ADVANCING LEARNING ANALYTICS: DETECT AND PREDICT CONFUSION IN LEARNERS THROUGH AI

Master by Research Thesis

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, *Chaitali Samani* declare that this thesis is submitted in fulfilment of the requirements for the award of *Master of Analytics (Research)* in the *Faculty of Engineering and Information Technology* at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Preface

This research investigates the complex interplay of epistemic emotions in online learning environments, focusing on confusion. The growth of digital education platforms has enabled flexibility and convenience, yet high dropout rates persist, highlighting a need for deeper insight into learners' cognitive and emotional states. This thesis seeks to address gaps in understanding how confusion impacts learner engagement and success by developing predictive models that use clickstream data and Artificial Intelligence (AI). By bridging concepts from learning analytics, emotional dynamics, and machine learning, the study aims to offer educators actionable insights for timely interventions, contributing to theory and practice in educational data science.

Abstract

As digital education platforms continue to evolve, understanding learner engagement and emotional states has become critical for improving academic outcomes and reducing dropout rates. This thesis explores the detection and prediction of confusion—an essential epistemic emotion that influences positive and negative learning experiences. Using clickstream data from online platforms, this study develops predictive models with AI, specifically focusing on confusion in online learning. The methodology integrates clustering, time series analysis, and advanced AI algorithms, including Generative AI, to detect confusion patterns and provide real-time interventions. Results indicate that predictive modelling based on clickstream data can effectively identify confusion and its influence on learner engagement. This research offers a framework for improving learning analytics, contributing to personalised learning experiences and broader educational interventions.

Published works

The research presented in this thesis has contributed to several publications, each addressing distinct aspects of the study:

1. Samani, Chaitali & Goyal, Madhu. (2021). Modeling Student Confusion Using Fuzzy Logic in e-Learning Environments. 10.1007/978-981-16-3246-4_50.

2. Samani, Chaitali & Goyal, Madhu. (2021). Confusion detection using neural networks. 1-6. 10.1109/CSDE53843.2021.9718422.

3. Samani, Chaitali & Musial, Katarzyna. (2023). Cluster Analysis Using Explainable AI for Confused Learners. 1-6. 10.1109/CSDE59766.2023.10487715.

4. Samani, Chaitali & Atif, Amara & Musial-Gabrys, Kaska. (2022). Using Emotional Learning Analytics to Improve Students' Engagement in Online Learning. ASCILITE Publications. e22129. 10.14742/apubs.2022.129.

These publications reflect the progressive development of this research, from initial concept validation to advanced AI applications, contributing to the growing field of emotional learning analytics.

Chapter 1: Introduction

1.1 Background

Steep advancements in Internet technologies have changed our lives, and learning is no exception. Learning has been extended to deploy online platforms that provide learners with more flexibility and convenience in their learning process. Educational institutes and facilitators are taking advantage of great online tools available via Learning Management Systems (LMS) such as Moodle, Blackboard, Canvas, and others, providing the courses in blended (Hybrid) or fully online mode. Massive Online Open Courses (MOOC) platforms offer classes in a fully online mode where learners can enrol and complete the course at their own pace.

Persistently high dropout rates have accompanied the increasing enrolment in Massive Open Online Courses (MOOCs), often cited as below 10% for course completion (Rohan et al., 2021; Patel, 2024; Gharahighehi, 2023; Bawa, 2016). Despite the surge in participation, the dropout issue remains a critical drawback of this educational model, with some courses experiencing dropout rates exceeding 90% (Gharahighehi, 2023). Factors contributing to these high dropout rates include lacking academic and emotional support, which is essential for sustaining learner engagement (Luo, 2024; Psathas, 2023). Research indicates that while emotional and academic support can enhance user engagement, many MOOCs fail to provide adequate systems to support learners (Luo, 2024). A systematic review by Huang et al. (2023) identified various factors influencing dropout, including learner characteristics and course design. Gamification and interactive elements have been proposed to enhance engagement and retention to address dropout rates (Rohan et al., 2021). However, the effectiveness of these strategies depends on their implementation and the specific context of the courses. The lack of face-to-face interaction in fully online courses limits social inclusion and engagement among learners. Nevertheless, advancements in digital education technology can create personalised learning environments that cater to individual needs, potentially improving course completion rates.

The effectiveness of online discourse in fostering engagement and meaningful learning experiences remains an area requiring further exploration. Online learning platforms generate a wide range of activity logs. These activity logs can be explored, analysed, and visualised to foster active, meaningful, and applied learning. For instance, Kizilcec et al. (2020) highlight the importance of analysing behavioural data to predict student dropout and engagement, suggesting that understanding these patterns can help educators intervene effectively to support learners (Kizilcec et al., 2020). Similarly, Kim & Park (2022) emphasise the significance of log data analysis in understanding student behaviours, such as participation in discussions and time spent on activities, which can inform strategies to enhance individualised learning experiences (Kim & Park, 2022). Such exploration will help improve the learning achievements and assist in making evidence-based decisions. Not all the online behaviours of learners from such logs have been fully understood, considering their knowledge tracing and the effectiveness of their overall learning process. Learning is a complex process, and it can be challenging for a learner to keep track of their learning on an optimal learning route. Learning can be affected by various factors like personality traits, epistemic emotions, the difficulty level of the content or task being learnt, and the mode of how the content is being delivered. Given the complexity of the learning process, learners go through various positive and negative states of mind that trigger positive and negative emotions. It has been found that positive emotions can result in a sense of achievement and positive learning gains, whilst negative emotions can result in disengaged learners who may soon give up on learning that course (Shanshan & Wenfei, 2022). Hence, controlling learners' negative emotions is vital to keep them on their learning paths, especially on online digital learning platforms (Shen et al., 2009; Jumaat & Termidi, 2022).

Emotions are categorised into two categories: basic emotions like anger, happiness, fear, sadness, or disgust, and non-basic emotions like confusion, frustration, boredom, engagement, motivation, and curiosity (Kort, Reilly & Picard 2001). Non-basic emotions play an important role and those emotions are often referred to as epistemic emotions. Such epistemic emotions are dynamic and interrelated with students' cognitive interactions with various learning activities (Pekrun & Linnenbrink-Garcia 2012) and are crucial while performing cognitive tasks (Brun & Doguoglu 2016; Goldie 2009; Morton 2010). Some epistemic emotions are studied more than others, and few have studied the simultaneous effect of epistemic emotions in learning (D'Mello & Graesser 2012; Muis et al. 2015; Pekrun & Linnenbrink-Garcia 2012; Pekrun et al. 2017; Vogl et al. 2020; Ma 2023, Wang 2023) in terms of their shared antecedents and results. Hence, systematic research on such epistemic emotions affecting academic performance and learners dropping out of the course has many gaps to address.

Every learner displays unique personality traits (Chamorro-Premuzic & Furnham 2008), different engagement patterns and levels (Hoff & Lopus 2014), and emotional outcomes (Shen, Wang & Shen 2009). All of these factors can affect their academic achievements. Hence, a correct understanding of epistemic emotions can help predict their academic performance and design appropriate intervention strategies to help retain the learners on their optimum learning path.Such emotional dynamics in students are easily picked up by an experienced teacher in a traditional classroom environment, providing them with an opportunity to implement some intervention to control undesirable learning states in students. Over the past few years, there has been a steep increase in digital educational resources, Intelligent Tutoring Systems, and Massive open online courses (MOOCs). These virtual platforms provide students with increased opportunities and flexibility to learn in a self-paced environment. Such platforms are equipped with sophisticated techniques to track and predict their performances. However, despite such sophistication, online learning environments suffer high attrition rates (Mortada, Bolbol & Kadry 2018). The studies support that frustration and anxiety are usually the final emotions in students when they give up on the course, feeling disheartened (Jordan 2014).

In online learning environments, it is crucial to understand two key terminologies: Educational Data Mining (EDM) and Learning Analytics (LA). EDM – an Interdisciplinary field that emerged in 1990s (Romero & Ventura, 2007) focuses on understanding and generating new knowledge from large-scale educational data. At the same time, LA, a branch of EDM, is defined as the measurement, collection, analysis, and reporting of data about learners and their contexts to optimise learning and the environments in which it occurs (SOLAR, 2022). LA emphasises the analysis of learner behaviour using diverse data sources such as weblogs, sensor data, and Internet of Things (IoT) data to predict the effectiveness of the learning process. This focus on "learning" is critical, as it centres on the characteristics and behaviours of learners on online platforms. I aim to explore learner behaviour and epistemic emotions, particularly confusion detection and patterns, it is essential to identify gaps in current LA research in this dimension. This exploration will leverage the data generated on online learning platforms to develop comprehensive predictive models to detect confusion and confused learners' patterns, leading to better interventions. This thesis specifically focuses on detecting confusion during online quiz-based activities by analysing usage patterns from prior literature. I am to examine how learner discourse and interactions during online quiz relate to confusion as an epistemic emotion using fuzzy logic. In addition to this, the thesis also investigates confusion as time-dependent phenomenon using deep learning models. Specifically, a time-series analysis using Long Short-Term Memory (LSTM) networks is conducted on learner activity logs to detect confusion-related behavioural patterns over time, particularly in relation to skill-based interactions in Intelligent Tutoring System (ITS) environment using ASSISTment Dataset. Integrating Artificial Intelligence (AI – Broadly understood as - The use of machine learning, deep learning, or generative algorithms to make predictions, classifications, or create content) into these predictive models is particularly promising. AI technologies can analyse vast amounts of educational data more efficiently, uncovering patterns and insights that traditional methods may overlook. For instance, AI can enhance the personalisation of learning experiences by adapting content and feedback based on real-time analysis of learner interactions and emotional states (Naidoo, 2023; Jin et al., 2023).

The literature review in this thesis will also delve into the applications of AI within Learning Analytics, examining how AI-driven approaches can facilitate the identification and understanding of various epistemic emotions. By harnessing AI's capabilities, we can create more responsive and adaptive learning environments that predict and actively support learners' emotional and cognitive needs, ultimately leading to improved educational outcomes. When a learner engages in any learning task, the “learning process” complexly relates to their personality, dispositions, values, skills, and, most importantly, emotional state(s) while they learn. In the realm of online learning platforms, identifying learners' confusion is paramount in ensuring effective educational outcomes.

Confusion can impact a learner positively or negatively depending on the abovementioned factors. Because these factors influence the way learners respond when they are cognitively confused. A learner may be confused and work towards clarifying the confusion, hence resulting in a positive outcome as they will have an “achievement” feeling, while on the other hand, if they remain confused for a prolonged time, they may feel “anxious” or “frustrated” and decide to give up. While educational data mining has traditionally focused on analysing data from Learning Management Systems (LMS) to understand student behaviours, recent research underscores the necessity of developing models that offer actionable insights to comprehend and enhance student learning behaviours (Owan, 2023; Baigi et al., 2023).

Existing studies have delved into individual, emotional, and social factors influencing student behaviours but often fall short in capturing the dynamic nature of learning behaviours and providing a holistic view of students' learning experiences (Akgün & Greenhow, 2021; Shaik et al., 2022). The significance of identifying confusion among learners in online platforms lies in the need to move beyond static understandings of student behaviours within isolated courses. Students typically engage in multiple courses simultaneously, necessitating a comprehensive approach to grasp their learning behaviours across various contexts (Dahmash et al., 2020). By exploring large-scale data and examining the dynamics of learning behaviours, it becomes possible to develop student-centric models that offer nuanced insights into individual learning journeys (Maphoto, 2024). The evolution of research in educational data mining and artificial intelligence in education has underscored the importance of understanding and addressing student confusion in online learning environments. By leveraging generative AI technologies and sophisticated data analytics, educators can gain deeper insights into students' emotional states and learning challenges, paving the way for personalised interventions and support mechanisms (Salih, 2024; Jin et al., 2023).

The integration of AI tools not only enhances the detection of confusion but also contributes to the overall improvement of academic outcomes by providing tailored strategies to assist students in navigating complex learning environments (Ampofo et al., 2023). Recent studies have highlighted the potential of AI-powered tools in educational settings to enhance measurement, assessment, and evaluation processes, thereby offering a more comprehensive understanding of student learning behaviours (Hidayat et al., 2022; Alsobhi et al., 2022). By incorporating artificial intelligence into educational practices, educators can better support students in their learning journeys, identify areas for improvement, and provide timely feedback to foster academic growth (Luckin & Cukurova 2019; Pendy 2023). Moreover, the responsible implementation of AI technologies in education can lead to enhanced student engagement, personalised learning experiences, and improved academic performance.

In conclusion, identifying learner confusion in online learning platforms is critical to promoting effective teaching and learning practices. By harnessing the power of artificial intelligence, educators can gain valuable insights into students' emotional states, behaviours, and challenges, ultimately leading to the development of tailored interventions that support student success and academic excellence. The quest to understand and address learner confusion continues to drive advancements in enhancing students' educational experiences in online learning environments through ongoing research and innovation in educational data mining and AI in education.

1.2 Identified Literature Gaps

A learner may experience a wide range of emotions while attending a class, doing their assessments, attending an exam, or performing other cognitive activities (Spangler et al., 2002; Zeidner, 1995). As discussed earlier, learners experience emotions like anxiety, boredom, frustration, confusion, and others in an academic setting. In the past decade, there has been a growing body of literature on such academic emotions and their impact on learners' learning, achievement, drop-out, and overall well-being. Such studies have encountered challenges in validating the developed methods as they primarily depend on learners' self-assessment data. However, research in EDM and LA focussed on developing quantitative affect detection from LMS data to model learners’ emotional behaviours while learning. This section focuses on two main areas of exploration regarding affect detection using clickstream data from online learning systems.

- **Gap 1: Insufficient Research on Clickstream Data for Confusion Detection** While various studies have used clickstream data to analyse learner behaviours, there remains a lack of comprehensive research focused on leveraging clickstream data specifically for confusion detection. Current models either fail to accurately capture moments of learner confusion or lack the granularity required to provide actionable insights. This gap presents an opportunity to develop more robust models to identify confusion better, improving real-time intervention strategies in online learning systems.
- **Gap** 2: **Limited Application of AI Tools on Clickstream Data** Although AI tools have been employed in online learning analytics, their practical application in processing and interpreting clickstream data for affective states, such as confusion, is still underexplored. There is a significant gap in understanding how advanced AI techniques can be tailored for this specific type of data. My research seeks to bridge this gap by investigating novel AI models that enhance the detection of emotional and cognitive states through clickstream analysis.

1.3 Clickstream data for confusion detection

Online Educational learning platforms continuously generate many data when learners interact with such systems. The utilisation of clickstream data in educational settings has gained significant attention due to its potential to provide insights into learners' behaviours and interactions within such systems. Clickstream data, which captures learners' digital footprints as they navigate through online platforms, offers a wealth of information that can be harnessed to understand student engagement, learning patterns, and potential confusion (Baradwaj & Pal, 2012). While the potential of clickstream data to provide valuable insights into student behaviours is evident, the current challenge lies in effectively leveraging this data to accurately detect and address instances of confusion among students (Montgomery et al., 2004). Research by Baker et al. (2010) and recently by Zhou et al. (2022) has shed light on the cognitive-affective states of learners during interactions with computer-based learning environments, emphasising the significance of understanding learners' emotional and cognitive states, including confusion, to enhance the learning experience. By delving into the cognitive-affective aspects of student interactions, educators can gain valuable insights into the factors contributing to confusion and design interventions accordingly. Moreover, the work of Baker et al. (2020) and Hasnine et al., (2023) underscores the benefits and challenges of using clickstream data to understand student self-regulatory behaviours that may intersect with detecting confusion in learners.

While clickstream data provides researchers and instructors with a wealth of information on how students navigate and interact with online resources, there is a need to develop more sophisticated analytics techniques to extract meaningful insights from this data, particularly in detecting nuanced states like confusion (Kloft et al., 2014). To address the gap in accurately detecting confusion through clickstream data analysis, future research could focus on developing advanced machine learning algorithms tailored to interpret complex patterns within clickstream data (Sinha et al., 2014). By enhancing the analytical capabilities of clickstream data, researchers can potentially identify subtle indicators of confusion, such as repeated clicks, erratic navigation patterns, or prolonged dwell times on specific content areas (Rodríguez et al., 2021). However, current methodologies often fail to accurately detect these nuanced states of confusion. Therefore, it is essential to explore integrating qualitative data sources, such as student surveys or interviews, with clickstream analytics. This integration could provide a more comprehensive understanding of student confusion and its underlying causes (Coetzee, 2023). By triangulating quantitative clickstream data with qualitative insights, researchers can validate the accuracy of confusion detection algorithms and gain a deeper understanding of the factors contributing to student confusion in online learning environments Liu et al. (2022). This approach is not yet widely adopted, highlighting a significant gap in the current research landscape. Moreover, while there have been advancements in using clickstream data to analyse student interactions, the challenge remains in developing robust methodologies that effectively capture and interpret the complexities of learner confusion.

Future research should focus on creating advanced analytical frameworks combining quantitative and qualitative data, thereby enriching the understanding of students' emotional and cognitive states during their learning experiences. However, while clickstream data holds immense potential for detecting confusion in students during online learning activities, it is critical to enhance the analytical methodologies and techniques used to interpret this data effectively. By refining clickstream data analytics (broadly understood as The analysis of learner interaction logs (e.g., clicks, time spent, forum posts) to infer behaviours or states) and integrating multiple data sources, educators and researchers can gain valuable insights into student confusion and tailor interventions to support meaningful learning experiences. Research by Akpinar (2020) has explored the analysis of student strategies in blended courses using clickstream data, highlighting the potential of clickstream data to uncover valuable information about how students engage with course materials and assignments (Ninaus & Sailer, 2022).

The work of Crossley et al. (2016), Lee et al. (2021) and many other researchers also demonstrated the integration of clickstream data with natural language processing (NLP) tools to understand MOOC completion rates better. By combining clickstream data with NLP techniques, researchers were able to extract deeper insights into students' interactions and behaviours within online courses. By training algorithms on labelled datasets that capture instances of student confusion, researchers can create predictive models capable of identifying early signs of confusion based on clickstream interactions. Furthermore, integrating real-time monitoring and alerts based on clickstream data analysis could enable educators to intervene promptly when students exhibit behaviours indicative of confusion (Mubarak et al., 2020). By implementing automated systems that flag instances of confusion in students' clickstream data, educators can provide timely support and guidance to help students navigate challenging concepts or tasks.

In conclusion, the analysis of clickstream data presents a valuable opportunity to detect student confusion in online learning environments. By identifying specific patterns and indicators associated with confusion within clickstream data and leveraging advanced analytical techniques, educators can develop targeted interventions and support mechanisms to enhance learners' learning experiences and outcomes. Thus, the current challenge lies in identifying specific patterns or indicators within clickstream data and text data that are reliably and meaningfully associated with student confusion and leveraging these insights to develop effective interventions and support mechanisms (Ha & So, 2023; Baker et al., 2020), I aim to extend this research that will help pinpoint those specific clickstream behaviours that are associated with confusion.

1.4 Effective use of AI tools

Integrating AI technologies with clickstream data analysis from online learning platforms presents a promising avenue to enhance the detection of learner confusion and enable timely interventions to support students' learning experiences. Clickstream data, which captures learners' digital interactions and behaviours within online learning platforms, offers a wealth of information that can be leveraged to identify patterns indicative of confusion. However, the challenge lies in optimising machine learning algorithms to analyse this data in real-time and provide actionable insights to educators. Thus, it is vital to not only bridge the research gap but also bridge the gap between research findings and practical implementation of such research that will help devise effective strategies to translate research evidence into actionable interventions that can improve learners' outcomes. There is the potential where such AI algorithms can be used to translate clickstream data into real-time alerts to notify educators of potential instances of learner confusion and, in turn, help such confused learners on time to avoid learner anxiety or frustration and thus avoid learner dropout. The research can potentially dive deeper where researchers can gain insights into the underlying factors contributing to learner confusion and tailor interventions that address such systemic and personal issues within the scope of education.

Using AI tools can focus on developing predictive models to detect confusion in learners, possibly in the following two ways:

- **Learner's confusion levels during an assessment** – For example, a learner can be confused, and their interactivity within the task, when they are confused, can be studied to determine the exact concepts they struggle with and then define actionable strategies to intervene in such spikes of confusion.
- **Course-level confusion in learners**—For example, many learners struggle with one concept, and AI and ML tools can be used to determine these spikes in confusion across the course, defining actionable strategies for better course design and continuous improvements.

My research seeks to address these gaps by investigating the following:

1. Enhancing clickstream data analytics using AI to improve confusion detection during online activities such as quizzes (Research Question 1). This addresses the gap in optimising machine learning algorithms to analyse clickstream data in real-time, providing actionable insights that help educators intervene at the right moment.

2. Identifying specific patterns and indicators in clickstream data that reliably reflect learner confusion (Research Question 2). By pinpointing the behaviours and interactions that signify confusion, my research will develop more accurate models for confusion detection, filling the gap in understanding the exact learner behaviours that indicate confusion.

3. Utilising Generative AI to provide real-time, actionable strategies for individual learner interventions and course-level improvements (Research Question 3). This research will explore how AI tools can be employed to notify educators of learner confusion and generate targeted strategies that reduce confusion and prevent dropout. This also

ties into course-level improvements, where systemic issues in course design can be identified and addressed based on spikes of confusion detected across many learners.

Through these approaches, my research aims to bridge the gap between research findings and their practical implementation by developing models that offer real-time alerts and strategies to improve learner outcomes and course quality. It will also delve into the underlying factors contributing to confusion and create interventions that address individual learner challenges and broader course design issues. Integrating AI tools will enhance confusion detection and provide a practical framework for improving educational outcomes, which still needs to be explored in the current literature.

In conclusion, my research will bridge the gap in understanding how AI-driven models can improve confusion detection, offering immediate support for learners and long-term strategies for better course design and continuous improvement.

1.5 Research Questions

Improving the detection of confusion in students during online learning activities through clickstream data analytics presents several challenges. Current methodologies often struggle to accurately identify and address instances of confusion solely through clickstream data analysis. To advance the field of confusion detection in online education, it is crucial to investigate specific patterns or indicators within clickstream data that are reliably associated with student confusion. Research has shown that digital educational environments significantly impact student motivation and learning engagement, highlighting the importance of understanding how students interact with these platforms (Li, 2024). By focusing on the affective dimensions and environmental constructs that influence student learning, innovative methods for detecting confusion can be developed. This understanding is essential for creating effective predictive models for student emotional behaviours.

Furthermore, integrating Generative AI with confusion detection predictive models offers a promising avenue for enhancing the support provided to learners. While Li (2024) discusses the potential of Generative AI in educational contexts, this thesis proposes to explore its application specifically in confusion detection. By examining students' interactions with online platforms and recognising patterns indicative of confusion, Generative AI can deliver personalised interventions in real-time, enhancing students' self-learning capabilities and fostering lifelong learning. In summary, utilising clickstream data analytics, identifying patterns associated with student confusion, and integrating Generative AI with confusion detection and patterns can enhance online learning experiences. These advancements not only improve student learning experiences but also facilitate the development of personalised interventions that promote effective learning outcomes. This leads to the following research questions that guide this thesis:

1. How can clickstream data analytics be enhanced using AI to improve confusion detection in learners during online activities or assessments like quizzes? (This question will address Research Gap 1 predominantly with the help of AI, impacting Research Gap 2)
2. What patterns or indicators within the clickstream data can be reliably associated with learner confusion in online learning environments? (This question will address Research Gap 2)
3. How can we use Generative AI with these confusion detection models and help learners develop actionable strategies to address their confusion effectively? (This question will address Research Gap 2)

1.6 Research Objectives

We aim to extend our research to work on the following objectives from the above Research Questions (RQs):

Objective 1 Conduct Literature Review (All RQs)

This objective will be achieved by performing a comprehensive literature review on relevant research fields in learning analytics (LA) concerning epistemic emotions. This stage will explore various features that help track learners' confusion on online learning platforms. It will also help determine various research threads in the area that will form the basis of the next exploratory steps in the research.

Objective 2 Develop techniques for detecting confusion (RQ 1)

This research will develop techniques to determine confusion and their levels. We aim to use the appropriate and relevant data set using various Artificial Intelligence (AI) techniques to experiment in determining techniques for detecting the learner’s confusion and the level of their confusion. For example, determine if a learner is less or more confused while performing an online activity, like an online assessment, such as a quiz.

Objective 3 Detect patterns from clickstream data that profile confused learners or identify a learning pattern for a confused learner who is likely to drop out (RQ 2)

The research will develop identifying specific patterns or indicators within clickstream data indicating learner confusion in online learning environments like Intelligent tutoring systems. This research objective will use labelled data of confused learners to validate these patterns.

Objective 4 Develop a Framework for Integrating Generative AI for Effective Confusion Detection. (RQ 3)

In this objective, we focus further on developing a deeper understanding and designing a framework that comprehensively uses model detection with Generative AI to develop an intervention framework that helps create a real-time intervention system that handles learners’ confusion in a timely manner to avoid frustrations and dropouts.

1.7 Research Contributions

1. **Enhancing Clickstream Data Analytics for Confusion Detection:** This study contributes by proposing clickstream data analytics to improve the detection of confusion in students during online learning activities. By addressing the current limitations in accurately identifying and addressing instances of confusion solely through clickstream data analysis, the research aims to develop models that can effectively pinpoint moments of confusion in students' online learning journeys.
2. **Identification of patterns in Clickstream Data:** The research contributes by identifying patterns within clickstream data that can be reliably associated with student confusion in online learning environments. By leveraging AI algorithms, the study seeks to uncover unique patterns in students' online interactions that signify confusion, thereby enabling educators to intervene promptly and provide targeted support to students in need.
3. **Framework of Integrating Generative AI for Effective Confusion Detection:** This study introduces innovative ways to utilise Generative AI with confusion detection models to help learners address their confusion effectively. By combining the power of AI algorithms with clickstream data analytics, personalised interventions will be delivered in real-time to guide

students through moments of confusion, ultimately enhancing their self-learning capabilities and academic performance.

1.8 Research Methodology

This research will be conducted by the steps shown in the figure 1-1

Step 1. Literature Review. In this step, state-of-the-art research on relevant research fields will be reviewed. These fields include online learning, epistemic emotions that affect learning, and transitional flow of epistemic emotions. The literature review will investigate indicators helpful in tracking and decoding learners' behaviour and in turn, having the potential to detect confusion. This stage will also cover the applications of artificial intelligence (AI) used in learning analytics. In this stage primary problems (such as indicators of epistemic emotions and their combined effect) will be explored and refined to identify research questions and objectives to address the gaps and their significance.

Step 2. Develop techniques for detecting confusion.

This step will focus on developing techniques for detecting confusion, one of the key epistemic emotions that significantly impact learning outcomes. The development of these techniques will be grounded in the findings from the literature review.

Step 2.1 – Determine factors affecting confusion.

This step will explore possible indicators or behavioural data in activity logs collected by the learning management systems to help determine possible confusion and explore any pre-processing required to get the data set ready for further exploration in defining and detecting the levels of confusion. Using findings from the literature review, In this step we also hypothesise around behavioural patterns that may signify confusion, such as repeated attempts at a quiz question, frequent back-and-forth navigation between sections, long pauses between clicks, or abrupt disengagement.

Step 2.2 – Detect confusion using techniques in Artificial Intelligence (AI)

AI algorithms will be leveraged to develop models that can analyse and interpret clickstream data, to detect learner confusion in online learning environments. These techniques will enable the identification of confusion in learner and the level of their confusion, ultimately potentially enabling the ability to provide timely interventions.

Step 3. Develop specific patterns from clickstream data that profile confused learners or identify a learning pattern for a confused learner who is likely to drop out.

Clustering and time series analysis are used to identify patterns in clickstream data that signal confusion or potential dropout. Clustering groups learners with similar behaviours, such as repetitive clicks or erratic navigation, highlighting those showing confusion. Time series analysis tracks changes in behaviour over time, helping to identify trends like declining engagement or prolonged confusion that may indicate dropout risk. Together, these methods profile at-risk learners for timely intervention.

Step 3.1 – Identify optimal data set to profile confused learners.

In this step, we focus on the dataset labelled for confusion using the BROMP-coded ASSISTment dataset, which captures emotional states from learners' interactions. By isolating the data specific to confused learners, we analyse their behaviours and key patterns within their interactive logs generated in the Intelligent Tutoring System. This analysis aims to profile the characteristics and actions associated with confusion.

Step 3.2 – Formulate the learning pattern for a confused learner.

In this step, we determine the selected validated data of confused learners generated in the Intelligent tutoring system and detect learning patterns for confused learners that have the potential to pinpoint the struggling learners or topics where the learners are most likely to struggle, this will help the future research in taking such patterns into account to design their interventions or course design.

Step 4. Develop a Framework for Integrating Generative AI for Effective Confusion Detection.

In this step, we propose a theoretical framework that integrates the new AI techniques like Generative AI for a practical intervention strategy that can potentially help confused learners timely and more accurately.

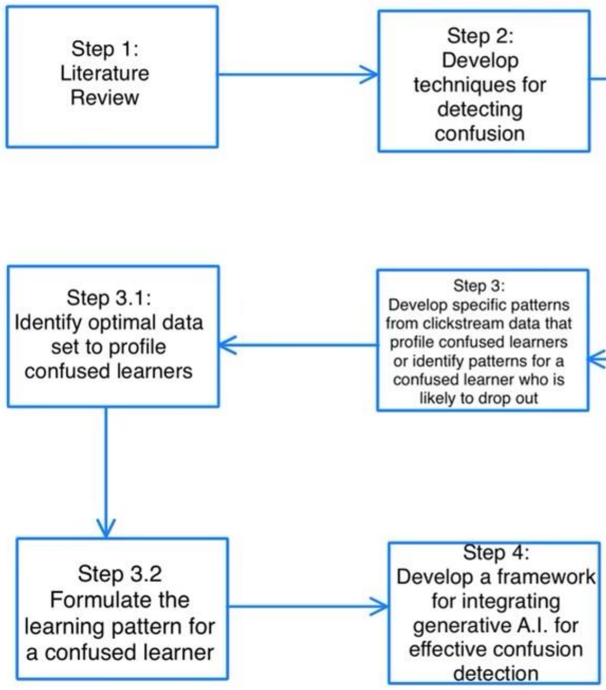

Figure 1-1 Research Methodology

1.9 Thesis Outline

Chapter 1: In this chapter, a background of the problem space is provided and details about the specific problem areas this dissertation addresses. The research questions and objectives and the broader impacts of this research are discussed in the chapter. Finally, the research methodology is presented.

Chapter 2: This chapter reviews the literature related to the problems defined in this thesis. This chapter also covers current digital learning environments, the affective dimensions of student learning, learning analytics, and relationships. **(RO 1)**

Chapter 3: This chapter focuses on the two studies on confusion detection methods using AI that help capture learners' confusion from digital learning environments. This chapter will discuss the importance of detecting such confusion moments and how it can help in providing predictions that may feed into Generative AI models in future for actionable interventions. **(RO 2)**

Chapter 4: This chapter details two studies that determine a method of profiling confused learners and dive deeper in learners' interactions with the Intelligent tutoring system to create a learning pattern that activates confusion. It also details a method of understanding predictions given by machine learning models using concepts from explainable AI. **(RO 3)**

Chapter 5: This chapter focuses on developing a theoretical but student-centric framework that explores on how the emerging technologies in AI like Generative AI can be utilised in creating a comprehensive intervention system that provides real-time holistic interventions to learners to avoid learner frustrations and dropouts. **(RO 4)**

Chapter 6: This is a conclusion chapter for the final discussion and future work.

Chapter 2: Literature Review

2.1 Overview

Emotions influence how learners learn and perform. There has been increased integration of online learning environments in teaching and learning. This raises the question of what epistemic emotion(s) arise when interacting on online platforms. Learning analytics (LA) allows educators to analyse the data about learners produced on such platforms. Learning analytics have matured in utilising multimodal data with advanced techniques like machine learning (ML), warranting a deeper systematic study of epistemic emotions in past research.

This chapter examines key factors that significantly impact the learning experience within online environments. While the realm of online learning is vast, this chapter focuses on the following critical elements:

- learner engagement,
- use of learning analytics,
- use of AI and ML in this space,
- learner's emotional state like confusion and its impact on academic success or failure.

Learner Engagement: Learner engagement is a critical factor in the success of online learning. It refers to how students actively participate, interact with course materials, and are motivated to achieve learning goals. Factors influencing engagement include course design, instructional strategies, feedback mechanisms, and creating a supportive learning community. High levels of engagement are correlated with improved academic performance, increased satisfaction, and higher retention rates.

Use of Learning Analytics: Learning analytics involves systematically collecting, analysing, and interpreting data about learners and their contexts to understand and optimise learning and teaching processes. By leveraging data on student behaviour, performance, and interaction patterns, educators can identify areas of strength and weakness, tailor instruction accordingly, and provide timely support. Learning analytics can potentially enhance student engagement, improve learning outcomes, and inform pedagogical practices.

Use of AI and ML: Artificial intelligence (AI) and machine learning (ML) technologies are increasingly being adopted in online learning to personalise the learning experience, automate administrative tasks, and provide intelligent support. AI-powered systems can analyse vast amounts of data to identify patterns and predict student performance, enabling tailored recommendations and interventions. Additionally, AI-driven chatbots and virtual assistants can provide students immediate support and guidance, enhancing their learning experience.

Learner's Emotional State: Students' emotional states significantly impact their learning experience and academic performance. Negative emotions such as confusion, frustration, and anxiety can hinder learning, while positive emotions like curiosity, interest, and satisfaction can facilitate it. Understanding and addressing students' emotional needs is crucial for creating supportive online learning environments. By identifying early indicators of student difficulties and providing timely interventions, educators can help students overcome challenges and maintain motivation.

Before diving further into above each area we also conducted a broader systematic literature review in the light of the use of Machine Learning (ML), Learning Analytics (LA) and interplay of five epistemic emotions that are thought to interplay with each other.

2.2 Academic success and learner's engagement

Learner engagement can be defined as the extent to which the learner is actively engaged in thinking, participating or interacting with the course content, other learners in the cohort and teachers (Dixson 2015). Engagement is the key factor connecting the learner to the course and keeps them on their optimum learning path (Dennen, Aubteen Darabi & Smith 2007; Kehrwald 2008; Robinson & Hullinger 2008; Shea, Li & Pickett 2006; Swan et al. 2000)

In a fully online learning format, which is often also referred to as distance education, Moore's theory of transactional distance in 1993 supports distance to be a pedagogical phenomenon (Michael Grahame 2018). The distance is more concerned with student interaction and engagement while learning than just the geographical distance and consists of three elements: dialogue, structure, and learner autonomy, all of which will affect learner's engagement. Based on Moore's theory, it has been rightly argued that "As understanding increases – misunderstanding decreases" (McBrien, Cheng & Jones 2009). A misunderstanding can be equally understood to be the cause of confusion. As this confusion is controlled by proper intervention, it will lead to deeper understanding, hence causing positive learning gains and a positive achievement outcome leading to increased engagement.

In cognitive tasks, such inference does align well with transitional flow of emotions amongst the most important epistemic emotions (D'Mello & Graesser 2014; D'Mello & Graesser 2012) in learning. The transitional flow of engagement and confusion, indicates that confusion when attended at the right time can decrease the misunderstanding over the concept, avoiding future misunderstanding. This increases the chance of improving overall learner engagement and keeps them going. Hence, it becomes inevitable to measure the level of engagement of online learners when they interact with the online content of the course, and as per the transitional flow can be done in conjunction of some constructive confusion. However, learner engagement has been studied across multiple dimensions (Azevedo 2015), and for online learning, key areas of exploration are social construction and the community of inquiry model(Dixson 2015).

In the dimension of social constructivism, the aim is to increase learner's engagement on online platforms it has been argued that while some learning tasks are better performed individually, some tasks show better performance and more profound understanding when learners work collaboratively (Ally 2004; Anderson 2004; Ashcraft, Treadwell & Kumar 2008; Hrastinski 2009; Stacey 2002; Vygotsky & Cole 1978) (Woo & Reeves 2007). Hence, we can confidently say that a successfully engaged learner is the one who interacts with other learners in filling their skills and knowledge gaps as we learn by observing how others behave or perform (Bandura, Ross & Ross 1961, 1963).

When learning online, the goal is to develop courses conducive to active learning and easily promote interactions with peers and instructors, which in turn initiates positive engagement. To support such courses' design, three key areas dimensions are identified and supported by various researchers: Social and community presence with meaningful interaction (Ally 2004; Bigatel et al. 2012; Dow 2008; Hill, Song & West 2009). This is no different from traditional learning, where teachers aim to induce active learning, where the learners are encouraged to construct meaningful knowledge by collaborating effectively (Ally 2004).

On the other hand, a community of inquiry dimension focuses on three key areas of presence: Social, teaching, and cognitive presence (Akyol & Garrison 2008, 2011; Annand 2011; Arbaugh 2008; Garrison 2007, 2011; Shea et al. 2010; Stodel, Thompson & MacDonald 2006). While we discussed the importance of social interactions on online learning platforms and its possible impacts on keeping the learners engaged, social presence is key qualitative differentiation between a highly interactive course to a course with mostly downloadable multimedia content (Garrison, Anderson & Archer 1999). It can be deemed to be the golden advice as despite of a long time before when this argument was made, it still stands true. Nevertheless, again due to the sophisticated technology available now, we can argue that the courses can be developed using such highly collaborative tools that can make the learner sense this social feeling. This social dimension may not be enough to encourage student engagement (Dow 2008). The community of inquiry (CoI) model focuses[1] on teaching that is concerned with the course design and organisation, facilitation of the course including the direct instructions (Akyol & Garrison 2008; Garrison 2007). It is extended to the cognitive presence involving triggering events that encourage learners to think about a new idea or concept or problem, explore new information, integrate ideas and finally resolve the task or the problem (Garrison 2011). Hence, it has been argued that the community of inquiry model is a stronger model in supporting online learning. The cognitive presence dimension of the CoI model provides a theoretical basis for interpreting learner engagement and confusion, which are central to detecting cognitive disequilibrium in Intelligent Tutoring Systems (ITS) and online quiz interactions on the LMS. This connection grounds the detection of confusion within a pedagogically meaningful framework.It is the cognitive presence dimension where the possible injection of confusion can either contribute to continued engagement or can induce more negative valence causing frustration. This leads to an understanding that a number of factors such as effective and productive learner-instructor interactions, an effective and interesting collaborative tasks and a good functional interface can contribute to high level of learners' satisfaction and in turn enhancing the quality leaner's engagement (Swan et al. 2000).

There are many models considered in measuring learner's engagement, like CLASSE – Classroom Survey of Student Engagement (Ouimet & Smallwood 2005), RAIQDC - Rubric for Assessing Interactive Qualities of Distance Course (Roblyer & Wiencke 2004) and SCEQ – Student Course Engagement Questionnaire (Handelsman et al. 2005). It has been argued that SCEQ is more holistic as this measurement is based on various factors like emotional engagement, skills engagement, participation and performance that fits more logically with the community of inquiry model of engagement (Dixson 2015).

However, when using online learning platforms, the learning management systems can be deployed to collect data relating to the above factors in helping to get a deeper picture of the

[1] https://coi.athabascau.ca/coi-model/

learners' engagement. The learners can be tracked on their behaviour like viewing the content (how long and how many times), interacting on forum discussions, reading and reacting to posts and performing online tasks. Learners engage on the learning platforms and exhibit two types of behaviours when engaging: Observation and Application. Observation happens when a learner is processing and interpreting the online content in understanding the new concept, and application happens when the learner is performing cognitive tasks after they have understood the new concept (Dixson 2015). Moreover, the learning management systems track both these types of behaviour from the online learner, which can help detect the levels of engagement and may also unhide some patterns that can be used to understand the transition from engagement to gradual confusion.

2.3 Towards methods for learners' activity analytics

Learners learn differently given they all differ in their prior knowledge, motivation and way of engaging with the content. For example, some learners are comfortable learning online while it can be a challenge for others. Therefore, courses delivered in blended or online modes should be designed with learner diversity in mind – accommodating a range of preferences, accessibility needs and interaction patterns. While the concept of fixed "learning styles" has been critiqued and lacks robust empirical support as a basis for instruction design, the broader principle of differentiated learning remains vital (Pashler et al. 2008; Coffield et al. 2004) Learning Analytics (LA) has advanced in sophisticated tools and techniques in collecting activity and transactional data, providing an important opportunity in understanding and responding to learner behaviours in more adaptive and personalised ways. Educators are increasingly using this data to monitor the learner's progress on such online platforms (Siemens 2013). However, LA is a multidisciplinary field drawing various methodologies in EDM, social Network analysis, AI (Artificial Intelligence), psychology, Educational theories and practice to name a few (Lockyer, Heathcote & Dawson 2013).

Standardised, scalable, and real-time indicators of teaching and learning outcomes has never been more important than now. Nevertheless, it is still a complex task due to the heterogeneous nature of the data on learners' engagements, various learning outcomes, and teaching practices. Data like how many times learners visited a particular content can be easily traced to determine the amount of engagement between the learner and the content (Bakharia et al. 2016; Coffrin et al. 2014; Fritz 2011). On the other hand the online learning platform can generate data at more detailed level, where it is possible to understand the emotional and cognitive states by understanding the learning sequence (d Baker et al. 2012; San Pedro et al. 2013). Thus, a thorough understanding of the pedagogical and technical context of the data generated on such online learning platforms is required to grasp the meaning of the data and its impact on learning.

Current online learning platforms generate a range of heterogeneous data like keyboard entries, mouse clicks, or more multi-modal data like pulse rate or pupil dilation (Ochoa, Lang & Siemens 2017). However, to unhide a meaningful data pattern and understand it within the context can be quite challenging, though worth it.

It is vital that a comprehensive list of factors or data points determining the epistemic emotional state of a learner on online learning platform remains a challenge (Harley et al. 2017). Some indicators are universally accepted and of course reliable, like time of submission. For example, a learner submitting all their work on time is an engaged learner against the learner submitting the work either in a short time or an extra-long time or not submitting at all are the signs of disengagement (Baker & Ocumpaugh 2015). Contrarily, it has been argued that time of submission for each task is just one dimension and to get a deeper understanding on emotions involved in performing specific cognitive tasks requires exploration of other data for an accurate and meaningful inference (Kovanovic et al. 2015).

Also, the interaction patterns of a learner with the online learning platform in the form of clicks and navigation has the potential to indicate a learner's emotional state (Conati & Maclaren 2009), and since epistemic emotions relate to learning gains, it has been argued that detecting such emotions timely can help a learner to maintain their optimal learning path (Baker et al. 2010). It has been studied that deep engagement in learning complexly relates to range of factors like learner's personality, emotions, dispositions, values, skills, and attitude towards learning. This means that the way a learner explores the content on online learning platforms can indicate their attitude, for example are they confident or cautious (Arguel et al. 2016), or their familiarity with the task or learning environments and prior knowledge. Overall, their attitude towards learning like are they risk takers or cautious learners (Arguel et al. 2016; Graesser et al. 2005; Tricot & Sweller 2014).

Much of this boils down to the fact that many researchers universally argue it that activity log data has the potential to unhide many patterns that can indicate or detect epistemic emotional states in leaners, and hence the online learning platform must be designed optimistically to collect such interaction data that helps the educators at various levels in determining a deeper understanding of learner's emotional states and in turn the impact of this on their overall learning. Again, this can form the base of various intervention strategies to help the struggling learners. It is important to design or tune the online learning platforms, as to what interaction data is being logged, as too many interaction points can lead to contrary results (Mayer, Heiser & Lonn 2001) and can lead to overall poor learning experience. Hence, to take advantage of such interaction data in a meaningful way, rather than designing the platform to collect all behavioural data leading to less effective learners' experience, it is advised to design the online learning platforms to collect the interaction data that principally align with the pedagogical goals of the lesson or task (Arguel, Pachman & Lockyer 2018).

Also, it is important to consider the technological aspects like usability of the interface and technology acceptance by the learners for them to enjoy the positive experience, otherwise even a quality content may end up with frustration and confusion in learners (Venkatesh & Davis 2000). Hence, it is suggested to look to various best practices in making design and support choices to learners to support them through various technical, usability and deployment issues. The design choices are important for both technical and ethical purposes because technical efficiency will benefit the optimal choices of hardware, software and network requirements, having the potential to produce better results with fewer resource requirements. Ethical efficiency on the other hand will provide a secured way of collecting learners' activity data by tracking their click-stream patterns (Arguel, Pachman & Lockyer 2018).

It may be rightly understood that LA can be effective if we can hold onto an intuitive and meaningful set of data via technological platforms. The data set could be complex as it needs to consider many dimensions. It may need to apply advanced technological developments like AI, Machine Learning (ML) and Deep learning to benefit the most.

2.4 Artificial Intelligence (AI) and Machine Learning (ML) in Learning Analytics

Current learning environments are complex due to the voluminous heterogeneous data that the online discourse of the courses generates. At the same time, learners' activities on such platforms are a mesh of complex structures. It has been argued that learners may benefit more if such complex activities can be mapped successfully to their learning states as they acquire new skills (Greller & Drachsler 2012), as it gives educators insight into how best they can help the learners through such states.

There is an enormous amount of structured and unstructured data uploaded on such learning platforms, and a voluminous amount of real-time log data is also getting generated while learners and educators use such systems to interact. The fact can be readily understood that using simple analysis techniques on such data may not reap enough benefits. This area needs to get more benefits from the advancements in the area of Big data Analytics and Data Mining (Papamitsiou & Economides 2014).

Learning Analytics (LA) has been studied in two interrelated directions :

- One working on Learners interactive track data on online platforms generating various patterns and predictions. It helps educators understand the overall performance and needs of the course offered on online platforms.
- Two, working on course structure design that works optimistically for a learner based on their characteristics like their learning style, preferences and learning ability.

Each of these directions will generate a large number of possibly complex and high dimensional data where Machine learning (ML) (Berral-García 2018) and furthermore Deep learning could prove to be beneficial as each learner is different to others in terms of their learning patterns and other specific characteristics (Kato et al. 2017).

Machine learning (ML) is a branch where raw data is taken as an input, and the algorithm learns some generalised patterns that can be used in the future for another set of unknown data. The quality of data has a direct impact on how well the Machine learning Algorithm will perform or learn. The benefit of Machine Learning (ML) is that it can work on a small set of training data, generally where ground truth information is available based on which we want to derive a prediction model. However, when no such ground truth information is available, then we can apply some unsupervised learning algorithms that can also do the data exploration before making predictions (Passalis & Tefas 2019).

The nonlinear layered feature of Machine learning brings data representations that are more intuitive and can result in better-performing predictive models. Hence it can be inferred that Deep learning can prove beneficial in the Learning Analytics (LA) area as well. Deep learning algorithms come up with abstractions based on raw data using non-linear transformation. The final output from the last layer could then be the input to other algorithms like classification, and it is a more effective input. (Najafabadi et al. 2015)

Machine learning algorithms mostly use voluminous unsupervised data to automatically extract complex distributed forms of data representation. This may result in many possible configurations of abstract features, providing a highly scalable data representation using known and unknown features. (Bengio, Courville & Vincent 2013). As discussed earlier, learning platforms are generating enormous amounts of Data on learning platforms. Effectively managing such data can be challenging. Hence, it may be useful to research deeper to highlight some issues with learning and learning platforms and how Machine learning (ML) can be used to increase the effectiveness of online courses.

Such online platforms allow learners to interact using forum discussions, which provide both emotional and cognitive engagement opportunities for learners. This collection of interactions can provide an opportunity to predict learning gains and has been of great interest to many studies in recent years. Even then, such relationships are quite challenging to fully understand and have not been thoroughly explored yet.

Learning online comes with the disadvantage of time-space separation, affecting the quality of learning engagements, but forum discussion is principally used for such interaction by the learners (Almatrafi & Johri 2019). This can be used as an important tool to monitor and understand the learning process. On MOOCs forums, such high-quality discussion has shown great potential in increasing engagement and learning gains (Antonaci et al. 2019; Atapattu et al. 2019; Crues et al. 2018; Peng et al. 2020; Wang et al. 2015).

However, the greater challenge here is the fact that statistically, there are usually only a few percentages of learners who are actively involved in such forum discussions. Hence, it may not give a deeper understanding of the emotional states of all the learners in a cohort. An integrated approach was studied to study “confusion” in learners. The course interaction patterns were studied together with discussion content using the Confusion Classification model – a computational approach using Machine learning to detect confusion in learners based on the data collected from online learning platforms. The study was investigated using two MOOC courses, achieving an overall accuracy of 70% or more (Atapattu et al., 2019). The study investigated the most popular click patterns and their prevalence, regardless of learners' participation in Forum discussions (Yang, Kraut & Rose 2016). However, this approach has been argued from the fact that clickstream data is not traced in the event of offline access to the learning material. Self-paced learning on such courses and other constraints can also demonstrate a low accuracy on such a classification model (Atapattu et al. 2019).

Researchers have used single and multi-sourced data to determine cognitive-affective states like Confusion, Frustration, and boredom by monitoring learner's postures (D'Mello & Graesser 2009), facial Features(McDaniel et al. 2007), audio and visual expressions (Zeng et al. 2009), as well as tutorial dialogue semantics (D'Mello, Dowell & Graesser 2009). However, many such detection models are expensive yet not fully automated and require human expertise to judge such states. Such models using multi-modal information cannot be established as a pervasive approach because it is hard to gain in a large-scale digital environment like MOOCs. Hence, to develop a more scalable solution, we need to focus on non-device-based research approaches studied earlier.

Apart from various classification models using single or multi-model features, fuzzy logic has also been widely applied in various domains, including educational data mining. These techniques are investigated due to their ability to adapt and deal with vagueness where elements belong to a category rather than exact values, resulting in human-like judgments (Guijarro-Mata-García, Guijarro & Fuentes-Fernández 2015). Fuzzy logic has been studied in e-learning settings to address various needs, features, and contexts.

In recent years, the mode of providing education took a steep turn and to which most of the world was unprepared. However, such needs have certainly opened doors to explore how advancements in AI can be effectively utilised in understanding learners' emotions for practical learning gains. Hence, effective use of AI using activity logs and interaction data like forum discussion messages in an online learning environment can provide a comprehensive understanding of such epistemic emotions. This will help understand both positive and negative emotional states. It can help intervene timely to control negative emotions that may lead to drop-out or academic failure.

2.5 Leaners' engagement and epistemic emotions

As we all learn differently, online learning can be a boon to some and a curse to others. This fact makes it necessary for courses offered in blended or online mode to reflect learners' preferences.

Decreased resources and increased competition in the educational market have put much weight on educational responsibility. Standardised, scalable, and real-time indicators of teaching and learning outcomes have never been more important than now. Nevertheless, it is a complex task because of the heterogeneous nature of the data on learners' engagements, various learning outcomes, and teaching practices. Thus, a thorough understanding of pedagogical and technical context is required to grasp the meaning of the data generated. More to add, LA is a multidisciplinary field drawing various methodologies in EDM, Social Network analysis, AI (Artificial Intelligence), psychology, Educational theories and practice, to name a few (Lockyer, Heathcote & Dawson 2013).

It has been studied that deep engagement in learning complexly relates to the learner's personality, dispositions, values, skills, and, most importantly, emotional state(s) while learning. LA can benefit more if such complex concepts are modelled and analysed using more traditional social science data using a validated multidimensional construct termed as "Learning Power" (Shum & Crick 2012). It is a term mainly used to measure learners' disposition using seven hypothesised "the power to learn" dimensions that lead to better learning and growth (Crick, Broadfoot & Claxton 2004).

Emotions play a critical role in teaching and learning and are often referred to as epistemic emotions. Such epistemic emotions are dynamic and greatly depend on learners' attitudes, behaviour, cognition, current skills, and knowledge. This ultimately impacts a learner's outcome in the course. Hence, learners experience a range of positive and negative states of mind, depicted in the form of positive and negative emotions, when trying to learn and understand new concepts. It is vital to control and manage such negative emotions to maintain the healthy learning process and avoid demotivated and frustrated learners who are more likely to give up on the course, leading them to leave or fail the course.

Hence, being able to detect negative epistemic emotions like frustration, boredom, de-motivation, and even confusion is the foundation for the progression of achievement of learning goals in online learning platforms (Shen, Wang & Shen 2009).

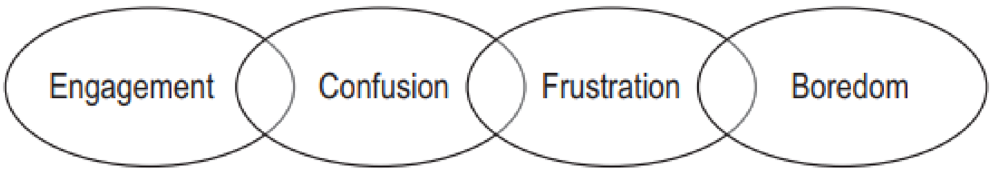

Figure 2: Emotional flow diagram as observed by D'Mello and Graesser (2012)

The above figure shows the consistent transitional flow of emotions amongst the most critical epistemic emotions (D'Mello & Graesser 2014; D'Mello & Graesser 2012) in learning. Also, interestingly, the direct transitions between Engagement and Frustration or Confusion and Boredom were not observed. Hence, it may be crucial to understand the critical epistemic emotions and their impact on learning separately to create the groundwork for our further research. We started our work with a systematic literature review to understand the role of epistemic emotions in learning.

2.6 Bridging the gap between Epistemic emotions and AI and LA

Emotions influence how learners learn and perform. There has been increased integration of online learning environments in teaching and learning. This raises the question of what epistemic emotion(s) arise when interacting on online platforms. Learning analytics (LA) allows educators to analyse the data about learners produced on such platforms. Learning analytics have matured in utilising multimodal data with advanced techniques like Artificial Intelligence (AI), warranting a deeper systematic study of epistemic emotions in past research. To bridge this gap, we conducted a Systematic Literature Review (SLR) to funnel down some research papers to study before we dived into confusion.

2.7 Planning the Systematic Literature Review

In the planning stage, our goal was to determine the research questions. As discussed in the introduction, emotions drive academic motivation and learners' engagement on online learning platforms, so it is essential to consider emotions while learning happens. Due to the wide range of structured and unstructured data generated on online learning platforms, it is possible to track such emotional patterns online when leveraged with advancements in ML. The following benchmarking has helped form our research question shown in this table:

Table 2-1 Benchmarking

Benchmark	Explanation
Outcome	Learning outcome or academic failure
Methods	Prescriptive and predictive analytics using ML methods or techniques
Scope	Online and hybrid learning platforms

Based on the above benchmarks and research question, we formulated the following criteria for inclusion and exclusion. We acknowledge that our study covered the five epistemic emotions: Confusion, Surprise, Boredom, Curiosity and Frustration because these emotional states are dynamic and interrelated and excluding other emotions will allow us to do a deeper analysis of these five first that can be extended in future. The nature of our study involves advance ML techniques and hence, we scoped the research from past 7 years starting from the most recent papers to the older papers. From the criteria shown in Table

2, we filtered and downloaded 145 papers from databases in learning analytics. To achieve the breadth of research in our systematic literature review and to use a tool that provides us with a range of abilities. We selected NVivo (QSR International) as our research tool to work efficiently and effectively in our systemic literature reviews to achieve better analysis and management of research data. We have used query and visualisation tools from the NVivo tool to achieve the results we report in our work

Table 2-2 Inclusion and Exclusion criteria

Criteria	Inclusion	Exclusion
Keywords	Learning analytics, Epistemic Emotions, Machine Learning	As the keywords evolve, the articles not included in the search list will be disregarded in scope.
Publication dates	2015 - 2022	Not explored outside this range of timeline
Publication Type	Journal articles and conference proceedings	Posters, book chapters, workshop papers, editorials, thesis and reports
Publication Status	Peer–reviewed and full-access papers only	Excluded non-peer-reviewed papers and unavailable papers
Language	English only	Non-English
Databases	ACM Digital, IEEE, SCOPUS	Articles not covered

2.8 Selection of Relevant Papers: PRISMA

This is the most important phase of the SLR as this is where we used PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Liberati et al. 2009) to show our reporting of items in this SLR using the inclusion and exclusion criteria. To conduct the SLR we used the following steps:

1. Set up folders/sub-folders in an NVivo project and import the references from Endnote (you can do it from other software, too, but in this case, we used EndNote).
2. Conduct basic analysis like word cloud to visualise the spread of keywords of the resources.
3. Create Nodes and child nodes based on the hierarchy of research focus.
4. Create Framework Matrix Coding queries to understand the breadth and concentration of our search to see the timeline progress made in the area of emotional learning analytics

PRISMA includes four phases, i.e., identification, screening, eligibility, and inclusion. Fig 2-1 shows the SLR's scope from identification to inclusion.

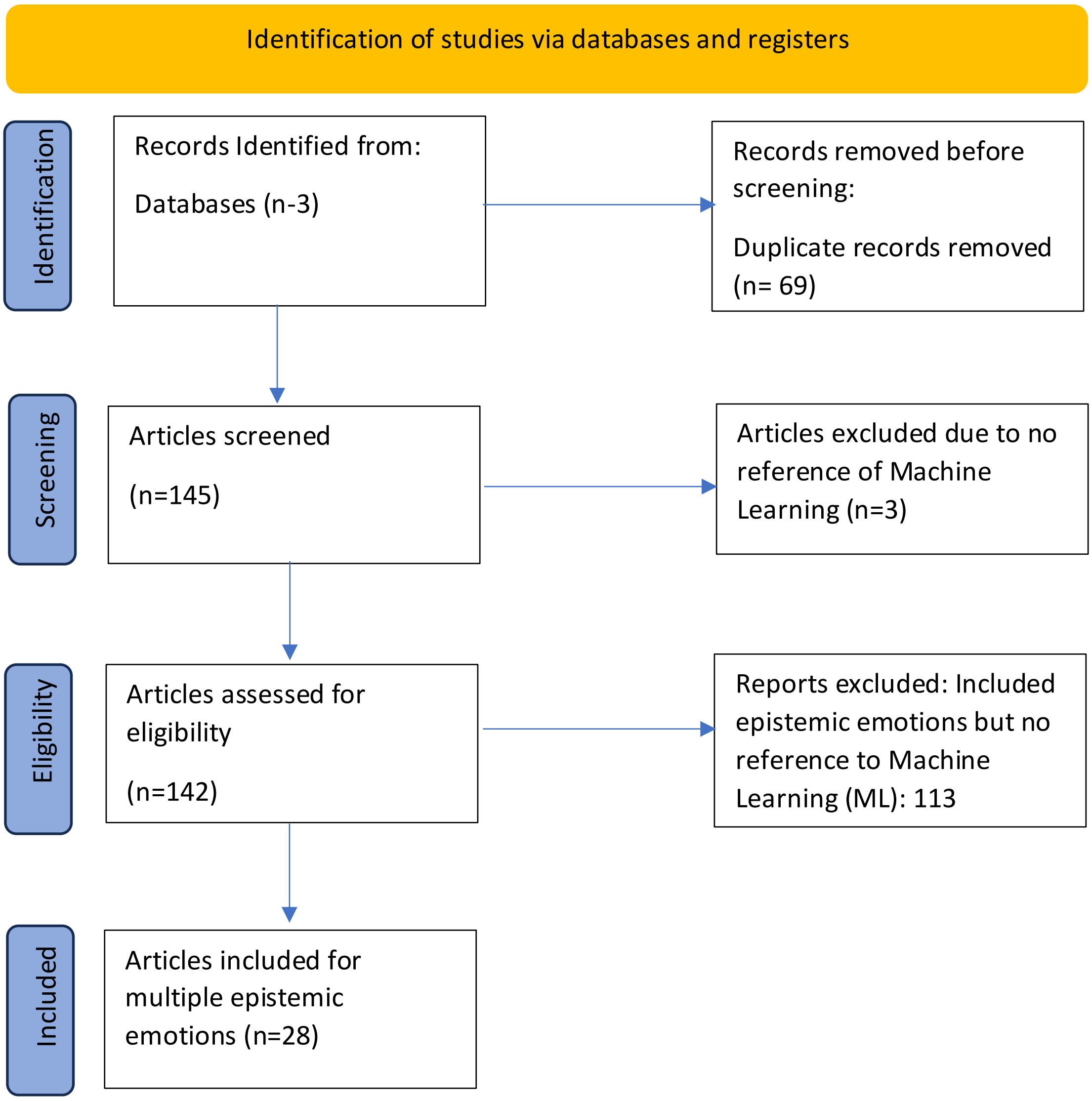

Figure 2-1 Prisma Flow Chart

We started the process by creating a simple word cloud and then created the following root nodes to funnel the papers on various epistemic emotions in different academic settings. The root node for learning analytics and performance as a child node listed 145 papers. Searching for individual epistemic emotions found Boredom (111), Confusion (86), Curiosity (45), Frustration (63), and Surprise (74) papers. Emotional learning analytics with Machine learning as a child node filtered 142 papers.

2.9 Analysis and Synthesis

This section presents the findings based on the analysis of the published case studies. Various empirical studies in emotional learning analytics have attracted a spike in recent years. Some epistemic emotions are studied more than others, with few covering the simultaneous effect of epistemic emotions in learning (e.g., Muis et al. 2015; Pekrun & Linnenbrink- Garcia 2012; Pekrun et al., 2017; Vogl et al., 2020) in terms of their shared antecedents and results. The following tables/heatmaps show how different authors have concentrated their efforts around individual and/or multiple epistemic emotion(s) in the light of LA in the NVivo Tool.

We analysed the papers that contribute to all the emotions under the scope of this study with machine learning. We filtered the papers that mentioned all the epistemic emotions in that process. This qualified 28 of the 141 papers we screened for our research question.

2.10 Discussions of Results

Various techniques and data sets have been used to study various Epistemic emotions from the articles we screened in recent years. Various epistemic emotions have been studied together and individually, and various activity, physiological and other contextual data have been used to detect such emotions, improve positive emotions and reduce negative emotions, and achieve cognitive performance and satisfaction.

2.10.1 Boredom

Boredom in the context of learning analytics using machine learning techniques has been studied by various researchers. A rich learning disposition and activity data were used to understand the motivation behind the active use of LMS, which resulted in high academic performance. Learners with procrastination attitudes were bored and invested less effort in deep understanding. They needed better planning and determination, resulting in boredom (Tempelaar et al., 2017). Boredom is also considered a successive state resulting from prolonged confusion. Successive emotion observations for the same learner in a temporal sequence help detect boredom using a metacognitive strategy (Zhang et al., 2020). Regression-based prediction models used trace data, survey data and assessment data to signalling students with various epistemic emotions, including boredom (Tempelaar et al., 2021). Continuous interaction and designing interactive learning materials is the key to avoiding boredom. Exploring robots in teaching design is the motivation to provide this interaction to avoid boredom in recent years (Hsieh et al., 2020). A deep learning approach has also been employed in the forum discussion of textual data on the MOOC (Massive-Open Online Courses) platform to understand various emotions by considering learners' antecedent and consequence words (Han et al., 2021). Most of the research articles found that boredom is not an initial emotion in the learner; however, a learner may lose interest, which may cause them to lose motivation and eventually become bored. However, boredom can be the final emotion before the learner quits learning. These highlights of the research on boredom shed light on identifying and controlling boredom on time.

2.10.2 Confusion

Confusion has been of interest for a few years now. Confusion can benefit learning if resolved on time. A recent study focused on how Metacognitive strategies relate to confusion. The study used a computer-based learning-by-modelling environment to collect the emotional data and action logs to assess the learning gains by using constructive confusion in learners (Zhang et al., 2021). Researchers have heavily used forum discussion comments to detect and predict confusion on online learning platforms. A newer approach to detect confusion in learners uses hashtags to generate labels reflecting the affective states of students using a rule-based approach. The rules were applied to a large set of comments to generate automatic labels using the bidirectional encoder representation from transformers. The results were promising as the approach was better in detecting confusion and helping the academics work on further interventions (Geller et al., 2021).

2.10.3 Curiosity

Curiosity in learners can be triggered by unexpected events revealing gaps; it has certainly been considered an essential aspect of a positive learning experience. It can promote in-depth learning and help retain memory, too (Marvin & Shohamy, 2016; Middlebrooks et al., 2016; Vogl et al., 2020). Surprise can also mediate curiosity, and both surprise and curiosity can provide positive learning benefits. These emotions can first be triggered by the novelty component in the learning environments (Vogl et al., 2020). Machine learning and deep learning techniques be used to detect such emotions to analyse the benefit of surprise and curious components in learners (Han et al., 2021).

2.10.4 Surprise

Surprise results typically occur when a learner comes across new information that does not align with their previous belief structures. Depending on the kind of information, the learner may adapt to the new information by integrating their existing belief structure or unlearning and creating a new belief structure. Unlike confusion, which involves sustained cognitive conflict and struggle to make sense of information, surprise is often an initial and short-lived emotional reaction to novelty or unexpected outcomes. They may discard the new information because they do not find the value attached to it appropriate (Munnich & Ranney., 2019). Surprise is part of the basic eight emotions. However, it is important to understand surprise from the cognitive-academic lens to explore how effectively surprise can be used to foster better learning. Surprise is known to capture attention and promote curiosity aimed to aid learning and long-term memory retention (Foster & Keane., 2019), backing up the theory that surprise is triggered by an event where a learner cannot explain why that happened (Kahneman & Miller., 1986) and prompts further explanation, and if they do not fully understand the explanation then that may trigger confusion This explanation and exploration aid in better learning; hence, it is vital to consider surprise as an essential epistemic emotion.

In recent years, automatic emotion recognition has been of great interest and includes traditional mood recognition techniques (Deng et al., 2017; Yin et al., 2017; Giatsoglou et al., 2017; Wegrzyn et al., 2017; Kanjo et al., 2015), speech recognition techniques (Deng et al., 2017; Panda et al., 2019), text mining approach (Giatsoglou et al., 2017; Vogl et al., 2020), using facial recognition and physiological techniques (Yin et al., 2017; Wingenbach et al., 2018; Seo et al., 2019; Giatsoglou et al., 2017;), recognising emotions from situational contexts (Salido et al., 2020) and some recent detection methods that use wearable smart devices like smart watches and phones (Kanjo et al., 2015; Politou et. al, 2017). Contextual information can be divided into two categories: the real world and the digital world. The data from such categories can form the context necessary to detect individual and compound emotions. Such data can be collected from various sources like smartphone data, typing behaviour and sensor data and then used to track data using machine learning algorithms like supervised classification to detect such epistemic emotions (Zhang et al., 2018; Salido et al., 2020; Shapsough et al., 2016).

This systematic literature review led us to become interested in Confusion, and we started to dive into research about confusion as an epistemic emotion. We devised ways to detect confusion, worked towards other research questions to detect confusion, and proposed how

AI and other emerging technologies can lead a robust framework of intervention based on confusion detection in learners.

2.11 Confusion – An Epistemic emotion

Confusion is one of learners' most highly affected and concerned epistemic emotions. Confusion is a complex epistemic emotion due to both positive and negative outcomes (Lodge et al., 2018a; Yang et al., 2016; Vilhunen et al., 2022). An affect dynamics model proposes four important epistemic emotions that include engagement, confusion, frustration, and boredom (D'Mello & Graesser, 2014; D'Mello & Graesser, 2012; D'Mello & Graesser 2012), showing the dual impact of confusion. The model establishes an interplay between positive and negative epistemic reactions or outcomes in students triggered by confusion. When learners overcome the confusion, they may feel a sense of achievement with positive learning gains. In contrast, pro-longed confusion can leave a learner frustrated and results in gaps in their learning if it keeps on increasing (Atapattu et al. 2019). It is also found that prolonged frustration and boredom cause possible dropouts and are learners' final emotional states before dropping out (Arguel et al. 2017, Clinton-Lisell 2024). The learners also suffer from low self-efficacy, creating unwanted negative feelings (Caprara et al. 2008). The strategy to handle confusion is as complex as confusion itself, given that it requires a deep understanding of each student's learning journey that considers various factors.

Formally, Confusion can be defined as:

"Confusion results from a cognitive disequilibrium (Almatrafi, Johri & Rangwala 2018, Ma 2023). It is an imbalance created when a learner struggles to understand the new information due to previous knowledge gaps or anomalies (D'Mello & Graesser 2012), and confusion is believed to be triggered due to such cognitive disequilibrium (Lehman, D'Mello & Graesser 2012)."

Confusion is a peculiar epistemic emotion. Some amount of confusion leads to better and positive learning gains, called constructive confusion (Pachman et al. 2016). On the contrary, a prolonged state of confusion leads to adverse reactions like frustration and boredom (Baker et al. 2010; D'Mello & Graesser 2014) also referred to as non-constructive confusion (Pachman et al. 2016). Hence, detecting accurate levels of confusion, ideally at the right time on online platforms, would help in retaining the students (Yang, Kraut & Rose 2016). Literature provides various techniques for productive confusion management (D'Mello & Graesser 2014).

From Figure 2, it can be deduced that confusion acts like a bridging emotion with both positive and negative valence. Hence, it becomes an interesting and important emotion to explore and devise ways to accurately predict confusion in real-time to prevent unwanted outcomes due to confusion. This is will also help to understand the interplay of engagement and confusion Vs frustration and confusion and their role in positive or negative learning gains. Furthermore, in preventing the negative outcomes of confusion, various Intervention techniques are also investigated (Baker et al. 2010; Chandrasekaran et al. 2015; Lehman, D'Mello & Graesser 2012; Pachman et al. 2016). Such intervention strategies may be beneficial to keep the confusion levels under the thresholds of the zone of optimal confusion, where this emotion is found to be most productive in learning and could generate positive learning gains (Arguel & Lane 2015; D'Mello et al. 2014).

However, such interventions can only be established if we have a deep understanding of the exact zone of optimal confusion and then detect levels of confusion (Lehman, D'Mello & Graesser 2012) that can help predict retention (Yang, Kraut & Rose 2016).

To effectively predict and manage confusion, it is essential to understand the optimal zone of confusion where it can be most beneficial for learning (Jaber et al., 2023). While traditional methods like posture tracking, eye tracking, and facial feature analysis have been used to detect confusion, newer approaches focus on leveraging learners' interaction data from online platforms to predict confusion levels more efficiently and cost-effectively (Nakamura et al., 2022).

Many device-dependent approaches use posture tracking (D'Mello & Graesser 2009), eye tracking (DeLucia et al. 2014; Pachman et al. 2016), facial features (McDaniel et al. 2007), and other audio-visual expressions (Zeng et al. 2009) have also been exploring. However, most of these models are expensive to implement due to the requirements of purpose-specific equipment and lack complete expertise and requiring some form of human intervention in understanding the emotion and can only be deployed experimentally under observed environment. That is why such methods cannot be easily implemented on large-scale digital platforms like MOOCs, Moodle, and others. Hence, given the importance of confusion in learning, it becomes important to research novice approaches to predict confusion that is less resource intensive by exploiting learners' interaction data generated from the activity logs on such online learning platforms (Mulqueeny et al. 2015).

To begin with, confusion detection can start with learners who participate in forum discussions on MOOC platforms. Their participation text has been understood using basic bags of words and meta information (Agrawal et al. 2015) as well as using Support Vector Machines (SVM) (Bakharia 2016), however, has been counter backed for being very domain-specific (Atapattu et al. 2019). A content-based and community-related feature used in another study achieved better accuracy even in cross-domain experimentations, also determined that bags-of words and question marks in the posts were strongly related to confusion (Zeng, Chaturvedi & Bhat 2017). Lexical analysis was also experimented with to study various epistemic emotions, including confusion in a student-tutor dialogue environment (D'Mello & Graesser 2012). All these approaches need students to participate actively in forums and discussions to understand the patterns in detecting confusion. Given confusion can affect learning both positively and negatively, and it is important to detect the confusion level for all learners, regardless they are active on forums to help manage their levels of confusion.

A consolidative approach using both click-stream patterns and forum participation was deployed to detect the confusion on two MOOC courses producing good accuracy. The study explored the popular patterns in learners when confused most, regardless of their participation in forum discussions (Yang, Kraut & Rose 2016). Even when the scope of this study was MOOCs, the study still provides insight into learners' behaviour when confused on an online learning platform, which can be critical regardless of the mode of study.

2.12 Role of Confusion in Academic Success

As discussed, confusion is a multifaceted epistemic emotion that significantly influences students' learning process and academic success. Given that confusion is a complex emotional state that can have both positive and negative outcomes on learners' educational journey, understanding the role of confusion in academic success requires delving into its dynamics, impact on learning outcomes, and strategies to manage it effectively.

Detecting and managing confusion levels in real-time is crucial, given our understanding that prolonged confusion can lead to frustration in learners and ultimately contribute to academic failure, particularly in online learning platforms. Thus, to improve learner retention and enhance learning outcomes (Audrin & Coppin, 2022) for better academic success, detecting confusion at the right time and managing the confusion with appropriate intervention strategies will ultimately improve the learner's academic success. To predict and manage confusion effectively, educators need to understand the optimal zone of confusion where it can be most beneficial for learning. Educators need to evaluate students' progression in cognitive activities by considering confusion as an essential factor in their learning journey (Vilhunen et al., 2022). Educators can facilitate more efficient learning and higher task engagement by objectifying and understanding the occurrence of confusion and factors that regulate it effectively (Vilhunen et al., 2022). Moreover, confusion resolution can be influenced by students' abilities to apply metacognitive strategies, highlighting the importance of metacognition in addressing confusion and enhancing learning outcomes (Dorak et al., 2014).

Confusion is pivotal in academic success as it influences students' learning experiences and outcomes. Educators must recognise the complexity of confusion as an epistemic emotion and implement strategies to manage it effectively. Educators can create a conducive learning environment that promotes positive academic success by leveraging innovative approaches and understanding the interplay between confusion, learning outcomes, and metacognitive strategies.

Emerging technologies, particularly AI and generative AI, offer exciting possibilities for enhancing emotional learning analytics. AI can analyse vast clickstream data in real-time, providing insights into learners' emotional states and engagement levels. For instance, AI algorithms can detect patterns of confusion and trigger adaptive interventions, such as suggesting additional resources or modifying instructional strategies (Muñoz et al., 2020). Generative AI, on the other hand, can create personalised learning experiences that adapt to learners' preferences. By analysing learners' interactions and emotional responses, generative AI can generate tailored content that addresses specific areas of confusion. For example, if a learner struggles with a particular concept, Generative AI can provide alternative explanations, examples, or practice problems Moreover, AI-driven chatbots can offer immediate support to learners experiencing confusion, providing real-time answers to questions and guiding them through challenging material. This immediate feedback loop can help alleviate confusion and promote a sense of agency in learners, ultimately enhancing their academic success.

2.13 Conclusion

Confusion is a complex yet integral part of the learning process that can significantly impact academic success. By leveraging clickstream data to detect and predict confusion patterns and harnessing AI's and generative AI's power, educators can develop effective strategies to manage confusion. Establishing a holistic framework for emotional learning analytics will empower educators to create adaptive learning environments that support learners in navigating confusion, ultimately setting them on a path to academic success. The next two chapters cover the confusion detection and pattern recognition studies of confused learners.

The final chapter then proposes a holistic framework that utilises these proposed confusion detection, pattern recognition and Generative AI tools for a better meaningful intervention for confused learners to set up such learners for academic success.

Chapter 3: Confusion Detection

3.1 Overview

This chapter explores the critical role of clickstream data analytics in enhancing confusion detection among learners during online activities, particularly quizzes. The studies presented herein demonstrate how advanced analytical techniques, including fuzzy logic and machine learning algorithms, can identify and address confusion in real-time. In the first study, we established a fuzzy logic inference system that utilises clickstream data to assess confusion levels based on parameters such as topic browsing, forum browsing, productivity, performance, and question difficulty. This approach allows for a nuanced understanding of learners' emotional states, enabling timely interventions to support those struggling. In the second study, we expanded our investigation by incorporating additional features related to quiz behaviour and performance. By analysing time taken per question, question difficulty, and outcomes, we employed a Multi-Layer Perceptron (MLP) neural network to predict confusion levels more accurately. This study highlights the potential of machine learning classification algorithms to process large volumes of data efficiently, providing educators with actionable insights into students' emotional states. Together, these studies underscore the importance of leveraging clickstream data analytics and AI technologies to improve confusion detection, ultimately enhancing the learning experience in online environments.

This chapter builds on the work presented in my two published papers, both of which directly contribute to addressing the research question: **"How can clickstream data analytics be enhanced using AI to improve confusion detection in learners during online activities or assessments like quizzes?".** Through these studies, I explore how AI techniques can be applied to clickstream data to detect learner confusion.

The publications that form the foundation of this research are:

5. Samani, Chaitali & Goyal, Madhu. (2021). Modelling Student Confusion Using Fuzzy Logic in e-Learning Environments. 10.1007/978-981-16-3246-4_50.

6. Samani, Chaitali & Goyal, Madhu. (2021). Confusion detection using neural networks. 1-6. 10.1109/CSDE53843.2021.9718422.

3.2 Study 1: Confusion Detection Using Fuzzy Logic

3.2.1 Introduction

As students navigate complex learning environments, particularly online, confusion can arise from various sources, including cognitive dissonance and the challenge of reconciling new information with existing knowledge. While confusion can sometimes stimulate curiosity and deeper learning, prolonged confusion often leads to frustration and disengagement, ultimately impacting students' academic performance. Despite its importance, the detection and management of confusion in educational contexts remain underexplored, particularly in the realm of online learning. This study aims to address this gap by proposing an approach that utilizes fuzzy logic techniques to detect confusion levels based on learners' clickstream data during online quizzes. By leveraging the interactive nature of quizzes, we argue that analysing clickstream behaviour can provide valuable insights into learners' confusion levels, akin to the intuitive assessments made by experienced educators in face-to-face classrooms.

Fuzzy logic has been investigated to represent a teacher and learner-assisted evaluation system based on imprecise information and applying a membership function to linguistic labels for fuzzy reasoning (Hawkes & Derry 1996; Hawkes, Derry & Rundensteiner 1990). Fuzzy logic has been used to formulate, represent, and analyse individual learners' behaviour (Beck, Stern & Woolf 1997) and group behaviour (Barros & Verdejo 2000; Redondo et al. 2003). Early works on Fuzzy logic included an inference of learner's knowledge level and cognitive characteristics using membership functions (Mihalis & Maria 1995). Data-driven fuzzy rule induction and inference mechanisms were investigated to evaluate student's academic performance (Rasmani & Shen 2006).

Fuzzy logic has been studied from various aspects in Fuzzy models' design for learning to represent learners' cognitive and knowledge abilities (Di Lascio, Gisolfi & Loia 1998; Hogo 2010; Xu, Wang & Su 2002). Despite such vague concepts under investigation, Fuzzy logic has been successful in producing reliable results. However, while much research exists in utilising Fuzzy logic e-learning systems, little attention has been paid to investigating Fuzzy logic in epistemic emotions. This research posits that fuzzy logic, with its ability to handle vagueness and uncertainty, can effectively quantify human-like judgments regarding confusion, thereby offering a robust framework for developing targeted interventions to enhance learners' academic success. Through this exploration, we aim to contribute to the growing body of literature on emotional learning analytics and the application of fuzzy logic in educational contexts.

3.2.2 Detailed Study

While various methods have been employed to detect confusion in online learning environments, including clickstream data analysis, sentiment analysis, and self-reporting mechanisms, these approaches often fall short of capturing the nuanced and dynamic nature of epistemic emotions. In particular, the application of fuzzy logic in detecting epistemic emotions like confusion has not been thoroughly explored, presenting an opportunity for more adaptable detection mechanisms. Confusion is the central factor in learning, and due to its complex impact on a learner's future affective states, it becomes an important factor to explore.

This study explores the potential of using Fuzzy logic techniques to detect confusion levels to address this gap. During the sessions, the learners' clickstream data can be deemed most interactive, even when it is shorter than the time, they spend browsing the course pages. We argue that learners' behaviour is most engaging when taking online quizzes as a part of their assessment. The clickstream behaviour of a learner can help detect the underlying Confusion using a Fuzzy logic inference system despite supporting the vagueness and the potential to quantify human-like judgment.

We begin by postulating that the most effective way to determine if someone is confused is usually from the questions, they ask their instructors, as question-asking often reflects underlying knowledge gaps or cognitive disequilibrium (Graesser & Person, 1994; Chin & Osborne 2008). This learner-instructor communication may be missing on online learning platforms, and even if it is present, it may not be as instant in face-to-face classrooms. Not ignoring that face-to-face also comes with the benefit of body language observations that experienced teachers use in their face-to-face sessions to determine a possible level of Confusion and change their class discourse accordingly. Simultaneously, as discussed in the earlier section, multi-modal information used in Confusion detection may not have the potential to become a pervasive approach on online platforms, given various constraints.

Such platforms may benefit from a powerful prediction technique like Fuzzy logic by detecting a learner's confusion level when taking the quiz. We propose that attempting the quiz online is the most engaging activity that a learner will do online. Click-stream data generated over that period can provide some meaningful insights.

Yang et. al (2016) describe top ten ranked clicked patterns using Exact Pattern Mining method with possible Confusion in two students' group: Students with posts on Forum and students without any posts. They found that both the groups have similar click patterns on MOOC on two courses. That raises us with a hypothesis that if we used the parameters from these highly ranked click patterns and feed to a Fuzzy logic inference system, we would map the learner's confusion level just like an experienced teacher would map in their mind in a face-to-face classroom session.

The proposed Confusion model is based on the above-discussed click patterns. The model comprises factors like Topic browsing, Forum browsing, Productivity, and Performance while the learner is attempting the quiz online. With these parameters, we also propose that the quiz difficulty level may further refine the results in determining the levels of Confusion.

Table 3-1 - Confusion Parameters

Parameter	Explanation
Topic browsing	TB(x) = {very low, low, medium, high, very high}c . The value of this parameter is pre-determined. This parameter's value is pre-determined and is the number of times a learner visits any learning materials page while attempting the quiz.
Forum browsing	FB(x) = {very low, low, medium, high, very high}. The value of this parameter is pre-determined and is the number of times a learner visits the Forum discussion page while attempting the quiz.
Productivity	PRO(x) = {very low, low, medium, high, very high}. The value of this parameter describes how long the learner took to complete the quiz. The range is pre-determined.
Performance	PER(x) = {very low, low, medium, high, very high}. The value of this determines a learner's raw marks, and level ranges are pre-determined.
Level	L(x) = {very low, low, medium, high, very high}. The value of this parameter indicates the level of the question, considering very low to be the easiest questions to very high to be advanced questions. The level is pre-determined at the time of designing the quiz.

Fuzzy logic has been studied from various aspects in Fuzzy models' design for learning to represent learners' cognitive and knowledge abilities (Di Lascio, Gisolfi & Loia 1998; Hogo 2010; Xu, Wang & Su 2002). Fuzzy logic has successfully produced reliable results despite such vague concepts under investigation. However, while much research exists on utilising fuzzy logic e-learning systems, little attention has been paid to investigating fuzzy logic in epistemic emotions like confusion. Confusion is the central factor in learning, and due to its complex impact on a learner's future affective states, it becomes an important factor to explore.

Our work investigates the potential of using Fuzzy logic techniques to detect confusion levels to address this gap. During the sessions, the learners' clickstream data can be deemed most interactive, even when it is shorter than the time they spend browsing the course pages. We argue that learners' behaviour is most engaging when taking online quizzes as part of their assessment.

The clickstream behaviour of a learner can help detect the underlying Confusion using a Fuzzy logic inference system despite supporting the vagueness, the potential to quantify human-like judgment. For the first study Fuzzy-logic technique is investigated to predict the confusion level because the fuzzy logic inference system can be improved, considering the criteria chosen and their levels to incorporate subjectivity brought from various subjects. Also, Confusion is an epistemic emotion, and to measure such concepts, we need a model that supports inferring such abstraction, be meaningful, and at the same time be implemented pervasively using some web technologies.

A typical Fuzzy logic system has three components: Fuzzifier, Rule-based inference, and De-fuzzifier. The process involves membership functions, fuzzy logic operators, and If-Then rules that determine various input parameters' values to a fuzzified value from the Universe of Discourse. Then If-Then rules identify a de-fuzzified output value in the output Universe of discourse that is then converted to a crisp value as an output using De-fuzzification (McNeill, 1994). Detecting the clickstream log data along with the performance data can help detect the level of Confusion. Given the two-folded impact on Confusion, it requires great attention to detect Confusion's optimum zone (Arguel et al. 2017). Hence it may be beneficial to use a comprehensive prediction technique that is easy to apply via a web interface. Such a Fuzzy-logic prediction system can be attached to any quiz assessment to detect the confusion level to help design intervention strategies around it.

Figure 4 suggests the overall proposed Confusion detection in learners using Fuzzy-logic System.

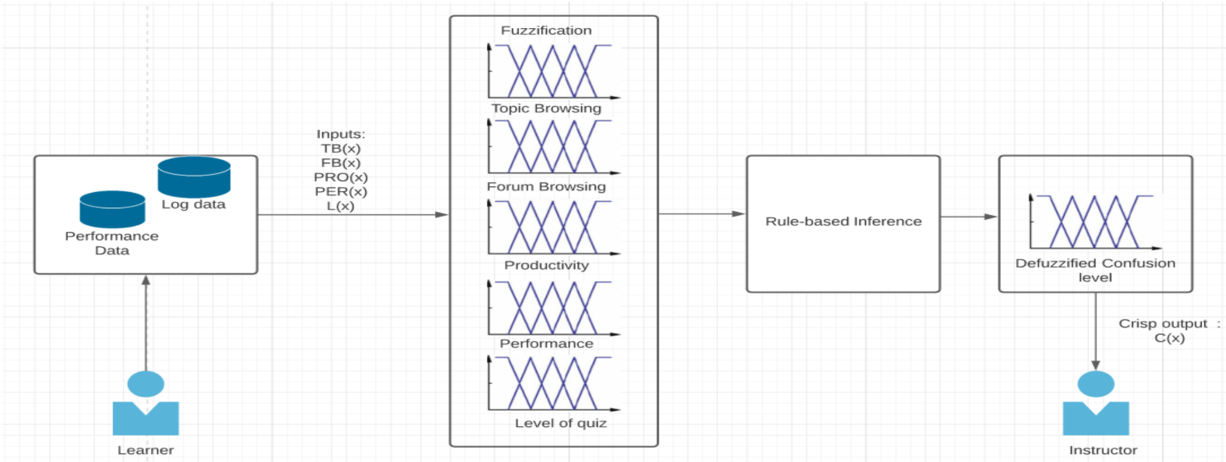

Figure 3-1 Confusion detection using fuzzy logic

Figure 3-1 shows the Triangular membership function for all parameters in percent as an input with a range of 5 values. The ranges are scaled to percent depending on how they are calculated.

For example, the set TB(x) = {very low, low, medium, high, very high} compares the number of times the learner browsed the course pages while attempting the quiz, with the average click-pattern of other learners as a group and determines a percentage.

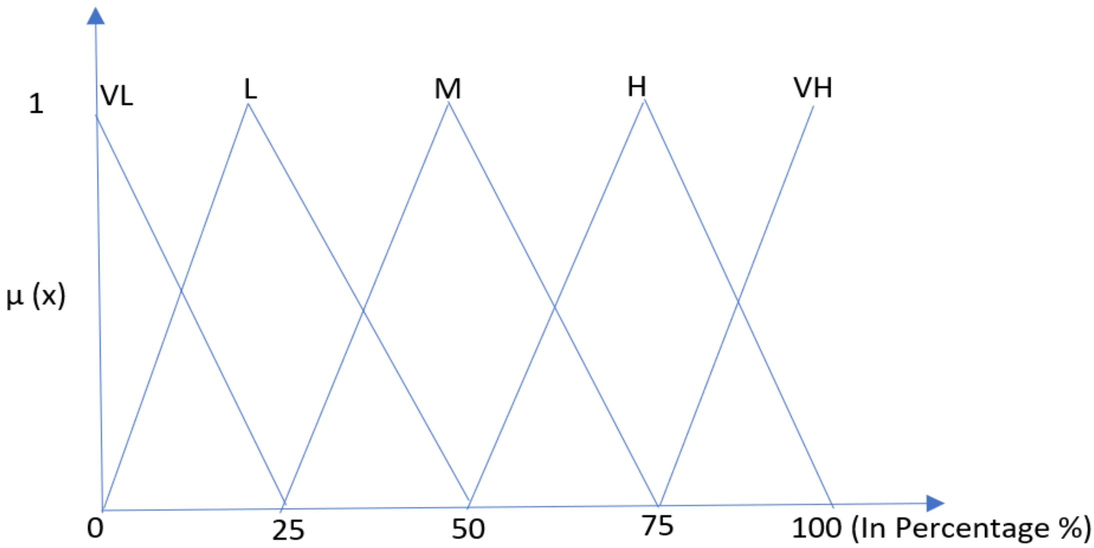

Figure 3-2 Input Parameters triangular function

All input parameters are five linguistic variables: {very low, low, medium, high, very high}.

Furthermore, Figure 3-3 shows the Membership functions for all the input parameters:

$$\mu_{vL}(x) = \frac{25 - x}{25} \qquad 0 \le x \le 25 \tag{1}$$

$$\mu_{L}(x) = \frac{x}{25} \qquad 0 \le x \le 25$$

$$= \frac{50-x}{25} \qquad 25 \le x \le 50 \tag{2}$$

$$\mu_{M}(x) = \frac{x - 25}{25} \qquad 25 \le x \le 50$$

$$= \frac{75-x}{25} \qquad 50 \le x \le 75 \tag{3}$$

$$\mu_{H}(x) = \frac{x - 50}{25} \qquad 50 \le x \le 75$$

$$= \frac{100 - x}{25} \qquad 75 \le x \le 100 \tag{4}$$

$$\mu_{vH}(x) = \frac{x - 75}{25} \qquad 75 \le x \le 100 \tag{5}$$

Figure 3-3 Membership functions

The inference Engine will store all the possible combinations in the form of if-then statements, and the output from the combination will be denoted as C(x) as a value in percentage derived from a possible set of confusion levels: {very low, low, medium, high, very high} using Mamdani Method.

Below are some examples of such rules defined in the Inference engine to determine the Confusion level:

[Rule 1]

```
if (TB(x) == 'high'&& FB(x) == 'high'&& PRO(x) == 'low'&& PER(x)
== 'medium'&& L(x) == 'low') then:

          C(x) == 'very high'
```

[Rule 2]

```
if (TB(x) == 'low'&& FB(x) == 'medium'&& PRO(x) == 'low'&& PER(x)
== 'medium'&& L(x) == 'low') then:

          C(x) == ‘high’
```

[Rule 3]

```
if (TB(x) == 'low'&& FB(x) == 'low'&& PRO(x) == 'high'&& PER(x)
== 'medium'&& L(x) == 'low') then:

          C(x) == ‘low’
```

[Rule 4]

```
if (TB(x) == 'low'&& FB(x) == 'low'&& PRO(x) == 'very high'&&
PER(x) == 'very high'&& L(x) == 'low') then:

          C(x) == 'very low'
```

3.2.3 Details of rules

Rules for "Very High" Confusion

1. If TB(x) == 'high' && FB(x) == 'high' && PRO(x) == 'low' && PER(x) == 'medium' && L(x) == 'low', then: C(x)=='veryhigh' C(x) == 'very high' C(x)=='veryhigh'
2. If TB(x) == 'very high' && FB(x) == 'high' && PRO(x) == 'low' && PER(x) == 'low' && L(x) == 'low', then: C(x)=='veryhigh' C(x) == 'very high' C(x)=='veryhigh'
3. If TB(x) == 'high' && FB(x) == 'very high' && PRO(x) == 'low' && PER(x) == 'medium' && L(x) == 'low', then: C(x)=='veryhigh' C(x) == 'very high' C(x)=='veryhigh'
4. If TB(x) == 'very high' && FB(x) == 'very high' && PRO(x) == 'very low' && PER(x) == 'low' && L(x) == 'medium', then: C(x)=='veryhigh' C(x) == 'very high' C(x)=='veryhigh'

Rules for "High" Confusion

1. If TB(x) == 'low' && FB(x) == 'medium' && PRO(x) == 'low' && PER(x) == 'medium' && L(x) == 'low', then: C(x)=='high' C(x) == 'high' C(x)=='high'
2. If TB(x) == 'medium' && FB(x) == 'high' && PRO(x) == 'medium' && PER(x) == 'low' && L(x) == 'medium', then: C(x)=='high' C(x) == 'high' C(x)=='high'
3. If TB(x) == 'high' && FB(x) == 'medium' && PRO(x) == 'medium' && PER(x) == 'low' && L(x) == 'low', then: C(x)=='high' C(x) == 'high' C(x)=='high'
4. If TB(x) == 'medium' && FB(x) == 'medium' && PRO(x) == 'low' && PER(x) == 'medium' && L(x) == 'medium', then: C(x)=='high' C(x) == 'high' C(x)=='high'

Rules for "Medium" Confusion

1. If TB(x) == 'medium' && FB(x) == 'medium' && PRO(x) == 'medium' && PER(x) == 'medium' && L(x) == 'medium', then: C(x)=='medium' C(x) == 'medium' C(x)=='medium'
2. If TB(x) == 'low' && FB(x) == 'medium' && PRO(x) == 'medium' && PER(x) == 'medium' && L(x) == 'medium', then: C(x)=='medium' C(x) == 'medium' C(x)=='medium'

3. If TB(x) == 'medium' && FB(x) == 'low' && PRO(x) == 'medium' && PER(x) == 'medium' && L(x) == 'medium', then: C(x)=='medium' C(x) == 'medium' C(x)=='medium'
4. If TB(x) == 'medium' && FB(x) == 'medium' && PRO(x) == 'high' && PER(x) == 'low' && L(x) == 'low', then: C(x)=='medium' C(x) == 'medium' C(x)=='medium'

Rules for "Low" Confusion

1. If TB(x) == 'low' && FB(x) == 'low' && PRO(x) == 'high' && PER(x) == 'medium' && L(x) == 'low', then: C(x)=='low' C(x) == 'low' C(x)=='low'
2. If TB(x) == 'low' && FB(x) == 'low' && PRO(x) == 'high' && PER(x) == 'high' && L(x) == 'medium', then: C(x)=='low' C(x) == 'low' C(x)=='low'
3. If TB(x) == 'low' && FB(x) == 'medium' && PRO(x) == 'medium' && PER(x) == 'medium' && L(x) == 'high', then: C(x)=='low' C(x) == 'low' C(x)=='low'
4. If TB(x) == 'low' && FB(x) == 'low' && PRO(x) == 'very high' && PER(x) == 'medium' && L(x) == 'high', then: C(x)=='low' C(x) == 'low' C(x)=='low'

Rules for "Very Low" Confusion

1. If TB(x) == 'low' && FB(x) == 'low' && PRO(x) == 'very high' && PER(x) == 'very high' && L(x) == 'low', then: C(x)=='very low' C(x) == 'very low' C(x)=='very low'
2. If TB(x) == 'very low' && FB(x) == 'very low' && PRO(x) == 'very high' && PER(x) == 'very high' && L(x) == 'very high', then: C(x)=='very low' C(x) == 'very low' C(x)=='very low'
3. If TB(x) == 'very low' && FB(x) == 'very low' && PRO(x) == 'high' && PER(x) == 'high' && L(x) == 'high', then: C(x)=='very low' C(x) == 'very low' C(x)=='very low'
4. If TB(x) == 'low' && FB(x) == 'low' && PRO(x) == 'high' && PER(x) == 'high' && L(x) == 'very high', then: C(x)=='very low' C(x) == 'very low' C(x)=='very low'

The motivation behind Rule 1 is that if a student must take a lot of assistance with low productivity and performance on low-level questions, the underlying level of Confusion is high and needs to be addressed soon before it frustrates the learners leading them to give up on the course, but as per Rule 4 the student is performing very well on low-level questions without any assistance, then the underlying level of confusion is very low, and the student will likely keep learning on the course.

Confusion in Percent will be calculated based on the simple yet powerful Mamdani Method (centroid) after calculating the maximum of all the input variables' minimum values. The maximum value will then be substituted for the output Membership function. The membership function's aggregate value will be the final output as a percent of the learner's confusion.

$$\mu\_R\ c(x) = \max\left[\min\left(\mu\_TB\ (x), \mu\_FB\ (x), \mu\_PRO\ (x), \mu\_PER\ (x), \mu\_LEV\ (x)\right)\right]$$

The crisp value of confusion level is calculated the Mamdani(Centroid) method. In the simplest form, consider that out of five factors. Currently, two factors: Topic Browsing (TB(x)) and Performance (PER(x)) are known to be 80% and 40%, respectively. With these two factors, if we apply the membership functions, we end up with the following values:

```
Min(4/5,2/5)  = 2/5 (Topic Browsing HIGH and Performance LOW)
```

```
Min(4/5,3/5) = 3/5 (Topic Browsing HIGH and Performance
MEDIUM)
```

```
Min(1/5,2/5) = 1/5 (Topic Browsing VERY HIGH and Performance
LOW)
```

```
Min(1/5,3/5) = 1/5 (Topic Browsing VERY HIGH and Performance
MEDIUM)
```

Hence, from the above 4 rule inferences, the maximum strength is 3/5. According to our Rule 1, when TB is 'HIGH' and Performance is 'MEDIUM', we are assuming the Confusion level to be 'VERY HIGH.'

Finally, by substituting 3/5 to the membership functions of the output variable, we will get two values of Confusion: 90 and 85. Since we are using the Centroid method, our final Confusion level will be:

$$\mu_C(x) = (90+85)/2 = 87.5\% \text{ (Very high)}$$

Hence, the final level of Confusion corresponds to 87.5%, which is very high and may indicate some intervention to avoid dropout. The other factors have been disregarded just to show a simplified version of derivation, but the model with all the factors under consideration will give more confidence in the confusion level calculation.

3.3 Study 2: Confusion detection using Neural Networks

3.3.1 Introduction

The framework for confusion detection presented in this study focuses on analysing students' responses to quiz questions and their corresponding behaviours in relation to their peers. By comparing individual performance metrics against cohort averages, we can derive meaningful insights into the levels of confusion experienced by learners. The input features selected for this analysis—time taken per question, question difficulty level, and outcome—provide a comprehensive view of the factors influencing confusion. Normalizing the time taken for each question against cohort performance allows for a more accurate assessment of a student's engagement and understanding. Moreover, this study employs machine learning classification algorithms, specifically Multi-Layer Perceptron (MLP), to predict confusion levels in real-time as students submit their quizzes. MLP's ability to handle large volumes of data and produce real-time results makes it an ideal candidate for this analysis. By identifying patterns in quiz behaviour and performance, we aim to develop a robust model that not only detects confusion but also informs educators about the specific needs of their students. This proactive approach to confusion detection has the potential to enhance support mechanisms within online learning platforms, ultimately leading to improved academic outcomes.

3.3.2 Detailed Study

In the second study, we extended our previous findings by considering some other features. We also offer an opportunity to create a flag for students who are most likely struggling. Such flags can be used to make decisions about improving student support. Figure 3-4 shows the framework used in confusion detection. The online platform generates log and performance data as students interact and attempt course quizzes. In this study, we explore a few features as inputs for quiz attempts to detect the level of confusion in students, and online learning platforms can produce a large volume of such data.

In this study, we are specifically interested in studying the quiz questions that students go through. Based on their responses and attempt behaviour compared to the other students' performances on the same questions, we predict the levels of confusion. Hence, the next stage is to decide which factors to consider as input and impact the final level of confusion.

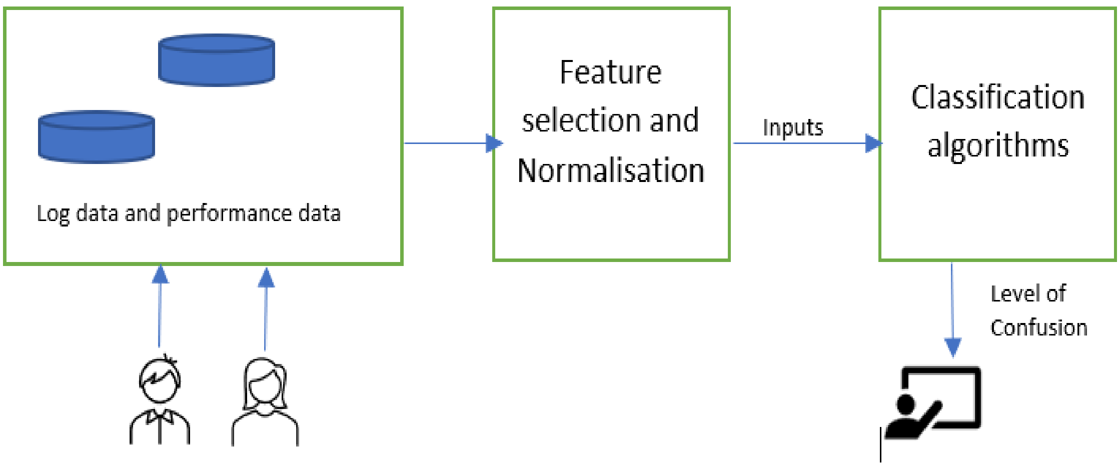

Figure 3-4 Framework of confusion detection

In this study, we consider the following inputs(x):

- **Time-Taken:** For question, the individual question time-taken is normalised between 0 and 1 based on the individual performance for that questions compared to the cohort performance. Also, it is a common practice to normalise the input data leading to better performances due to gradient descent converges faster on normalised data.
- **Question-Level**: Each question gets a level: Easy(1), Intermediate(2) and Difficult(3) based on the average time taken by the group for that question based on the following rules:

```
If 'Time-Taken'<= 1/3(MaxTime – MinTime) then Level = '1' (Easy)

If 'Take-Taken'> 1/3(MaxTime – MinTime) and 'Time-Taken'<=2/3(MaxTime- MinTime) then Level = '2' (Intermediate)

If 'Time-Taken'> 2/3(MaxTime-MinTime) then Level = '3'(Difficult)
```

The assumption here follows the normal frequency bell curve and labels a question as 'Easy' if the average time is less than 1/3rd of the range of time for the quiz because, on average, the students found the question easy and were able to attempt it faster, while the question is difficult if the average time stretched higher than 2/3rd of the range.

- **Outcome:** The outcome for each question is either Correct (1) or Incorrect (2). Here, we have assumed that the question is either correct or incorrect.

The following table depicts the list of features used in this study:

Table 3-2 Input parameters for confusion detection

Feature	**Description**	**Possible values**
Time-Taken	Normalised values of the time taken by the student per question-based on the cohort performance	Normalised values between 0 and 1
Question Level	The level of the question determined based on the cohort performance	1 = Easy 2 = Intermediate 3 = Difficult
Outcome	The outcome is the result of the question of whether the student got it correct or not	1 = Correct 2 = Incorrect

As discussed in Study 1, Fuzzy logic has been studied in e-learning settings to address various needs, features and contexts. AI techniques like fuzzy logic have been widely applied in various domains, including educational data mining. These techniques are investigated due to their ability to adapt and deal with vagueness where elements belong to a category rather than exact values resulting in human-like judgments (Guijarro-Mata-García, Guijarro & Fuentes-Fernández 2015). Fuzzy logic has been investigated to represent a teacher and learner-assisted evaluation system based on imprecise information and applying a membership function to linguistic labels for fuzzy reasoning (Hawkes & Derry 1996; Hawkes, Derry & Rundensteiner 1990). Fuzzy logic has been used to formulate, represent, and analyse individual learners' behaviour (Beck, Stern & Woolf 1997) and group behaviour (Barros & Verdejo 2000; Redondo et al. 2003). Early works on Fuzzy logic included an inference of learner's knowledge level and cognitive characteristics using membership functions (Mihalis

& Maria 1995). Data-driven fuzzy rule induction and inference mechanisms were investigated to evaluate student's academic performance (Rasmani & Shen 2006).

In this study we extended the features by understanding the learners quiz behaviour with respect to the whole cohort of learners who attempted the quiz. Study 2 explored fuzzy logic further with neural network algorithms that can thrive on larger volumes of data with fewer resources and something easier to experiment with. The next section discusses further on how MLP was used in predicting the levels of confusion at the end of the quiz. The features discussed in the previous section are considered, and the output (y) is the level of confusion where 0 – "low confusion," 1 – "medium confusion," and 2 – "high confusion."

In the second study, we extended our study in investigating the potentials of using Machine Learning Classification algorithms to detect the level of confusion in real-time when the quiz is submitted by the student online. In this study, we selected to study the performance and tuning on neural network algorithms like multi-perceptron because the algorithm thrives on larger volumes of data with fewer resources and can be easily used to produce real-time results.

In this study, we focus on Multi-Layer Perceptron (MLP), an evolutionary supervised learning algorithm that brings in the advantage of learning models in real-time.

MLP learns a function: $f(^{o}) : R_m \longrightarrow R_o$

Where R_m is the set of input features with m defined as the number of dimensions for input features and R_o is the set of output features with o defined as the number of dimensions for output.

In MLP, the left-most layer is known as the input layer containing the set of neurons $\{x_i | x_1, x_2 \ldots x_m\}$ and at the rightmost layer is the target y or the output layer. The input and output layers contain one or more non-linear layers, and they are called hidden layers. Each neuron from the input layer transforms the values to the next layer with a weighted linear summation followed by some non-linear activation function $g(^{o})$: R -> R, for example, hyperbolic function. The output layer accepts the values from the last hidden layer and transforms into the output value. Each layer has a list of weight matrices with an index i representing the weights between layer i and (i + 1), and the bias vectors add the bias vector values in the next layer (i +1) based on the non-linear function selected.

The intermediate nodes use the sigmoid function:

$$f(z_i) = \frac{1}{1 + e^{-z_i}}$$

And the goals of MLP are:

- To derive an approximate function f∗. A feedforward network defines a mapping y=f(x;θ) where θ is the learned value of the parameters (Time-Taken, Level of question, and Outcome) that result in the best function approximation.

- The function f is composed of a chain of functions:

  $f=f^{(k)}(f^{(k-1)}(\ldots f^{(1)}))$ where f(1) is called the input layer, and so on. The **depth** of the network is k. The final layer of a feedforward network is the output layer that, in our case, will be the level of confusion detected.

The capability to learn from non-linear layers makes them appropriate for real-time learning for our study. However, MLP may require tuning several hyperparameters and experimentation to explore its usability in our study.

We used Apache spark for our synthetic data set and studied the performance of Multi-Layer Perceptron (MLP) using a synthetic dataset for about 520 records of the attempts. To detect the levels of confusion in a student, we considered the normalised time-taken on each question, level of the question, and the outcome of that question. The levels of confusion will be labelled for each question giving an opportunity to tag more features in the future to make this decision more comprehensive.

There are three levels of confusion considered in this study: Low, Medium, and High produced as output. It is assumed that the student who gets a lot of questions under the 'Medium' level need some attention to retain them for a long time; however, the student who gets a lot of questions under the 'High' level is deemed to be struggling and need urgent attention for some effective intervention strategies.

With a few iterations on tuning the number of hidden layers and the number of neurons in each of the hidden layers, we got about 95% accuracy with 2 hidden layers and 6 neurons on each layer.

We evaluated our results against the other two popular Classification models, Naïve Bayes and the Decision tree as below:

Table 3-3 Comparisons between MLP, NB and Decision Tree

Metric Name	MLP	Naïve Bayes	Decision Tree
Accuracy	0.957	0.628	0.943
Recall by Label	0.956	1.0	0.956

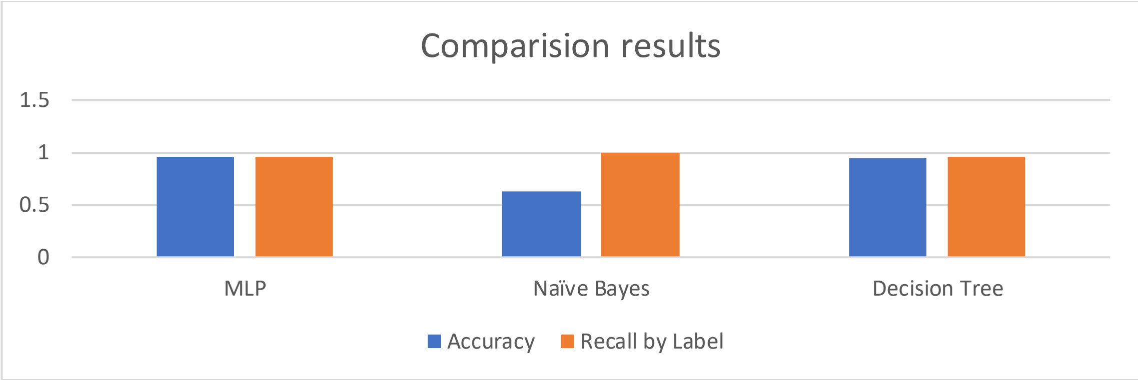

Figure 3-5 Graphical representations on comparison results

3.4 Conclusion

In conclusion, the findings from both studies illustrate the significant potential of clickstream data analytics, enhanced by artificial intelligence, to improve confusion detection in learners engaged in online activities such as quizzes. We can effectively analyse learners' interactions and emotional states by employing fuzzy logic and machine learning algorithms, allowing for timely and targeted interventions. This proactive approach not only addresses confusion as it arises but also fosters a more supportive learning environment that can lead to improved academic outcomes. Integrating AI technologies in educational settings offers a promising avenue for enhancing emotional learning analytics. As we continue to refine our models and expand the features considered in confusion detection, we anticipate that these advancements will contribute to a deeper understanding of learners' emotional experiences. Ultimately, by harnessing the power of clickstream data and AI, educators can create more adaptive and responsive online learning platforms that cater to the diverse needs of students, ensuring that confusion is managed effectively and that learners are set on a path to academic success.

Chapter 4: Using AI and ML to detect patterns or indicators within the clickstream data for Confused learners

4.1 Overview

In this chapter, we delve into two distinct studies that utilise the ASSISTments dataset to explore the emotional dynamics of learners, mainly focusing on confusion. The first study employs clustering techniques and Explainable AI (XAI) methodologies to identify distinct profiles of confused learners and the underlying factors contributing to their confusion. By analysing the interaction data and affective state labels; we aim to uncover patterns and clusters that characterise confused learners, as well as the decision-making processes that underpin the formation of these clusters. The second study extends this exploration by employing multivariate time series analysis using Long Short-Term Memory (LSTM) networks to predict levels of confusion over time. This approach utilises various behavioural indicators related to confusion, such as skill, time taken to answer questions, and the number of hints used. By leveraging the temporal nature of the data, we aim to provide insights into how confusion evolves and changes as learners engage with different mathematical tasks. Through these studies, we aim to enhance our understanding of confusion in educational settings and inform the development of targeted interventions to support learners in overcoming confusion and improving their academic performance. By leveraging the rich interaction data from the ASSISTments dataset, this chapter contributes to the growing body of literature on emotional learning analytics and applying advanced machine learning techniques in educational research.

This chapter builds on the work presented in one of my published papers and another study, both of which directly contribute to addressing the research question: ***"What patterns or indicators within the clickstream data can be reliably associated with learner confusion in online learning environments?"*** Through these studies, I explore how AI techniques can be applied to clickstream data to uncover indicators that associate to confusion in learners and extend it further to detect patterns in confused learners.

The publications that form the foundation of this research are:

1. Samani, Chaitali & Musial, Katarzyna. (2023). Cluster Analysis Using Explainable AI for Confused Learners. 1-6. 10.1109/CSDE59766.2023.10487715.

4.2 ASSISTments[2] DataSet

The ASSISTments dataset is a comprehensive repository of student interaction data derived from the ASSISTments online learning platform, which was designed to support K-12 mathematics education. This platform functions as an Intelligent Tutoring System (ITS), developed by Heffernan and his team, to facilitate learning various mathematical skills while providing instant feedback to learners. The dataset encompasses detailed records of learners' interactions with the system, including metrics such as problem-solving attempts, hints requested, time spent on tasks, and overall performance. This rich dataset is particularly valuable for researchers aiming to understand the dynamics of student learning, engagement,

[2] https://drive.google.com/file/d/1cU6Ft4R3hLqA7G1rIGArVfelSZvc6RxY/view?usp=sharing

and emotional states during online educational activities. A key feature of the ASSISTments dataset is its incorporation of ground truth labels for affective states, coded using the Baker Rodrigo Ocumpaugh Monitoring Protocol (BROMP). Developed by Baker in 2004 and later expanded by Rodrigo et al. (2007), the BROMP framework provides a standardised methodology for systematically observing and categorising students' emotional and cognitive states during learning activities. Certified coders trained in the BROMP methodology utilise momentary time samplings to capture students' affective states—such as confusion, frustration, boredom, and engagement—while they interact with the learning platform. Observations are conducted using the round-robin technique at 20-second intervals, ensuring each learner's emotional state is recorded accurately. The dataset used in this research consists of 756 students from diverse demographic regions (rural, suburban, and urban), with 7,663 successful field observations collected, ensuring that each student was observed at least ten times on average.

The BROMP coding system is particularly noteworthy for its focus on the nuanced and transient nature of students' emotions. It employs predefined categories that capture the complexity of learners' experiences in real time. For instance, confusion is identified when a student exhibits behaviours indicative of uncertainty or difficulty in understanding a problem. This coding process allows researchers to analyse the relationship between these emotional states and learning outcomes, providing insights into how affective dynamics influence student performance. Moreover, the BROMP framework enables researchers to track changes in affect over time, offering a dynamic view of how students navigate their learning processes. In the context of this study, the ASSISTments dataset, augmented by BROMP codes, serves as a foundational resource for exploring the profiles of confused learners. By leveraging the rich interaction data alongside the affective state labels, we aim to uncover patterns and clusters characterising confused learners and the decision-making processes underpinning these clusters' formation. This approach not only enhances our understanding of confusion in educational settings but also informs the development of targeted interventions to support learners in overcoming confusion and improving their academic performance. The list of features in the dataset is as shown below.

Field Name	**Description**
Student ID	Unique identifier for each student
School ID	Identifier for the school or institution
Teacher ID	Identifier for the teacher associated with the student
Problem ID	The ID of the problem being worked on by the student
Problem Type	Describes the type of problem (e.g., multiple choice, short answer)
Opportunity Number	Number of times a student has attempted the problem or skill
Correct First Attempt	Whether the student answered correctly on the first attempt (binary)
Hints	Number of hints requested by the student before solving the problem
Scaffolding Request	Whether the student requested scaffolding for additional help
Time Taken	Time spent solving the problem (in seconds)

Attempts	Number of attempts made to solve the problem
Completion Time	Total time taken to complete all problems in a set
Correctness	Indicates whether the student's final answer was correct or incorrect
First Response Time	Time taken for the student's first response
Engagement	Observation of the student's engagement levels
Confusion	Whether the student was observed to be confused
Frustration	Whether the student was observed to be frustrated
Boredom	Whether the student was observed to be bored
Engaged Concentration	Whether the student was observed to be focused on the task
pCorrect	Percentage of correctness on previous problems
pCorrectClass	Percentage of correctness in the class
Answer Percentage	Percentage of a specific answer given among all students
Common Wrong Answer	Whether the answer was a common wrong answer
Number of Hints	Number of hints requested by the student before getting a correct answer
skill	Skill name associated with the problem (different skills are in different rows).
start_time	Timestamp when the problem starts.
original	1 = Main problem 0 = Scaffolding problem
correct	1 = Correct on first attempt decimal values are calculated as a partial credit based on the number of hints and attempts needed to solve (based on teacher setting) 0 = student either saw the answer, exhausted partial credit from too many hints/attempts, or (based on teacher setting) answered incorrectly on the first attempt When observed as a dependent variable, it is recommended that this value be converted to a binary variable using the formula: 1 = correct, <1 = Incorrect
bottom_hint	Whether or not the student asks for all hints.
hint_count	Number of hints on this problem.

Figure 4-1 ASSISTMents dataset features

4.3 Study 1 – Clustering and using Explainable AI for Clusters

4.3.1 Introduction

We used a synthetic data set as our base in the previous two studies. As discussed above, we extend our following two studies using the existing validated dataset called ASSISTMents dataset with BROMP-coded affective states. The ASSISTMents dataset consists of learners' interaction data/ clickstream data as they learn on such Intelligent Tutoring Systems (ITS). As learners engage with ITS and tackle cognitive tasks such as mathematical problem-solving, they often encounter cognitive disequilibrium, leading to confusion. This emotional state can significantly impact their learning trajectory, making understanding and addressing confusion at the individual learner level essential. This study aims to explore the patterns and decision-making processes associated with confused learners by employing clustering techniques and Explainable AI (XAI) methodologies. By analysing a refined dataset derived from ASSISTments, including learners' interaction data and affective state labels coded by certified coders, we identify distinct profiles of confused learners and the underlying factors contributing to their confusion.

4.3.2 Detailed Study

This study focuses on detecting and understanding confusion at the learner level. We also proposed confused learners' profiles using clustering and tree-based Explainable AI that helps understand the boundaries and decision-making used in these clusters' formation. The study adopts an improved dataset (Wang et al., 2015) from ASSISTments and an online learning platform that consists of learners' interaction data and ground truth labels for affective states coded by BROMP (certified coders to develop and validate these states). The following subsections will define our cluster formation process and explain the clusters.

4.3.3 Data preprocessing

In this first step, our primary focus was handling missing and noisy data and detecting and removing outliers. We also checked the dataset for any duplication. Even when this dataset is clean, it is anticipated that the data will be messy in the real world as it will be created and stored by various systems and stakeholders. This will result in missing individual data in a field, may be duplicated or even some manual input errors. We performed and checked all the data in the dataset for validity to ensure a clean data set. The dataset was then normalised to transform the features on a standard scale before applying for clustering.

Thus, we checked the dataset for the following:

- Missing Data
- Detecting and removing outliers: We applied statistical methods, including Z-score analysis (threshold of +/- 3 was used for this) and the Interquartile Range (IQR) methods.
- Checking for duplicates.
- Normalisation: Before applying clustering algorithms, we normalised the dataset to transform the features onto a standard scale. This step was crucial to ensure that no single feature disproportionately influenced the clustering results due to differences in scale.

4.3.4 Feature Selection

In this study, we want to start with cluster analysis, and the dataset has already been labelled for their affective states. The purpose of cluster analysis is to understand the profiles of confused learners and the decision-making used in each cluster formed. Due to this, in the cluster analysis, we removed the columns that were not required, like the label column 'Confused' that stated whether a learner is confused. For the above data set, we have the label column that indicates whether the learner was confused with the values of about 207 parameters. However, labelling the epistemic emotions in the real world will involve field observations or self-reports from learners. That is both time-consuming and expensive. Hence, the advantage of this clustering will be to extend it in non-labelled datasets using similar parameters identified during the use of the Explainable AI section. Before proceeding, we performed correlation analysis and removed highly correlated columns to improve the algorithm's performance. The correlation analysis resulted in 96 columns on which we trained the model.

4.3.5 Training the Model

With steep advancements in computing and rapid growth in the availability of heterogeneous large-scale data repositories, gaining meaningful insights from the data is increasingly becoming possible. Machine Learning (ML) broadly classifies its algorithms into supervised and unsupervised. Supervised learning is a function that learns from the data provided in the form of input-output pairs (Kairouz et al., 2021), but as given in the definition, it requires labels in the form of output from which it can learn. In any case, gathering such labels is almost always expensive and often challenging. Therefore, where labels are challenging, unsupervised learning approaches are more helpful (Bishop, 1995). One of the most popular sets of unsupervised learning is clustering algorithms that exploit the underlying structure of data and define some rules that will characterise and group the data using these rules (Jain et al., 1999).

Clustering is used in many data-driven applications mainly because this type of learning processes the data in the partition of a given dataset according to the clustering criteria without prior knowledge. This makes clustering quite versatile and is used in many fields of applications. Among many clustering algorithms, the K-Means algorithm is the most popular and aims to minimise cluster performance index, squared error and error criterion (Li & Wu, 2012). For the scope of this study, we used K-Means clustering and determined the optimal number of clusters using the Elbow method. The following sections will discuss the results of cluster formation and the explainability of each cluster.

4.3.6 Interpretation of Clusters

We begin exploring each cluster and its data distribution of the columns to understand the shape of the data distribution. We have used a histogram graphically to show the frequency of every value in a data set. Since Histograms are an easy visualisation of which values are most common, it is easy to identify the three clusters with respect to the data being measured.

Our first histogram shows the Average bottom hints used in each cluster. This is an important visual, as it shows that the learners in the first cluster (Cluster—0) have used more bottom hints. The bottom hint is the answer to the problem; hence, this column indicates whether the learner used the bottom hint directly to get the answer rather than taking some time to understand. The below figures show how many learners (on the y-axis) clicked on the bottom hint vs. the time taken for a task (on the x-axis).

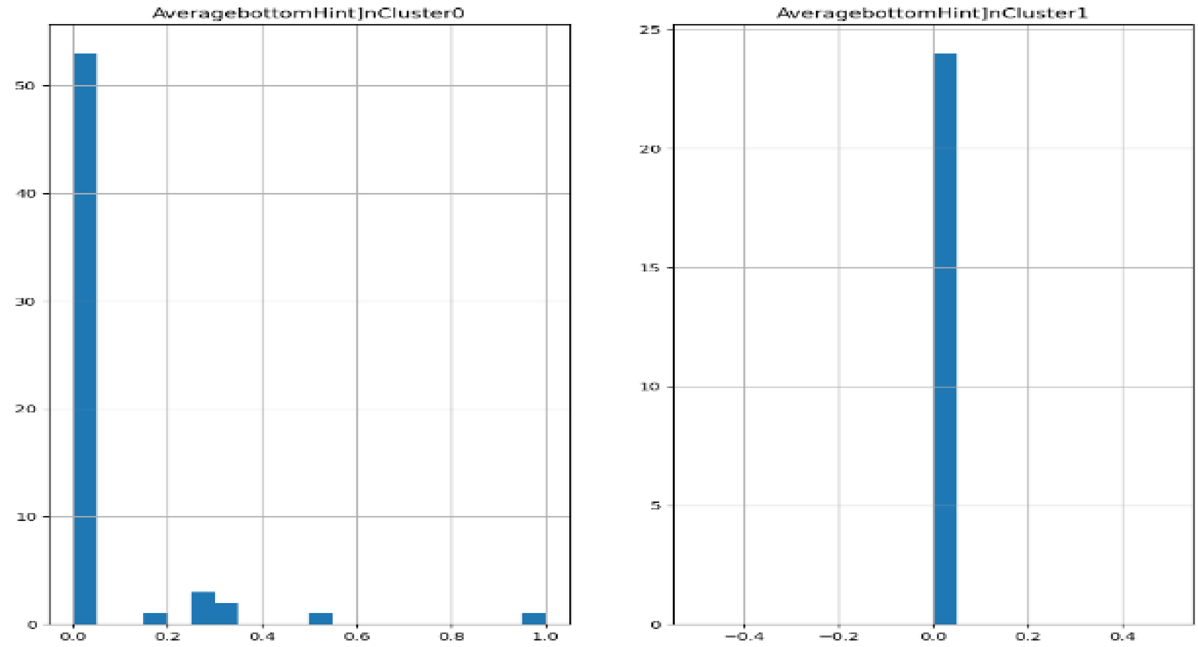

Figure 4-2 Data Distribution of learners choosing to straight ask for the answer - shows how many learners (on the y-axis) clicked on the bottom hint vs. the time taken for a task (on the x-axis)

The second histogram shows the distribution of average consecutive errors in a row in both clusters. The figure below shows the number of learners (on the y-axis) vs. the average number of consecutive errors (on the x-axis).

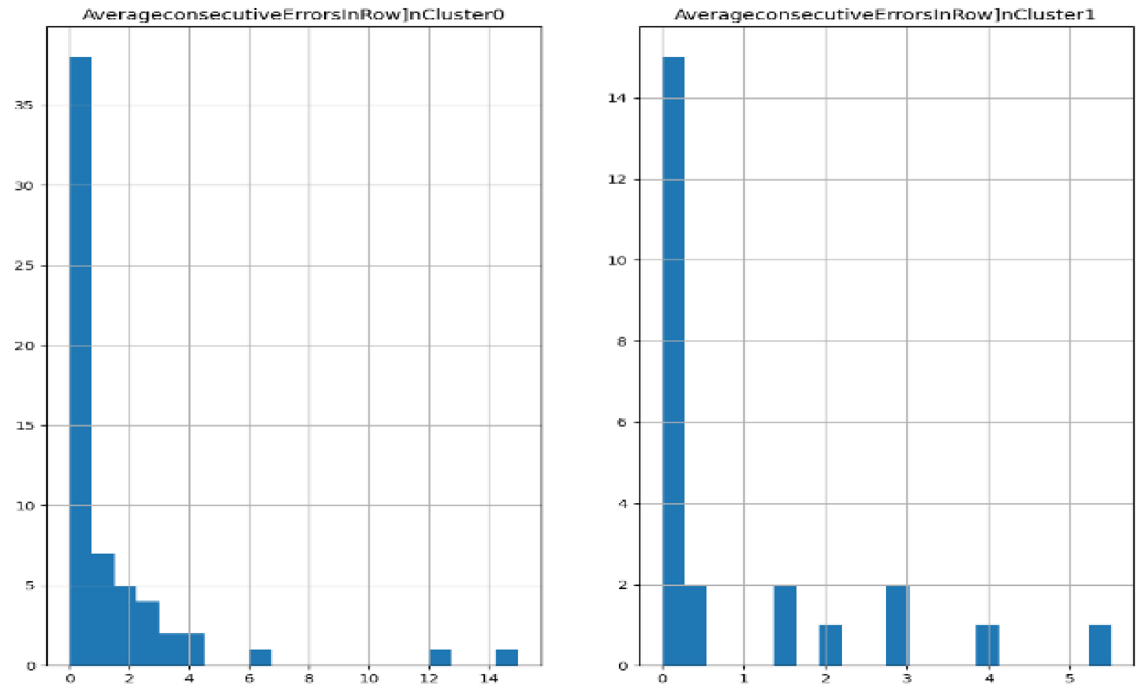

Figure 4-3 Data Distribution of learners making consecutive errors in each cluster - shows the number of learners (on the y-axis) vs. the average number of consecutive errors (on the x-axis)

We saw similar patterns in many other related data features, and using the same thought, we named Clusters in the following way:

- Cluster 0 – ***More confused***
- Cluster 1 – ***Less confused***

4.3.7 Quality of Clusters Separation

As discussed above we have used Elbow method to determine the optimal number of clusters in this dataset. We also performed Silhouette analysis to determine the separability between clusters. Silhouette analysis computes the average distance between all the data points in the same cluster (Ai). Then computes the average distance between the data points in the closest cluster (Bi). Then the method calculates the coefficient (takes the value between [-1,1]) using the following equation:

$$Coeff = \frac{B_i - A_i}{max(A_i, B_i)} \quad (1)$$

The interpretation of coefficient is:

- If Coeff → 0, the data point is very close to their neighbouring clusters.
- If Coeff → 1, the data point is far away from their neighbouring clusters.
- If Coeff → -1, the data point is wrongly placed in the cluster.

As the Coeff moves more towards 1 shows good clustering in terms of data points separation. Using this method, we achieved the following separability. However, we anticipate it to increase as we have more data points.

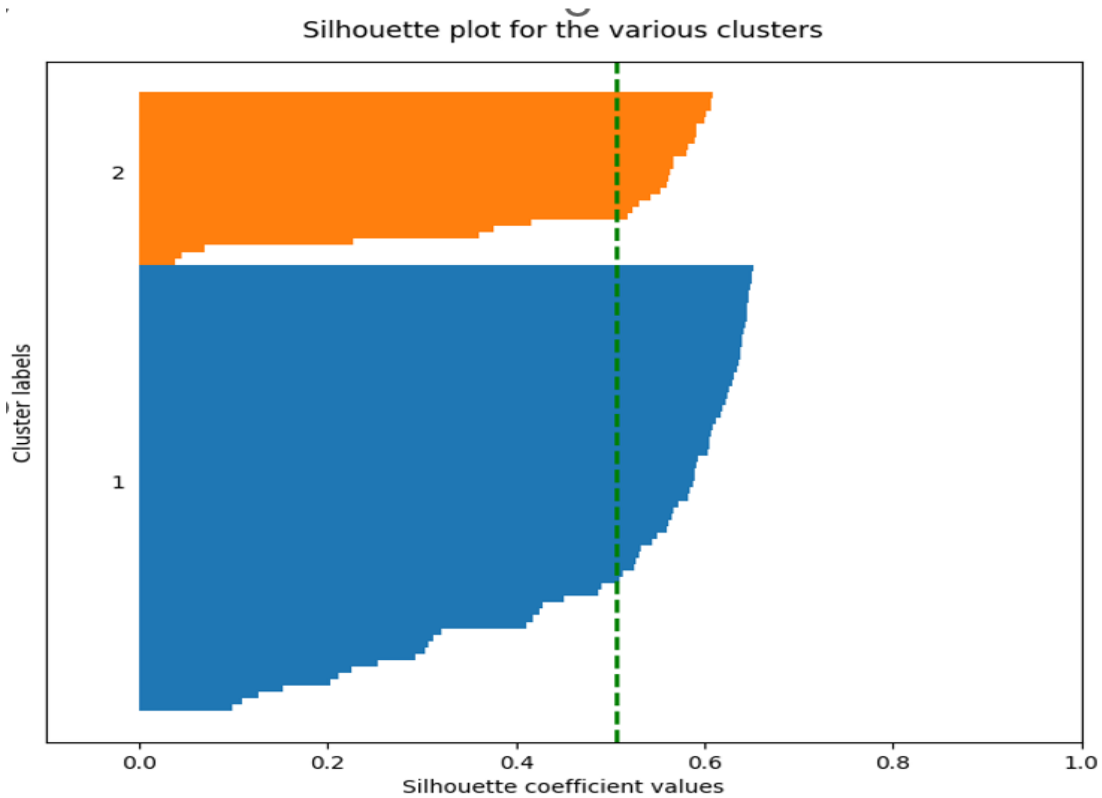

Figure 4-4 Silhouette Plot for both the clusters

4.3.8 Bringing Explainability to Clusters

The KMeans clustering technique does not provide any explainability and behaves much like a Blackbox. It is often not easy to deduce why a particular row of data is classified in a particular cluster. In the above analysis, knowing these boundaries will help determine some intervention techniques when migrating learners from one cluster to another, given that some form of confusion can provide some learning benefits.

In this study, we used an algorithm Dasgupta et al. (2020) developed that focuses on bringing explainability and accuracy to clustering. This algorithm centres around partitioning a dataset using decision trees into k clusters. The method is called IMM (Iterative Mistake Minimisation) clustering, which builds a decision tree with the same number of leaves as the number of clusters considered in K-Means. The algorithm uses the following high-level steps to achieve this:

- Find clusters using Clustering algorithms like K-Means
- Attach the cluster number to each record.
- Call a supervised algorithm that learns a decision tree.

We then extended IMM, using ExKMC, where the number of leaves exceeds the number of clusters and achieves better partitioning. ExKMC starts with the set of reference centres taken from any clustering algorithm and followed by building a threshold tree with K leaves from IMM. Then after it calculates the best feature-threshold pair and expands the tree one node at a time. The tree is expanded by splitting the tree node with most improved surrogate cost, that is the sum of squared distances between data points and their closest centroid.

The ExKMC decision-tree we achieved with these two clusters is as below:

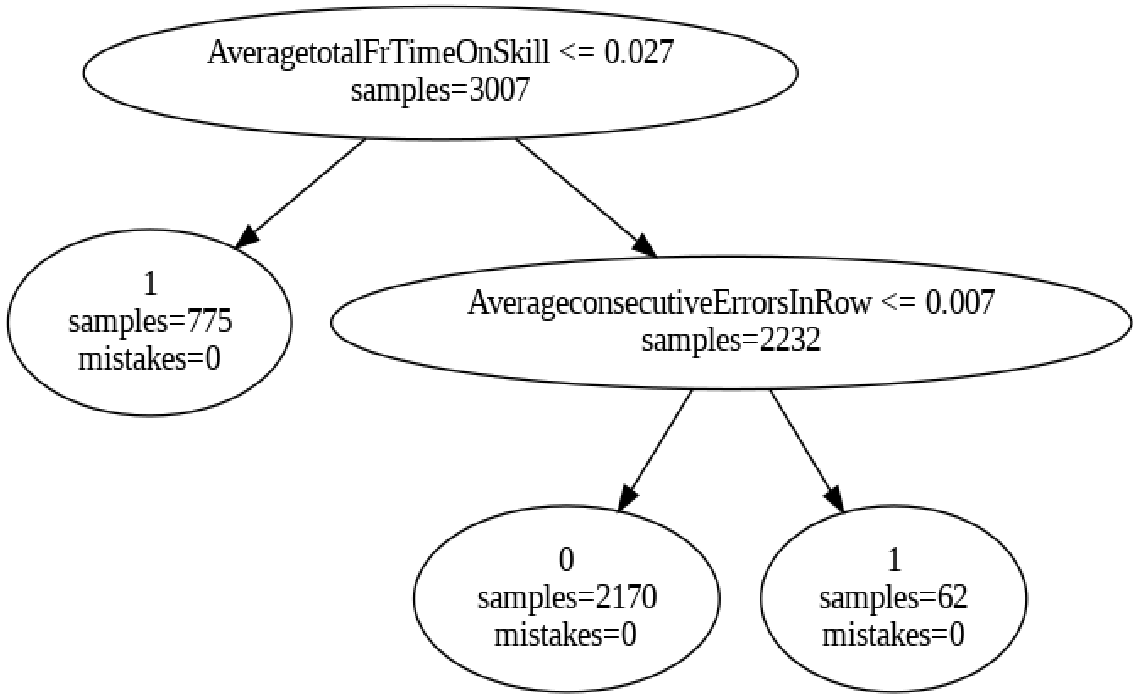

Figure 4-5 Decision tree-based explanation on Cluster Formation

This decision-making logically aligns with our observations and visualisation. Thus, we can use the Average time a learner spends on a skill and then compare the number of mistakes they made in consecution as key parameters to decide if a learner may be confused, and target recommendations and interventions based on these cluster boundaries.

4.3.9 Conclusion and Future Direction

In this study, we used K-Means clustering on an ASSISTment-labelled dataset of confused learners. We focused on confused learners and applied K-means clustering to gain insights within the group of confused learners based on the relevant prominent and highly correlated data points. We then proposed that standard clustering techniques may provide a black-box approach and are challenging to interpret because they cannot explain the reasons behind the formation of the clusters. We proposed finding patterns or profiles of confused learners and determining the rules or boundary conditions that push a data point to a particular cluster, which can provide us with some insights into the kind of interventions we can use on such learners. We brought explainability to these clusters using IMM and ExKMC algorithms and provided the explainable tree structure involved in the decision-making of clusters. We can also see some usage behaviour on bottom hints amongst both clusters, which may indicate another hidden pattern that may need to be uncovered. Thus, this study uncovers indicators in confused learners that can identify less and more confused learners. This differentiation can help identify learners who may need immediate attention to control dropouts or frustration. Thus, reinforcing the research question (RQ 2) – ***“What patterns or indicators within the clickstream data can be reliably associated with learner confusion in online learning environments?”***

4.4 Study 2 – Time Series Analysis

4.4.1 Introduction

In this study, we use multivariate time series analysis using LSTM to predict levels of confusion over a period. The approach would involve utilising the time series data of various behavioural indicators related to confusion using the ASSISTment dataset. These indicators could include skills, the amount of time to answer a question, and the number of hints used.

4.4.2 Detailed Study

The initial stages of this study included predicting trends for future time periods using ARIMA. However, the model failed to predict any patterns. To extend the time series analysis, we focused on the potential use of LSTM approaches, given their usability in related works. The study aims to study how multivariate time series using LSTM networks can predict immediate and extended trends of confusion in a learner.

4.4.3 Methodology

The next section will discuss the data preprocessing steps, and exploration performed to prepare the data for LSTM implementation. The following section explains LSTM networks and the architecture of the LSTM developed for this study.

4.4.4 Data Pre-processing and Exploration

For this dataset, to get the data ready for LSTM, we needed to perform data pre-processing steps such as handling missing values, “Not A Number (NaN)” values and encoding the categorical variables. The first step is handling missing and NaN values in the dataset. Missing values can disrupt the data sequence and affect the LSTM model's performance. One approach to handle missing and NaN values is to remove the corresponding data points entirely. This can be done by identifying the rows or columns containing missing NaN values and dropping them from the dataset. This ensures that the remaining data is complete and ready for further analysis (Lipton, 2015). We dropped the rows with NaN values in the "skill" feature for this dataset. The "skill" is categorical data, and replacing the NaN values with another meaningful value was impossible. After removing the NaN values rows, the dataset mainly was clean and did not require further cleaning.

After cleaning up the data, we explored the learners and their change in confusion levels using data visualisation. Some visualisations, such as the one shown below, provide an understanding of how the learners' confusion levels change as time passes. As shown in the figures, the learner seems to be struggling with "Properties and classification of Pyramid" and "Tree diagram, lists for Counting" skills.

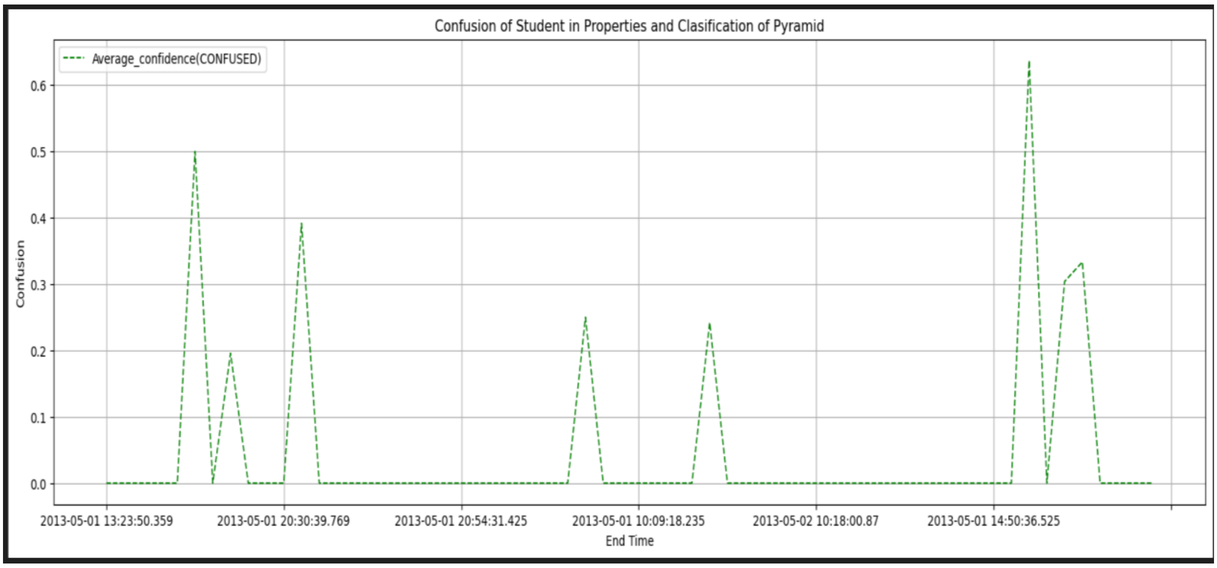

Figure 4-6 Confusion levels for one learner in Pyramid skill

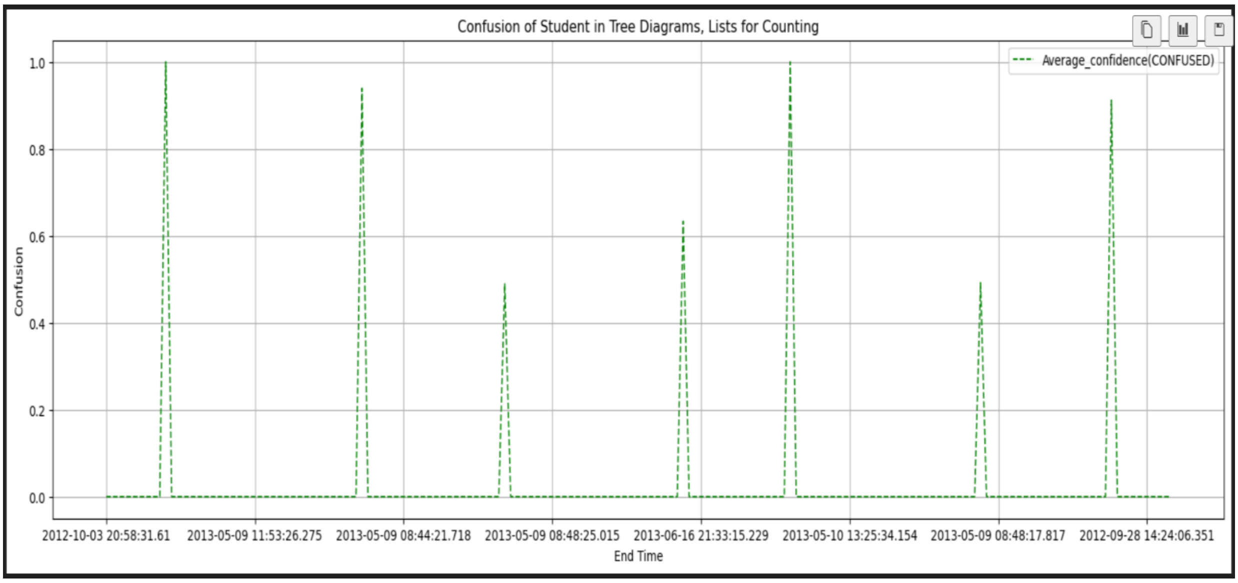

Figure 4-7 Confusion levels for one learner in Tree diagrams, Lists and Counting skill

Given the above visuals, skills are an essential factor to consider when analysing the time-series data for a learner. Over time, the learner attempts problems based on a particular skill, and changes in the values of confusion suggest the temporal effect of skill on confusion.

As we use LSTM networks to analyse this time series, we need to encode categorical variables, such as the skill feature, into numerical representations. In any multivariate time series analysis, it is expected to have categorical variables associated with each data point. LSTM models require numerical inputs, so it is necessary to encode these categorical variables. One way to do this is by using one-hot encoding, which assigns "1" to the category in the skill feature and will set "0" for the rest of them. This allows the LSTM model to process the data effectively and capture the relationships between different skills (Lipton, 2015). By performing these data pre-processing steps of handling missing values and encoding categorical variables, the dataset is prepared for multivariate time series analysis using LSTM. The cleaned and encoded data can then be used to train the LSTM model.

4.4.5 Feature Extraction

In the LSTM network approach, we analysed the past 14 days' transactions to make predictions. To prepare the data for LSTM, we extracted features and transformed data to make the data ready for LSTM. We extracted time-based features, frequency-based features, and some numerical and categorical features. The time-based features measure the time spent on a particular question, for example, the time stamp when the question started and the time for the first response. The frequency-based features measure the counts of learners using a number of hints, attempts and others. There are some numerical values, such as whether the learner chooses to see the answer in their attempt. With initial data visualisation on each skill, we also found that the level of confusion changes over time per skill.

To reduce the LSTM's complexity, we dropped 'overlap time' from our feature build. Overlap time means the learner's total time to complete the problem; however, many data sets from ASSISTments have this column erroneous. The dataset used in this study displays the overlap_time, which is the same as the first response time for all the observations. The following is the correlation heatmap to support our argument.

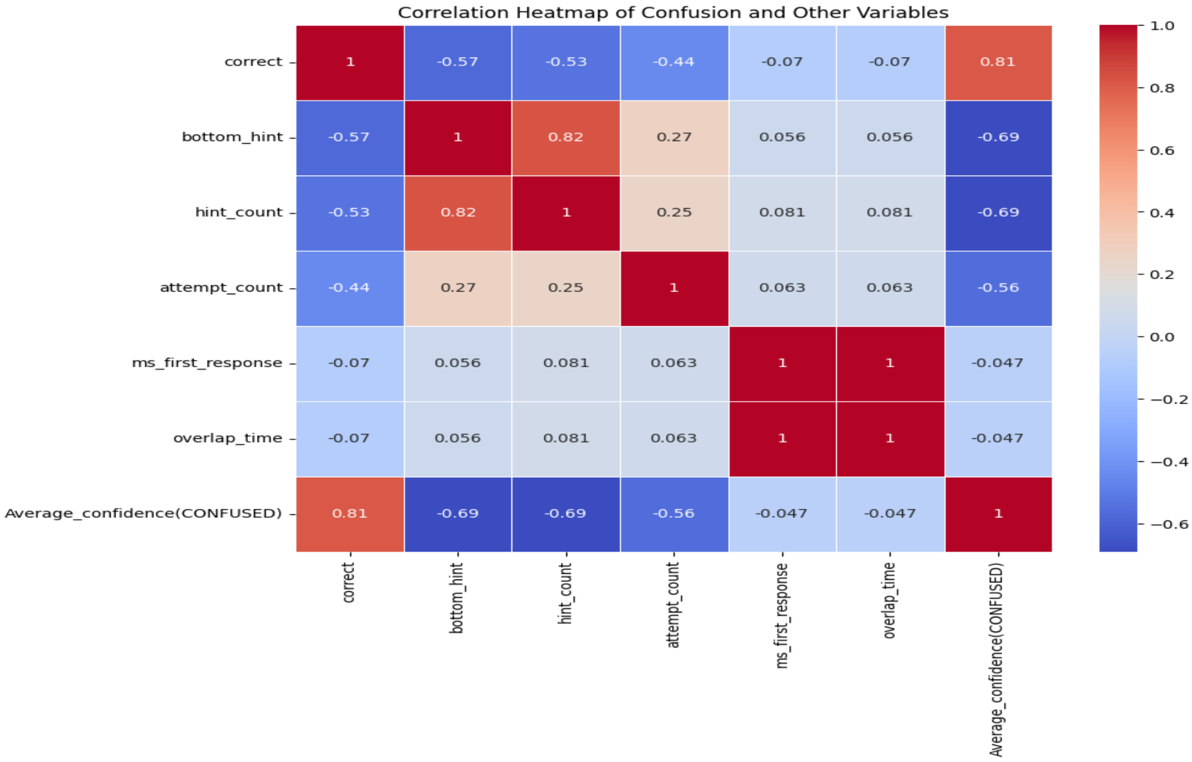

Figure 4-8 Correlation Heatmap

4.4.6 LSTM Networks

In our study, we utilised LSTM networks as a deep learning approach to predict learners' confusion using time series log data. To perform the prediction, we first took one learner and arranged their log data in the ascending order of their time of attempt time. We focused on the previous 14 days from the dataset (This data set consists of observations from 2012 to 2013) and converted the categorical data of skill as one-hot encoding. The resulting dataset consisted of click frequency data with 7 days time slots, which served as input for the LSTM network. The outputs of this network provided predictions of levels of confusion. We implemented LSTM networks for time frames of next 7 days based on the past 7 days time slots and explored the predictions using deep learning techniques.

The LSTM networks were implemented using the Keras library in Python. LSTM networks are a type of recurrent neural networks (RNNs) that are specifically designed to handle temporal information. RNNs, including LSTM networks, utilise loops to transmit information from one time slot to the next, making them effective for modelling time series data. However, traditional RNNs can suffer from the vanishing or exploding gradient problem, especially when dealing with long data sequences. This problem arises due to the repeated multiplication of the recurrent weight matrix during backpropagation, leading to gradients that either vanish or explode. As a result, RNNs are typically better suited for learning over short data sequences. We employed LSTM networks, a variant of RNNs introduced by Hochreiter and Schmidhuber (1997) to address the challenges of learning from long sequences. LSTM networks overcome the vanishing and exploding gradient problem by incorporating a forget gate, an input gate, and an output gate within each LSTM cell. These gates enable the network to selectively retain or discard information, allowing for the exploitation of long-term memory in learning from long data sequences.

The following figure demonstrates the architecture of the LSTM network used in this study. The architecture is built on 14-day multivariate data. Also, the dataset is filtered by each learner. Since each learner has attempted a different number of skills, the total number of features in the LSTM will change every time the learner changes. This provides flexibility and supports the hypothesis that each learner has a different time series pattern, and this data captures the temporal nature of epistemic emotions.

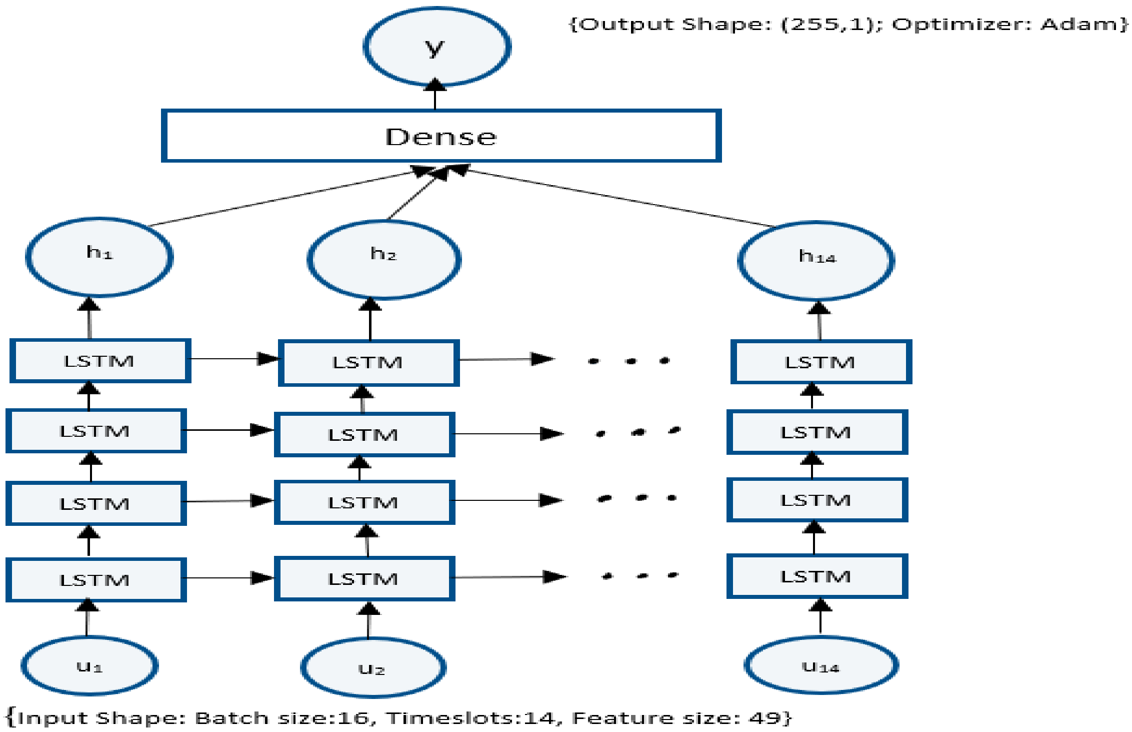

Figure 4-9 LSTM Architecture

The input data are of three dimensions: a batch size of 16 samples, 7 days time slots and the features resulting from one-hot encoding for skill. We only selected the analysis of learners who had enough time slots. The outputs of the LSTM layers are in three dimensions: batch size, time slots, and output node size. The last output is two-dimensional: batch size and node size. We have used a drop-out layer with 20% dropout stacked on the LSTM layer for regularisation to prevent the LSTM from overfitting (Gal & Ghahramami, 2016).

The details of LSTM architecture are as below:

- **Window Size**: Use a **7-day sliding window** to predict the next 7 days. This allows you to work with smaller datasets and ensures more students have sufficient data.
- **Hyperparameter Tuning**:
    - **LSTM Units**: Set at 128 and 64, allowing for sufficient learning capacity while preventing overfitting.

  - **Batch Size**: Set at 32 for better generalisation.
  - **Epochs**: Reduced to 50 with early stopping to prevent overfitting.
- **Dropout Regularisation**: Applied dropout layers to reduce overfitting, ensuring the model generalises unseen data better.

4.4.7 The experimentation steps

1. **Feature Selection**:

- Compute correlation between selected features and Average_confidence(CONFUSED).
- Retain features with correlation magnitude

2. **Learner-Specific Data Preparation**:

For each student in the dataset: Extract the student’s data and if the learner have sufficient data then scale the features and create a sliding window of size 7-days and create target confusion values for next 7 days.

3. **LSTM Model Construction**:

   1. Initialize an LSTM model with the following structure:
   2. Compile the model using the Adam optimizer and mean squared error (MSE) as the loss function.

4. **Training Phase**:

For each student with sufficient data: Split the student's data into training (80%) and testing (20%) sets, train the LSTM model using the training set and implement early stopping to stop the training when validation loss stops improving.

5. **Prediction Phase**:

For each student: Set the trained LSTM model to predict the confusion level for the test set and store the predicted confusion levels.

6. **Evaluation**:

For each student: Compare the actual confusion levels with the predicted confusion levels for 7 days and calculate evaluation metrics (e.g., mean squared error).

4.4.8 Evaluation

In compiling the model, we utilised the "adam" optimizer and Mean Squared Error (MSE) loss function. The "adam" optimizer, introduced by (Kingma & Ba, 2014), is a stochastic optimisation method that has demonstrated excellent performance in practice and outperforms other optimisation methods. It offers computational efficiency, requires minimal hyperparameter tuning, and is well-suited for handling large datasets and numerous parameters. The MSE loss function employed in this study measures the average squared difference between the predicted and actual values. This loss function is commonly used in regression tasks and provides a quantitative measure of the discrepancies between predicted and actual values. The choice of the "adam" optimizer and MSE loss function is particularly appropriate for LSTM models. LSTMs are a type of recurrent neural network (RNN) that are well-suited for capturing long-term dependencies and patterns in sequential data. The "adam" optimizer's adaptive learning rate and momentum updates make it effective in optimising the parameters of LSTM models, allowing them to learn complex temporal patterns. Additionally, the MSE loss function is commonly used in LSTM models for regression tasks, as it measures the model's ability to minimise the differences between predicted and actual values over time (Kingma & Ba, 2014).

We utilised the "adam" optimizer and MSE loss function, so we can effectively train the LSTM model to learn and generalise from the data, capturing the temporal dependencies and patterns present in the timeseries data. The analysis of the validation and training loss provides insights into the model's performance, convergence, and potential issues such as overfitting or underfitting (Kingma & Ba, 2014). Overall, the combination of the "adam" optimizer, MSE loss function, and LSTM architecture contributes to the development of a robust and accurate model for this study (Saltepe et al., 2021). Validation and training loss were monitored during the training process for convergence and performance of the LSTM model. Lower validation and training loss values indicate better model performance and generalisation ability (Shin et al., 2012). A decreasing trend in both losses as shown in the figure 3, indicates that the model is learning and generalising well, while any discrepancies or anomalies in the loss curves can provide insights into potential issues such as overfitting or underfitting.

4.4.9 Predictions

The results show predictions on the levels of confusion based on the learner's activity data, including the skill and their performance. The prediction of confusion levels based on learner activity data, including skill and performance, is analysed as a time-series LSTM predictive model in this study. This model leverages the temporal information in the data to make accurate predictions. The inclusion of skill information is crucial in understanding the learner's behaviour comprehensively, as different skills may require varying levels of cognitive effort and can lead to different levels of confusion. By considering the learner's performance in each skill transaction; the LSTM model can capture the individual's proficiency and mastery of specific skills, which further informs the prediction of confusion levels. This approach allows a more nuanced understanding of how confusion may evolve and change.

The following are the sample results of 5 learners on their predicted levels of confusion, compared with their actual levels.

Student ID	Day#	Actual Confusion	Predicted Confusion
78952	1	0.911765	0.8383580446243286
	2	0.911765	0.8570142388343811
	3	0.939394	0.8191736340522766
	4	0.911765	0.9021251201629639
	5	0.978947	0.8270092010498047

	6	0.978947	0.8691593408584595
		0.978947	0.8540151119232178

Table 4-1 Student ID: 78952

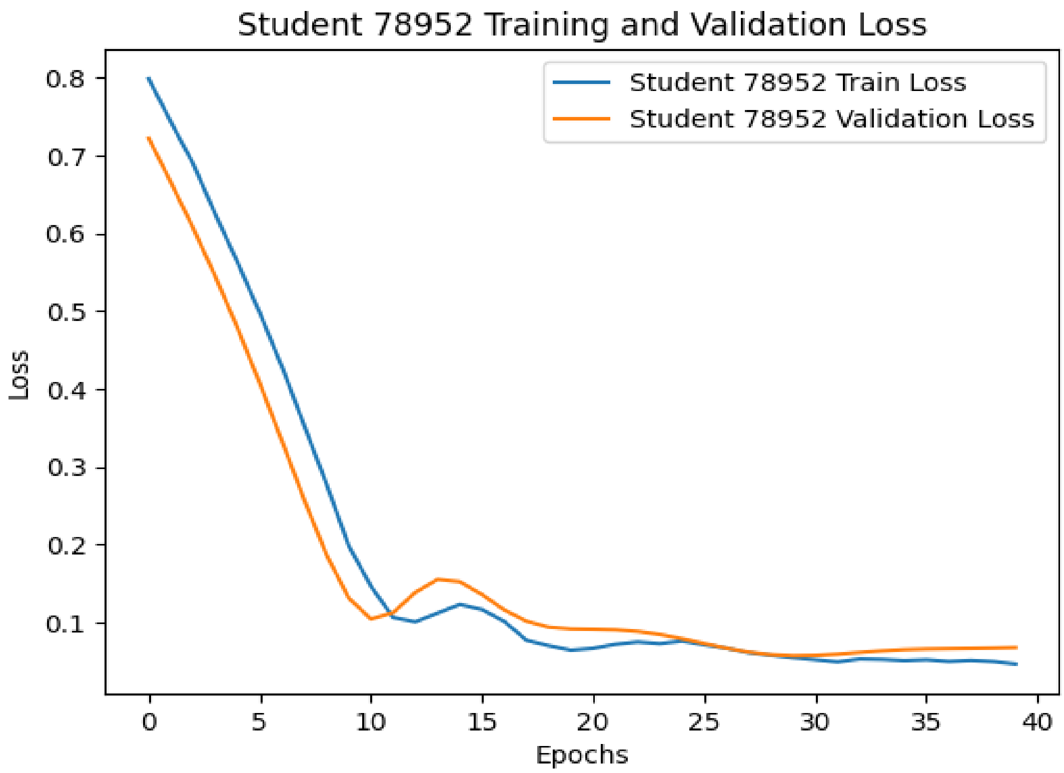

Figure 4-11 Student ID 78952 Training and Validation Loss

Student ID	Day#	Actual Confusion	Predicted Confusion
92680	1	0.911765	0.8427147269248962
	2	0.96875	0.8417473435401917
	3	0.96875	0.8938045501708984
	4	1.0	0.9262498617172241
	5	0.5	0.9182674288749695
	6	1.0	0.8776246309280396
		1.0	0.818462073802948

Table 4-2 Student ID 92680

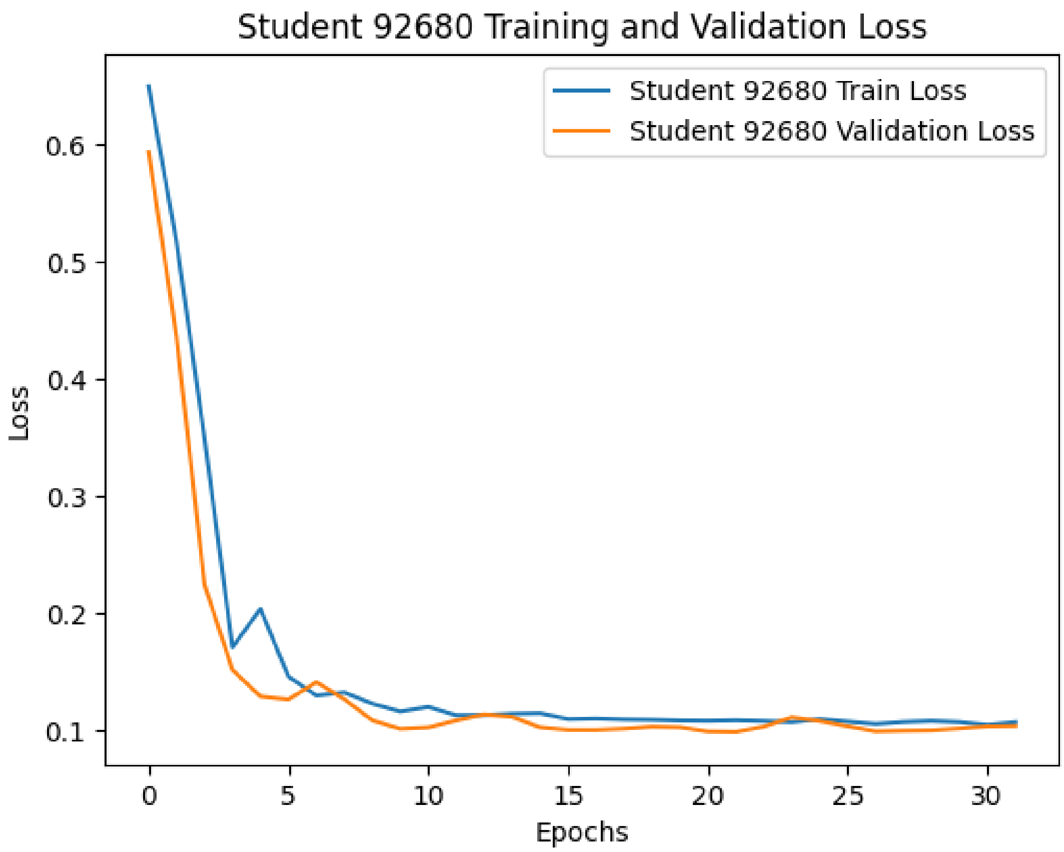

Figure 4-12 Student ID 92680 Training and Validation Loss

Student ID	Day#	Actual Confusion	Predicted Confusion
92684	1	0.946565	0.9169377088546753
	2	1.0	0.9087328910827637
	3	0.946565	0.9223535060882568
	4	0.946565	0.9149213433265686
	5	0.984127	0.9248941540718079
	6	1.0	0.9222097992897034
	7	0.308457	0.9070143103599548

Table 4-3 Student ID 92684

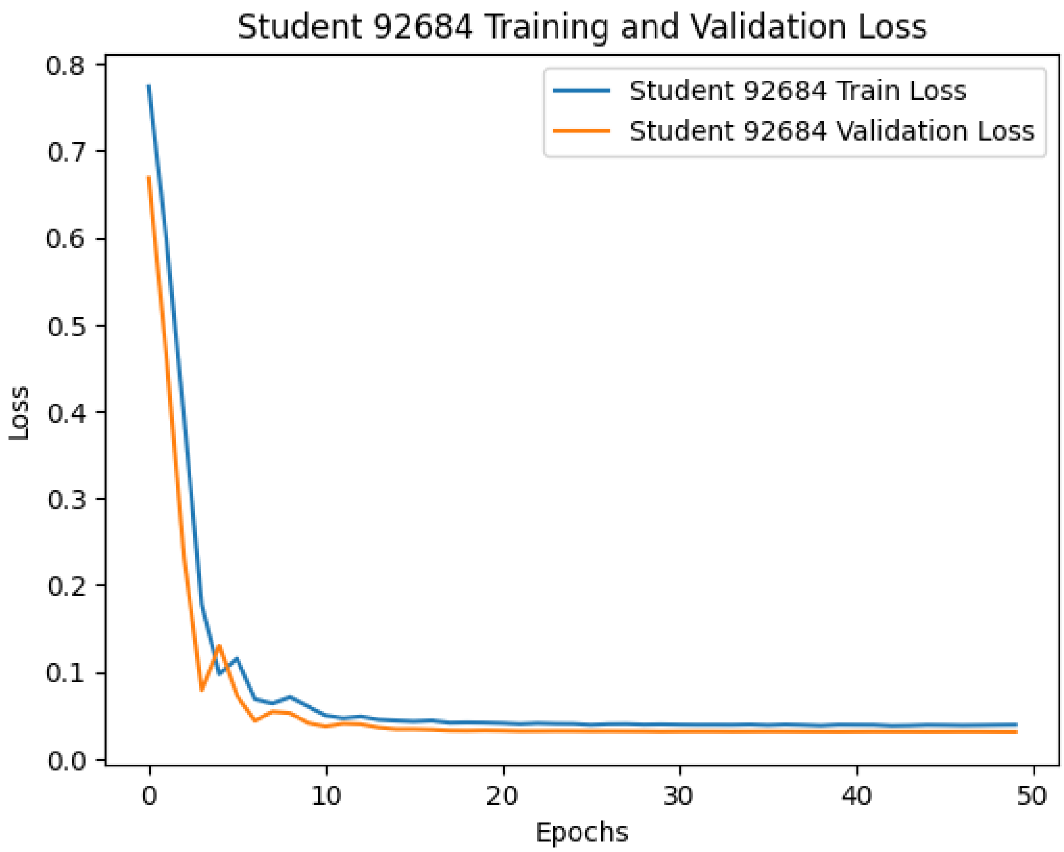

Figure 4-13 Student ID 92684 Training and Validation Loss

Student ID	Day#	Actual Confusion	Predicted Confusion
92707	1	0.978947	0.8016480207443237
	2	0.978947	0.7811886072158813
	3	1.0	0.8379073739051819
	4	0.978947	0.8216516971588135
	5	0.96875	0.8012709617614746
	6	0.978947	0.7941020131111145
	7	0.939394	0.7738519906997681

Table 4-4 Student ID 92707

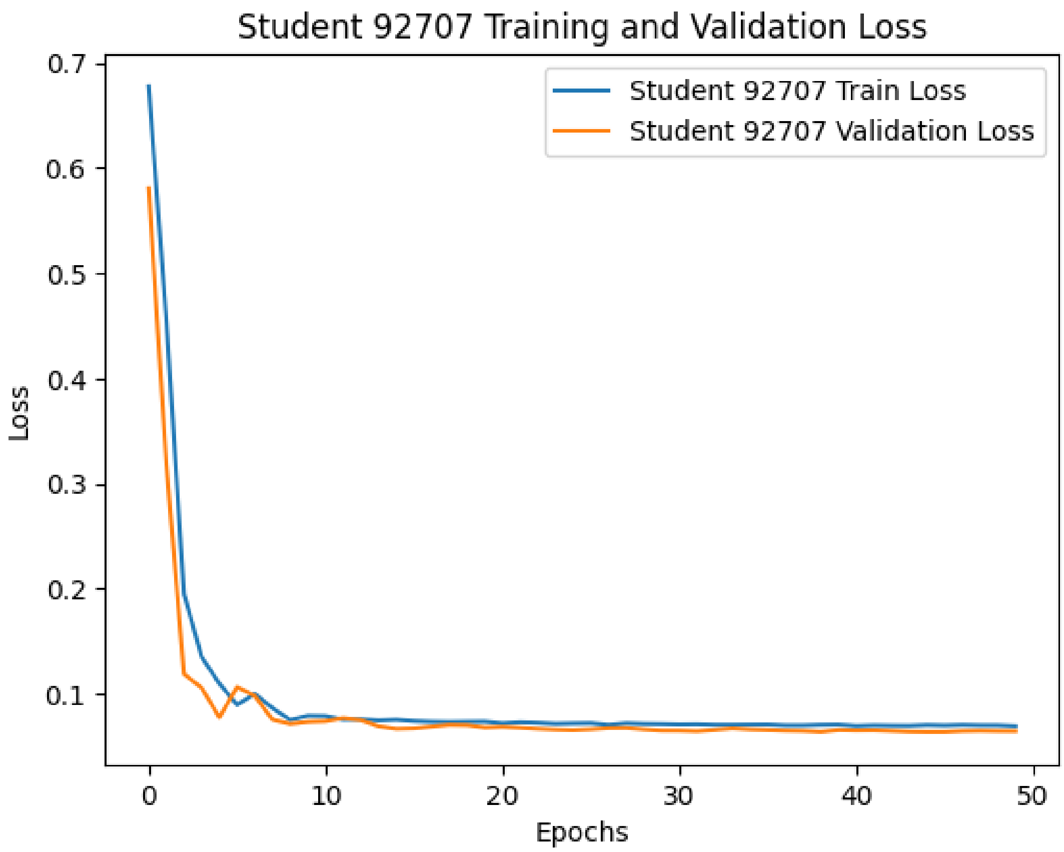

Figure 4-14 Student ID 92707 Training and Validation Loss

Student ID	**Day#**	**Actual Confusion**	**Predicted Confusion**
92711	1	1.0	0.8512983322143555
	2	0.4626865	0.8414613604545593
	3	0.978947	0.8594529032707214
	4	0.978947	0.8348771333694458
	5	0.978947	0.8729819059371948
	6	0.925373	0.884829580783844
	7	1.0	0.8735019564628601

Table 4-5 Student ID 92711

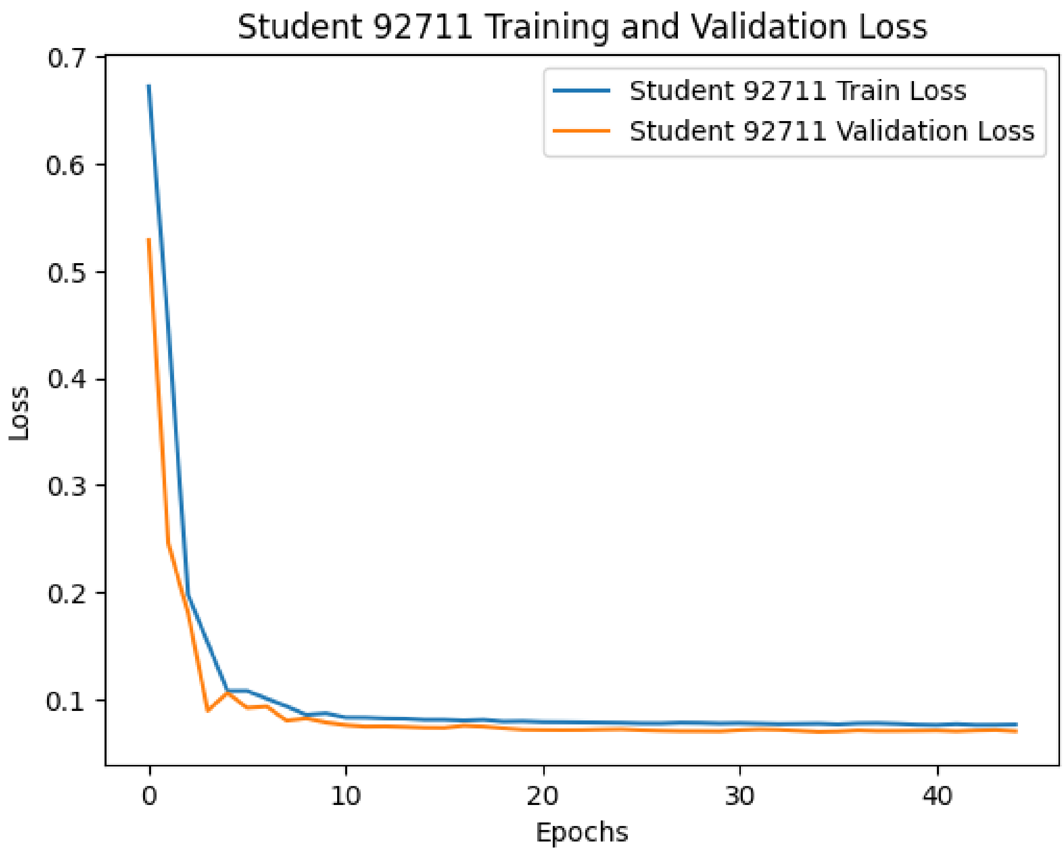

Figure 4-15 Student ID 92711 Training and Validation Loss

4.4.10 Conclusion and future work

In this study, we examined the potential of a deep learning approach – time-series analysis using LSTM networks using activity transaction logs based on their activity behaviour and skills. These predictions have important implications for educational interventions and support. By identifying learners who are predicted to experience high levels of confusion, educators and instructional designers can provide targeted help in addressing the learner's specific needs. However, it is important to acknowledge that confusion is a **repetitive and transient emotional state**, influenced by a range of contextual and individual factors. This makes real-time, actionable prediction a complex challenge. The accuracy and reliability of these predictions depend on the quality and representativeness of the activity data used in the model. Additionally, the predictive model should be rigorously evaluated and validated using appropriate metrics and techniques to ensure its effectiveness in predicting confusion levels. Regarding limitations, some learners' sample data sizes are small, and the predictions are based on the skills tested. Our future work will include some experimentation of learners using a single skill. However, the levels of the same skill or the learning outcome will be utilised in time-series data to determine the levels of confusion and provide predictions for improved interventions. Thus, reinforcing the research question (RQ 2) – ***"What patterns or indicators within the clickstream data can be reliably associated with learner confusion in online learning environments?"***

Chapter 5: Theoretical Framework for Intervention for confusion in learners using Emerging technologies like Generative AI

5.1 Overview

In the previous four chapters, we have covered how advanced analytical techniques like fuzzy logic, multi-layer perceptron (MLP), clustering, and time series analysis can detect and predict confusion. It is important to clarify that these models do not predict the internal emotional state of confusion directly. Rather they identify patterns in learner behaviour and interaction data, and that have been operationaly defined and labelled as indicative of confusion in prior literature. Thus, the term “confusion” in this context refers to a data-derived construct, not as directly measured emotion. Such techniques can form the foundation for future intervention techniques and can be used as tool for identifying learners who may be experiencing confusion-like behaviour. These methodologies can be integrated into newer emerging technologies like Generative AI and enhance the ability to address confusion in learners in a timely and meaningful way. This chapter explores how Generative AI can be utilised to develop innovative tools to improve the detection of epistemic emotions like confusion and provide more timely intervention to learners to help them keep up with their academic journey. In this research, the scope or an overarching goal is to create a theoretical framework that embeds confusion detection and prediction with Generative AI that will then guide educators and educational institutes strategies to mitigate its effects to aim for quality teaching and learning practices.

5.2 Generative AI – A New Frontier in Educational Interventions

As the landscape of Generative AI is unfolding very quickly, researchers are exploring potentials in using Generative AI innovatively predominantly to increase the overall satisfaction of the educational experiences from both educators’ and learners' perspectives. In the scope of this research, there is a significant amount of potential in using Generative AI tools to enhance confusion detection and predictions along with the insights gained from Fuzzy logic, MLP, clustering and time series analysis. Generative AI can analyse learners’ interaction data and emotional stages to generate customised feedback or even resources and learning activities that address the specific areas where the learner is confused. Generating customised or personalised feedback is very effective but resource-sensitive at the same time (Cardozo et al., 2019; Cebä & Karal, 2017). thus, the use of Generative AI can steeply increase the productivity of educators and, at the same time, provide timely help to learners.

There is much potential for using Generative AI to enhance the use of Intelligent tutoring systems that can adapt in real-time to learners' emotional stages. We have already seen how the ASSISTMents dataset can be used to predict confusion. Such adaption in the system can sharply increase the learners' performance, given that the system adapts in real-time to learners’ emotional states. Such Generative AI systems can be integrated to run in the background to continuously monitor learners’ interactions and affective states. They hence can be used to provide timely interventions or additional hints or resources. Such kind of adaptive approaches enhances the learning experience and promotes learners' engagement and retention, which in turn controls the dropout rates of learners (Wang, 2023).

In the context of online learning, we must acknowledge our challenges in designing resources catering to diverse learner profiles. Generative AI's ability to create personalised learning pathways can be of particular interest and need in curriculum design. Also, because such Intelligent Tutoring systems can generate rich interaction data, generative AI can more effectively identify learner behaviours and emotional response patterns.

In terms of curriculum design, the above patterns can be used to tailor educational content and resources to meet the specific needs of the cohort helping educators to create a curriculum that is more holistic and effective. Generative AI can generate additional practice problems, alternative explanations, or interactive simulations targeting that concept, facilitating a more effective learning experience (Andre, 2023). Our work in chapter 4 heavily relies on the quantity and quality of the ITS data set, and we also propose that Generative AI embedded in ITS design can increase the quality of interventions significantly, given ITS does generate rich interaction data as compared to other LMS.

In addition to personalised learning pathways, generative AI can also facilitate the development of clustering techniques in identifying groups of learners with similar emotional states or learning behaviours. By employing clustering algorithms, educators can uncover distinct profiles of confused learners, enabling targeted interventions tailored to specific groups. For example, clustering can reveal patterns in how different learners engage with content, allowing educators to design interventions that address the unique challenges faced by each group (Manzanares & Ochoa-Orihuel, 2021; McBroom et al., 2020). Furthermore, integrating time series analysis with generative AI can enhance understanding of how confusion evolves. By analysing behavioural indicators related to confusion, such as skill mastery and time spent on tasks, generative AI can predict future levels of confusion in learners. This predictive capability allows educators to implement proactive strategies to support learners before confusion escalates, thereby improving retention and engagement (Alqahtani et al., 2019; Zhang, 2023). LSTM networks, for instance, can capture long-term dependencies in learners' interaction data, providing valuable insights into the dynamics of confusion and enabling timely interventions.

5.3 Theoretical Framework

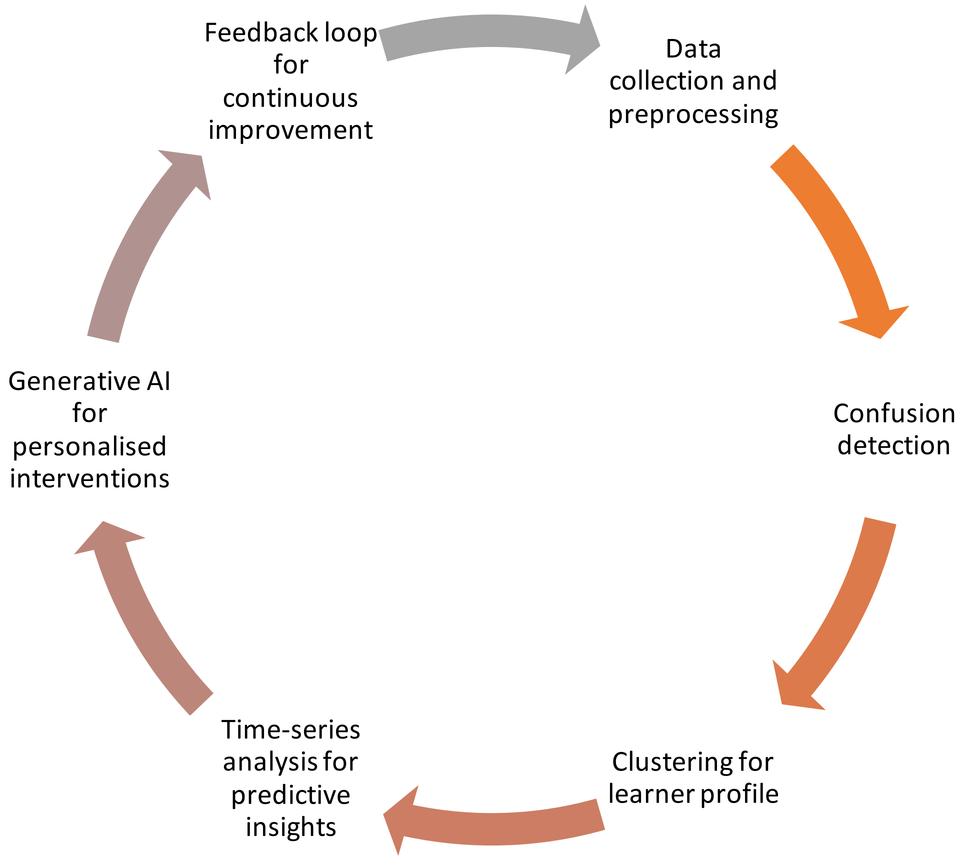

Figure 5-1 Theoretical Framework

5.4 Framework Components

5.4.1 Data Collection and Preprocessing

This component is all about getting the relevant data and making it usable. As we know raw data is hardly useful. So, this is an integral part of the framework to devise ways to collect meaningful data and apply appropriate data preprocessing like data cleaning, normalisation, and feature selection to ensure that the data set is ready for analysis. This is a moving goal due to continuous improvements and changes in existing online learning platforms; thus, utilising available rich interaction data from various data sources productively is one of the key components in this framework.

5.4.2 Confusion Detection

Fuzzy Logic Implementation: As discussed in Chapter 3, techniques like fuzzy logic can be used to detect confusion levels based on selected input parameters like time spent on tasks, hints requested, and others as discussed earlier. Again, this approach can be refined as newer data emerge from the system, but overall, such approaches allow for a nuanced understanding of confusion and enable educators to identify struggling learners needing support.

MLP for Classification: As discussed further in Chapter 3, deep learning techniques like MLP can be used to classify learners based on their interaction data and predict confusion levels. MLPs' ability to learn complex patterns from large datasets makes them particularly suitable for this task.

5.4.3 Clustering for Learner Profiles

Clustering Techniques: As discussed in Chapter 4, if online learning platforms can generate rich interaction data like from ITS, we can also employ clustering algorithms to group learners based on their affective states based on their interactions. This allows the identification of distinct profiles of confused learners that, in turn, enable targeted intervention strategies for tailored or customised support.

Explainable AI (XAI): Explainable AI techniques can be embedded in such decision-making processes to help educators understand what components are contributing to confusion in learners. Hence, they can help them create a comprehensive set of lessons learnt for continuous improvements and design future support strategies.

5.4.4 Time Series Analysis for Predictive Insights

LSTM Networks: As we extended our study in Chapter 4 to utilise an LSTM network to analyse confusion-related behavioural indicators over time, we can embed such time-series analysis in predicting near-future confusion to help educators design proactive strategies.

5.4.5 Generative AI for Personalised Interventions

Adaptive Learning Pathways: Generated AI does have a lot of potential in revolutionising personalised learning and creating adaptive learning pathways that can cater to various learners' needs. The insights gained from confusion detection and clustering analysis can form a strong foundation 4 generated AI tools to be in action. Generative AI tools can be used in generating customised feedback, resources and learning activities addressing areas of confusion in learners. Generative AI can continuously monitor the interaction data end of prediction from the underlying AI algorithms and can generate additional practice problems or alternative explanations or interactive simulations that can target the concepts the learner is struggling with. This personalised approach enhances the learning experience and fosters a deep understanding of concepts, leading to improved Academy performances and effective time utilisation of educators. Can the adaptive learning pathways dynamically adjust based on real-time data predictions, allowing for continuous refinement in learning experiences? The additional advantage is that Generative AI can then identify areas of confusion and provide insights to educators in future curriculum design that support search pain points. This capability aligns with the findings of Arvin (2023), who emphasises the transformative potential of AI in customising learning experiences and enhancing student engagement. By integrating generative AI into educational practices, educators can create a more responsive and effective learning environment that caters to the diverse needs of students.

Intelligent Tutoring Systems: As discussed in Chapter #4 where, we utilised the ITS data set for clustering and time series analysis. There is a strong future for utilising such ITS that can generate a lot of real-time rich interaction data representing another significant advancement in educational technology. Such systems can continuously monitor learners' interactions and use AI algorithms to identify their affective states in detecting confusion and other emotional responses. Confusion is identified, it allows one to design proactive approaches that can promote a supportive learning environment. Thus, by integrating generative AI into ITS allows for a more nuanced understanding of learners' needs, enabling the system to tailor its responses based on individual affective states and learning profiles. For example, if a learner exhibits frustration while attempting a challenging problem, the system can adjust its instructional strategy to offer more supportive resources or simplify the task. This capability aligns with the insights gathered from Arvin's (2023) study, which highlights the pedagogical benefits of AI, including personalised learning experiences that adapt to the unique challenges faced by each learner.

The landscape of generative AI is moving quickly, and there is a lot of promising research, including in education. Generative AI continues to evolve and enable educators to create more tailored and practical learning experiences addressing the diverse needs of learners. These teams are also identified in Arvin's (2023) research, acknowledging the importance of improving digital literacy and readiness for educators to ensure equitable access to AI resources. Developing comprehensive ethical guidelines to use AI responsibly in education is essential. Educators can then harness the power of generative AI and enhance learning outcomes to foster an inclusive educational environment that increases learners' engagement and deep understanding. This may also warrant educators effectively utilising AI tools and ensuring all learners can access the resources necessary for success.

5.4.6 Feedback Loop for Continuous Improvement

Data-Driven Decision-Making: This is an essential component as it assesses the effectiveness of the interventions based on the learner's outcome. In this stage, we must analyse the impact of targeted strategies on learners' performance and satisfaction that can, in the future, help educators who can then refine those approaches and improve the overall learning experience.

Iterative Model Refinement: The framework discussed earlier also supports continuous improvement, aligning with the need to redefine intervention strategies and data collection and preprocessing techniques as required. This will also support the need to continuously update the models used for confusion detection end predictions as new data and insights creep in, ensuring that the framework remains responsive to learners evolving needs.

5.5 Conclusion

Hence, we propose a theoretical framework that integrates advanced analytical techniques with generative AI to enhance confusion detection and develop targeted intervention strategies for learners to increase their engagement in an educational context. We also proposed that we can effectively predict confusion and end design intervention strategies around it by leveraging the rich interaction data like I TS AI algorithms like fuzzy logic MLP, clustering, time series analysis, and others. The framework discussed not only aims to understand how we can utilise it in creating personalised learning experiences that can address emotional dynamics of learning but also help educators utilise generative AI tools and techniques in a more meaningful and informed manner, helping them to support their learners timely. As research in this area continues to evolve, the framework can be adapted and refined to meet the diverse needs of learners, ultimately contributing to improved educational outcomes and quality education.

Chapter 6: Conclusions and Future Work

6.1 Overview

This thesis explores the critical role of epistemic emotions in learners' engagement, specifically the importance of confusion in the learning process. The thesis explored various researchers in confusion detection and prediction. Confusion plays a vital role in the learning process because confusion is found to be beneficial to learners and helps them achieve more. However, at the same time, prolonged confusion can contribute to frustration and boredom, ultimately leading to dropout. This research explores confusion detection in online learning platforms, mainly focusing on clickstream data analytics and AI techniques. Through a comprehensive literature review and empirical studies using fuzzy logic and MLP models, we establish a foundational understanding of the complexities involved in detecting learners' confusion and explore various indicators that contributed to it. The guiding research questions in the thesis targeted enhancing clickstream data analytics for confusion detection, identifying reliable patterns associated with learner confusion call mom and utilising emerging technologies like generative AI in developing actionable strategies. The studies presented in this thesis demonstrate the effectiveness of using AI models like fuzzy logic and MLP in detecting confusion levels, and they have the potential to be utilised in real-world data sets generated from various online learning platforms. Additionally, subsequent studies investigate the clustering of confused learners and apply time series analysis using long short-term memory bracket LSTM bracket close networks that can further enrich the understanding of how confusion evolves and can be predicted effectively to inform various intervention strategies for struggling learners. These findings show the importance of leveraging advanced analytical techniques and further developing a theoretical framework to integrate emerging technologies like generative AI techniques that can pave the road to personalise interventions in educational contexts.

While this research has made significant strides in understanding and detecting confusion in online learning environments, several avenues for future work remain.

6.2 Future Work

6.2.1 Expanding Data Sources

Future studies could explore integrating additional data sources beyond clickstream data, such as biometric data (e.g., eye-tracking, facial expressions) and social interaction data (e.g., discussion forum participation). This multi-modal approach could provide a more comprehensive understanding of learner confusion and emotional states.

6.2.2 Real-World Application

As future work, it will add more value when such proposed models are implemented in real-world educational settings to gain validation of their effectiveness. We propose future research on deploying these models in live online learning platforms and assess their impact on learner engagement and academic performance.

6.2.3 Longitudinal Studies

Future work could also include conducting longitudinal studies that will track the effectiveness of interventions over time to provide some valuable insights into the long-term impact of personalised learning strategies compared to student outcomes. This could be an ongoing process institute-wide and can help refine the predictive models and enhance their applicability across different educational contexts.

6.2.4 Improving Feature Engineering

As discussed in studies in this thesis, we selected features based on correlation. However, future work could also explore more sophisticated feature engineering techniques to capture more intricate relationships between student behaviour and confusion. For example, we can incorporate temporal features like time gaps between activities or interactions and experiment with the relationship using more controlled experiments to provide insights on prediction accuracies.

6.2.5 Incorporating Additional Data Sources

As discussed earlier, more data is generated as online learning platforms evolve. So, future work can include adding other contextual features as future research evolves to help enhance the model predictions.

6.2.6 Exploring Different Model Architectures

In Chapter 4, we discussed a study that used the LSTM model to predict confusion in learners. Future work could also explore alternative deep learning architectures like GRU (gated recurrent units), Transformers or hybrid models that can improve the prediction accuracy and computational efficiency. Such models can also increase accuracy by introducing an attention mechanism to capture the significance of different time steps in learners' history.

6.2.7 Incorporating Other Educational Outcomes

The thesis only focuses on confusion epistemic emotions; however, future work could expand the scope of other epistemic emotions and be used to detect and predict frustration, boredom or engagement. Implementing multiple epistemic emotions into the models can provide a holistic understanding of learners' behaviour.

6.2.8 Cross-Dataset Generalisation

The studies covered in this thesis only discuss models trained on a single data set. Future work can expand the testing of models' performance on multiple data sets from different learning environments or courses so that the models can experiment with to generalise across different contexts. Future work could also integrate confusion prediction into adaptive learning systems that can further allow personalised content delivery and support tailored for each learner based on the confusion level, including dynamically adjusting the lesson difficulty and pace.

6.2.9 Handling Data Imbalance and Noise

From our studies conducted and discussed in the previous chapters, it is to be noted that confusion data may not always be evenly distributed, with some learners experiencing confusion less frequently. This mainly happened because we depended on a single data set, and such data sets were balanced. This provides us with an opportunity to gather more of such data and explore other methods to handle the imbalanced data set, hence improving model robustness, using techniques like **SMOTE** (**Synthetic Minority Over-Sampling Technique**) or data augmentation.

6.2.10 Collaboration with Educators

The work discussed in this thesis can benefit from a close collaboration with educators and domain experts net, which can help develop better-contextualised interpretations of the results. These results can provide evidence-based decision-making in better curriculum adjustments and other educational intervention strategies that can be tailored to individual learner needs based on the predictions from such models.

6.3 Conclusion

In conclusion, this thesis discusses various studies that can enhance confusion detection in online learning environments by integrating advanced analytical techniques like fuzzy logic, MLP, clustering and time series analysis using LSTM networks. We address the research questions discussed in Chapter 1 and have established a comprehensive understanding of click stream data analytics with an I in improving confusion detection among learners. I was studying findings that demonstrate that methodologies are effective in identifying confusion levels based on behavioural indicators and have the potential to provide educators with timely insights to implement targeted and personalised interventions. As we look into the future, there are several avenues that this research can pay its way to. Our research yields a foundational understanding of behavioural indicators in existing online platforms. It allows them to expand their data sets, including the evolving online learning platforms and integrating additional contextual features. This understanding of the data sets can further guide our data collection and data pre-processing stages, which are critical to the success of any detection and prediction models. We have also explored different model architectures that form a good foundation for further research on how search models can enhance a more holistic understanding of learned behaviour. We also propose that collaboration is the key to the success of such endeavours. We propose that collaborating with educators to contextualise our findings will ensure that future-developed models are more effective and practical in real-world educational settings. By pursuing these future directions and by continuing to refine the understanding of confusion detection and developing innovative solutions to enhance the educational experience for all learners, we can create online learning platforms data highly inclusive and engaging to a variety of learners. Finally, we also propose that integrating emerging technologies like generative AI into personalised intervention provides a promising future in educational technologies, paving the way for adaptive learning platforms that will respond to the diverse needs of learners. As we advance this research, we remain committed to fostering improved educational outcomes and creating supportive learning environments that empower learners to succeed.

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