. Springer, 2004, p. 54–63.

[24] E. Gouli, A. Gogoulou, K. Papanikolaou, and M. Grigoriadou, "Compass: an adaptive web-based concept map assessment tool," 2004.

[25] A. T. Bimba, N. Idris, A. Al-Hunaiyyan, R. B. Mahmud, and N. L. B. M. Shuib, "Adaptive feedback in computer-based learning environments: a review," *Adaptive Behavior*, vol. 25, no. 5, pp. 217–234, 2017. [Online]. Available: https://doi.org/10.1177/1059712317727590

[26] E. Gouli, A. Gogoulou, and M. Grigoriadou, "Working with compass: Analyzing and evaluating students' concept maps," *IADIS International Conference on Cognition and Exploratory Learning in Digital Age, CELDA 2009*, 01 2009.

[27] S. Wang, D. Sonmez Unal, and E. Walker, "Minddot: Supporting effective cognitive behaviors in concept map-based learning environments," in *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, ser. CHI '19. New York, NY, USA: Association for Computing Machinery, 2019, p. 1–14. [Online]. Available: https://doi.org/10.1145/3290605.3300258

[28] T. Friedetzky, "Lecture slides about hashing in algorithms and data structures," January 2023.

[29] "Designing for ios," 2022. [Online]. Available: https://developer.apple.com/design/human-interface-guidelines/platforms/designing-for-ios

[30] J. R. McClure, B. Sonak, and H. K. Suen, "Concept map assessment of classroom learning: Reliability, validity, and logistical practicality," *Journal of Research in Science Teaching*, vol. 36, no. 4, pp. 475–492, 1999. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/\%28SICI\%291098-2736\%28199904\%2936\%3A4\%3C475\%3A\%3AAID-TEA5\%3E3.0.CO\%3B2-O