INVESTIGATING THE IMPACT OF TESTING AND SPACING ON STUDENTS' ACHIEVEMENT IN AN UNDERGRADUATE COURSE: UTILIZING A LEARNING ANALYTICS APPLICATION

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ABSTRACT

INVESTIGATING THE IMPACT OF TESTING AND SPACING ON STUDENTS' ACHIEVEMENT IN AN UNDERGRADUATE COURSE: UTILIZING A LEARNING ANALYTICS APPLICATION

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This study utilizes learner data from the Pearson MyLab® system, incorporating learning analytics (LA) technologies. It also employs Bjork's theory of disuse (1999), introducing desirable difficulties. Learners repeat through automated quizzes reinforcing the concepts learned in class with the system's Dynamic Study Modules (DSM). They receive actionable interventions based on their progress. Learning metrics are generated based on learners' DSM assignment attempts.

The study found that using DSM quizzes as a learning analytics intervention enhanced student performance. Furthermore, regression analysis indicated that DSM quizzes, as a form of retrieval practice, significantly improved retention for both midterm and final exams, supporting the testing effect.

The process mining results revealed that students who struggled with DSM assignments required more time to complete them and participated in fewer refresher activities. These findings highlighted the significance of retrieval practice in improving student exam performance. Similarly, sequence analysis demonstrated the relation between how students distributed their DSM quizzes throughout the semester and their achievement. When students spaced out their studies more evenly, they tended to achieve better results.

The study's findings demonstrate that innovative data analytics methods, such as process mining and sequence analysis, informed by learning theories, can potentially enhance our understanding of student performance. In addition, these methods provided insight into the effectiveness of a learning analytics application that incorporates retrieval practice.

Keywords: Learning Analytics, Process Mining, Sequence Analysis, Retrieval Practice, Spacing Effect, Motivational Dispositions

ÖZ

BİR LİSANS DERSİNDE TEST VE ARALIKLI ÇALIŞMANIN ÖĞRENCİ BAŞARISI ÜZERİNDEKİ ETKİSİNİN ARAŞTIRILMASI: BİR ÖĞRENME ANALİTİĞİ UYGULAMASINDAN YARARLANMA

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Bu çalışma, öğrenme analitiği (LA) teknolojilerini içeren Pearson MyLab® sisteminden alınan öğrenci verilerini kullanmaktadır. Ayrıca Bjork'un (1999) kullanmama teorisi kapsamındaki arzu edilen zorluklara dayanmaktadır. Öğrenciler, Dinamik Çalışma Modülleri (DSM) ile sınıfta öğrenilen kavramları pekiştiren tekrar ederler. İlerlemelerine göre eyleme geçirilebilir müdahaleler alırlar. Öğrenme metrikleri, öğrencilerin DSM ödev denemelerine dayalı olarak oluşturulur.

Çalışma, DSM ödevlerinin bir öğrenme analitiği müdahalesi olarak kullanılmasının öğrenci performansını artırdığını ortaya koymuştur. Ayrıca, regresyon analizi, bir geri çağırma pratiği olarak DSM ödevlerinin hem ara sınav hem de final sınavlarındaki performansı önemli ölçüde artırdığını ve test etkisini desteklediğini göstermiştir.

Süreç madenciliği sonuçları, DSM ödevlerinde zorlanan öğrencilerin bunları tamamlamak için daha fazla zamana ihtiyaç duyduklarını ve daha az tekrar yaptıkalırını ortaya koymuştur. Bu bulgular, öğrenci sınav performansının iyileştirilmesinde geri çağırma pratiğinin önemini vurgulamıştır. Benzer şekilde, sıra analizi, öğrencilerin DSM ödevlerini dönem boyunca nasıl dağıttıkları ile başarıları arasındaki ilişkiyi göstermiştir. Öğrenciler çalışmalarını daha dengeli bir şekilde dağıttıklarında, sinavlarda daha iyi sonuçlar elde etme eğiliminde olmuşlardır.

Çalışmanın bulguları, öğrenme teorileri tarafından bilgilendirilen süreç madenciliği ve sıra analizi gibi yenilikçi veri analitiği yöntemlerinin öğrenci performansına ilişkin anlayışımızı geliştirme potansiyeline sahip olduğunu göstermektedir. Buna ek olarak, bu yöntemler, geri çağırma pratiğini içeren bir öğrenme analitiği uygulamasının öğrenme üzerindeki etkililiğini göstermek acısından tatmin edicidir.

Anahtar Kelimeler: Öğrenme Analitiği, Süreç Madenciliği, Sıra Analizi, Geri Çağırma Pratiği, Ara Etkisi, Motivasyonel Eğilim

To my beloved ones…

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LIST OF ABBREVIATIONS

ABBREVIATIONS

DSM – Dynamic Study Modules

EDM – Educational Data Mining

EFLA – Evaluation Framework for Learning Analytics

ISE – Information Systems Engineering

JOL – Judgements of Learning

kNN – k-Nearest-Neighbors

LA – Learning Analytics

LAK – International Conference on Learning Analytics and Knowledge

LMS – Learning Management System

MAXQDA – Software Program for Qualitative Data Analysis

MOOC – Massive Open Online Course

MSLQ – Motivated Strategies for Learning Questionnaire

SNA – Social Network Analysis

SOLAR – the Society for Learning Analytics Research

SVM – Support Vector Machines

TAP – Transfer-Appropriate Processing

CHAPTER 1

INTRODUCTION

Throughout history, advancements in technology have consistently transformed human life. In the 20th century, the introduction of computers and the Internet revolutionized how we access, process, and control information. In today's technological era, individuals have unprecedented access to information with a single click. Moreover, they can communicate instantly through messaging and video calls, irrespective of geographic boundaries. These technological developments have also impacted educational practices, with online platforms and learning management systems making courses more accessible than ever before. The shift from traditional classrooms to online learning environments opens new opportunities for collecting data on learners' interactions with digital resources and learning communities.

Advancements in computer technology have allowed for the storage and analysis of large amounts of educational data in digital platforms, leading to the emergence of *Educational Data Mining (EDM)* and *Learning Analytics (LA)* (Calvet Liñán & Juan Pérez, 2015; Siemens & Baker, 2012). The research fields of digital footprints and learning analysis explore ways to gather and evaluate learners' digital interactions, providing valuable insights into the teaching and learning processes. The comprehensive analysis of all learner interactions within digital learning environments significantly impacts educational decision-making (Papamitsiou & Economides, 2014). Providing feedback to both instructors and learners is beneficial, but analyzing the large and complex data sets can be challenging. This difficulty has resulted in a growing interest in learning analytics in recent years.

Learning analytics provides a better understanding of learners and their learning processes, ultimately improving the effectiveness of instruction (Clow, 2013; Czerkawski, 2015; Lee et al., 2020; Piety et al., 2014; Reyes, 2015; Romero & Ventura, 2020; Siemens, 2013). Various efforts have been made to identify patterns in noisy learner-generated data in digital platforms to explore learning from different and multiple perspectives (Arnold & Pistilli, 2012; Chango et al., 2019; Keržič et al., 2019; F. Martin & Ndoye, 2016; Romero-Zaldivar et al., 2012; Strang, 2017; Svihla et al., 2015; D. T. Tempelaar et al., 2015). Extensive research has been conducted on student behavior modeling and performance prediction (Papamitsiou & Economides, 2014; Sin & Muthu, 2015). A number of researchers have reported that some types of activities that learners perform within online learning environments are associated with their academic performance (Gašević et al., 2015; Strang, 2017). In order to create more effective learning systems, researchers have investigated various factors that can serve as indicators of academic performance (Papamitsiou & Economides, 2014). In contrast, there is still considerable debate regarding which types of activities or student data predict better academic performance and can track changes in behavioral data (Ellis, 2013; Gašević et al., 2015; Wilson et al., 2017). Predictive algorithms are typically used to analyze datasets consisting of background information (such as demographics, socioeconomic status, prior academic experience, and performance) and online behavior (such as logfiles and trace data) (Yau & Ifenthaler, 2020).

According to studies, demographic information is not a reliable predictor of student performance in online courses (Strang, 2017). There are also conflicting findings regarding *checkpoint analytics* (Lockyer et al., 2013), which measure a student's interaction with the digital learning environment, including login frequency, access to materials, and submission of assignments. However, learning analytics can be more effective when it considers diverse data that reflects various aspects of learning, such as cognitive and social dimensions, in addition to basic metrics

(Dawson & Siemens, 2014; Pardo & Kloos, 2011; Siemens, 2013). Most research studies have highlighted that *process analytics* (Lockyer et al., 2013), which examines students' participation and demonstration of knowledge in online activities like quizzes, assignments, and forum posts, is highly associated with higher grades (Keržič et al., 2019; Papamitsiou & Economides, 2014; Strang, 2017). Tempelaar et al. (2015) also confirmed that student data from formative assessment strongly predicts their future performance. Another study further supports the role of spending more time revisiting complex activities to promote coherent student understanding (Svihla et al., 2015). Similarly, James (2018) found that completing topics and levels of difficulty within those topics had a greater impact on final grades than the number of practice problems attempted. Furthermore, there was no linear relationship between textbook or video lecture access and final grades. Therefore, learning analytics practice focusing on learning process data rather than event and performance data measures provides a better understanding of learning.

Despite its promises, learning analytics practice and research has many challenges. Learning analytics might present an incomplete picture of learning (Dollinger & Lodge, 2019; Mittelmeier et al., 2018; Yau & Ifenthaler, 2020). The selection of metrics from the datasets appropriately reflects the complexity of learning and learning processes, which is critical in learning analytics (Clow, 2013; Lockyer et al., 2013; Siemens, 2013). If researchers select an improper educational dataset, they are likely to have inaccurate results about learners and their processes, which unfavorably affect the optimization of learning processes (Klašnja-Milićević & Ivanović, 2018). In learning analytics studies, how academic success is operationalized and measured depends on the context - such as passing grade in a specific module or course, passing grade in a specific exam, passing grade point average, student's graduation, and student's graduation with no failures (Alyahyan & Düştegör, 2020; Knobbout & Van Der Stappen, 2020). Therefore, the accuracy of these study findings for predicting student success must be interpreted cautiously since learning analytics does not explain all variance in student performance (Archer & Prinsloo, 2020).

In this regard, few studies (Chango et al., 2019; Pardo & Kloos, 2011; Romero-Zaldivar et al., 2012) have investigated data from multiple sources (learning environments) with different formats and with different granularity levels, although extensive research has been carried out on discovering predictive values of single online data. A promising example is the study of capturing data on learning events outside the Learning Management System (LMS) (Pardo & Kloos, 2011). However, a comprehensive capture of the events of a learning experience taking place outside of online and digital systems, especially in-class sessions to monitor student progress, is a challenging practice (Chatti et al., 2012; Ellis, 2013; Romero-Zaldivar et al., 2012; Siemens, 2013) which would eventually prevent to see the full image of learner and learning. Papamitsiou and Economides (2014) reported that the accuracy of learning analytics objectives such as learner profiling and personalization depends on data from multiple sources, not only LMS-centric data in the systematic literature they reviewed. There is another concern about using learning analytics techniques such as classification, which would cause inappropriate categorization of students (Archer & Prinsloo, 2020; Mittelmeier et al., 2018). Despite the need for granular data points about learners, ethical issues and data usage restrictions have been widely debated in the field of learning analytics (S. J. Aguilar, 2018; Baker, 2013; Clow, 2013; Greller & Drachsler, 2012; Piety et al., 2014; Scheffel et al., 2014; Sclater, 2016; Seufert et al., 2019; Siemens, 2013; Snodgrass Rangel et al., 2015; Wintrup, 2017).

Along with these expectations in learning analytics, however, there is an increasing concern over the lack of theory-driven practice and research, as Clow (2013) stated, “a coherent and articulated epistemology.” Several researchers have doubted the current stress on processing and analyzing learner data rather than pedagogical grounds (Ellis, 2013; Francis et al., 2020; Gašević et al., 2015). The general opinion is that learning analytics can only achieve its objective when guided by theoretical frameworks, practical models, and pedagogical approaches (Gašević et al., 2017; Greller & Drachsler, 2012; Wilson et al., 2017; Wise & Shaffer, 2015; Yau & Ifenthaler, 2020). Therefore, many attempts have been made to develop learning analytics framework and models incorporating learning design (Bakharia et al., 2016; Chatti et al., 2012; Davies et al., 2017; Elouazizi, 2014; Gašević et al., 2017; Greller & Drachsler, 2012; Scheffel et al., 2014; Seufert et al., 2019; Wise, 2014; Wise et al., 2016).

1.1 Significance of the Study

Learning analytics has recently become an essential component in educational practices and has played a crucial role in designing ubiquitous online learning platforms with rich student data trails and essential insight into the learning process (Long & Siemens, 2011). On the contrary, the impact of learning analytics in improving learning and teaching has not yet been clarified (Durall & Leinonen, 2016; Francis et al., 2020). In particular, the critical question remains about how learning analytics effectively measure, monitor, predict, and improve student performance (Wilson et al., 2017). Most studies in this field are limited to plain learner data without theoretical orientations or have a weak connection with learning analytics foundations and data-informed learning design (Hernández-Leo et al., 2019; West et al., 2018). However, there is still a need for an approach to conceptualize learning analytics processes (Klašnja-Milićević & Ivanović, 2018). Little is known about designing compelling learning experiences incorporating analytics data (Bakharia et al., 2016; Wise et al., 2016). Moreover, much uncertainty remains about which metrics best explain student success and performance (Durall & Leinonen, 2016).

This study aims to contribute to this evolving area of research by exploring and testing metrics related to student-generated data within digital learning platforms. Thus, it will offer important insights into learning processes with validated indicators of successful learning and effective teaching. Additionally, this dissertation will significantly contribute to research on learning design by presenting design principles to support learning analytics consultation. (Bakharia et al., 2016; Thille & Zimmaro, 2017; Wise, 2014).

1.2 Purpose of the Study

This study aims to identify learner analytics data strongly associated with student success while also developing instructional design principles that can facilitate the implementation of learning analytics. More specifically, the study will investigate how students use Dynamic Study Module (DSM) assignments as a form of retrieval practice and examine the impact of spacing the DSM assignments on student learning over a regular term period.

1.3 Research Questions

1. Do the DSM Assignments as Learning Analytics Application support student learning across different achievement levels?
2. Which DSM variables contribute to predicting student success?
3. Do DSM assignments effectively promote learning as retrieval practice for students with different achievement levels?
4. How effective are DSM assignments in promoting learning when scheduled based on the spacing effect for students with varying achievement levels?

5 How do students with different achievement levels engage with DSM assignments?

CHAPTER 2

LITERATURE REVIEW

This chapter conceptualizes learning analytics as a practice and research field, its relationship with other disciplines, and its standard methods and promises for educational practices. Existing research on learning analytics, particularly prediction, and development of frameworks and models for learning analytics, was reviewed. The following sections present big data in education and data science. The similarities and differences between educational data mining and learning analytics were clarified. The standard techniques applied in learning analytics studies and some tools used in learning analytics practice were introduced. Then, the promises and objectives of learning analytics and its relation to learning design were discussed. The second part of the literature introduced the theoretical framework for student learning. It discussed in detail the pillars of the new disuse theory, which served as the basis for data collection and metric selection.

2.1 Big Data in Education and Data Science

Nowadays, we are swimming in a “digital ocean,” as DiCerbo and Behrens (2014) describe the considerable amount of data available from interactions with digital tools. These large datasets are beyond the ability of traditional and standard software and database methods to process is called *big data* (Klašnja-Milićević et al., 2017; Manyika et al., 2011; Sin & Muthu, 2015). Modern technology, including the Internet and ubiquitous computing systems, have regulated how people approach data. The dramatic increase in digital traces has changed the data generation, collection, process, and storage methods. Big data is distinctive from traditional data in some characteristics, starting with Vs. (Klašnja-Milićević et al., 2017). The first three attributes of big data were proposed by Laney (2001): *volume*, *variety*, and *velocity*. Volume specifies the vast amount of data generated daily that cannot be processed with traditional techniques. Variety refers to the various modalities of data types and data sources. The data in different forms, such as images, videos, speech recordings, and sensors collected through different settings, are primarily unstructured and require specific algorithms to reveal relationships among them. Velocity, however, indicates the speed of streaming data, which may be generated in split seconds. Another attribute, *veracity,* is associated with big data, which refers to the authenticity and credibility of the data. In Oracle's white paper, a fifth characteristic is mentioned: *value*, which stands for the added value for stakeholders (Dijcks, 2012).

As in every practice, big data is emerging in education through extensive educational media. Student interactions with the course activities, materials, and peers in the various learning management systems such as Moodle and Blackboard are captured and stored. Learners' "records of experience" (as cited in Behrens et al., 2018) have big data characteristics. In the current ubiquitous learning environments, learners' various and authentic digital footprints are generated in high volumes and reprocessed in almost real-time to provide valuable comprehension about their learning performance. As a technological solution, learning analytics handles large sets of educational data that cannot be dealt with manually or traditionally. (Ferguson, 2012). Learning analytics utilizes the methods and techniques of data science to collect, measure, analyze, and report big data. "Data science is a concept to unify statistics, data analysis, machine learning, and their related methods" (Romero & Ventura, 2020, p. 2), which differs from the traditional scientific approach - hypothesize, model, test.

Anderson (2008) argues that data science algorithms without hypotheses and models can find meaningful patterns in the massive amount of data, whereas it is difficult with conventional science. Klašnja-Milićević et al. (2017) also state that contemporary approaches are required to discover hidden patterns within the educational data automatically. Existing research on data-driven approaches reveals the power and importance of data science methods and systems in exploring educational data (Gašević et al., 2017; Romero & Ventura, 2010). Piety, Hickey, and Bishop (2014) point out that educational data science combines various emerging research fields, including learning analytics and educational data mining. The following section examines the similarities and differences between the two fields.

2.2 Educational Data Mining and Learning Analytics

In recent years, Educational Data Mining (EDM) and Learning Analytics (LA) have attracted a great deal of attention from scholars in the field of education. Both research communities serve a common purpose, supporting education research and practice by improving the quality of analysis of educational big data with the help of data-intensive approaches (Calvet Liñán & Juan Pérez, 2015; Siemens & Baker, 2012). Nevertheless, these communities have distinctive orientations and affiliations with different domains and rely on different fields of expertise, as seen in Figure 1, illustrated by Romero and Ventura (2013).

Educational Data Mining is defined as: "An emerging discipline, concerned with developing methods for exploring the unique types of data that come from educational settings and using those methods to understand better students and the settings in which they learn." by The International Educational Data Mining Society in 2007 (Baker, 2010, p. 1). Ferguson (2012) points out that educational data mining concentrates more on the technical issues rather than on the pedagogical challenges in the process of extracting useful information from vast amounts of educational data (Berland et al., 2014). Romero and Ventura (2013) highlight the computerized methods to detect patterns in complex educational datasets in EDM applications.

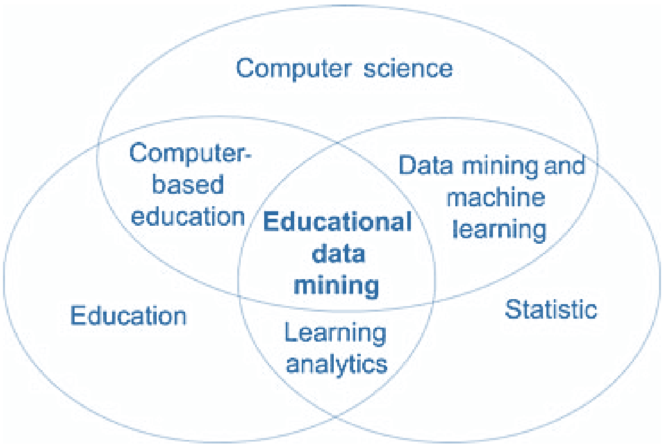


Figure 1 Educational Data Mining and Other Fields

Learning Analytics was first defined by the Society for Learning Analytics Research (SOLAR) during the first International Conference on Learning Analytics and Knowledge (LAK) conference as “the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs (Long & Siemens, 2011, p. 34)”. Several researchers have attempted to define and conceptualize learning analytics following this definition. Most of them agree that the input of learning analytics is learner product data, including the demographic, behavioral, and digital trace within authentic learning environments (Broughan & Prinsloo, 2020; Clow, 2013; Francis et al., 2020; Gašević et al., 2017; Reyes, 2015). Some scholars specify this learner data as dynamic or live (Mah, 2016; Zilvinskis et al., 2017). Winne et al. (2019) highlight that learner data is continuously updated rather than regular reports periodically exported with specific time points. Therefore, learning analytics uses both dynamic longitudinal learner data within learning environments and static learner data periodically exported from those environments, for instance, at the end of semesters.

Another critical aspect of learning analytics is analyzing learner data. This process includes applying big data analysis techniques, including machine learning and algorithmic processing (Clow, 2013; Francis et al., 2020) and Business Intelligence (Marcu & Danubianu, 2019). In this process, sophisticated analytic tools and techniques produce metrics related to the profile, progress, and performance of students, establish indicators of teaching quality (Clow, 2013; Lockyer et al., 2013), and report these metrics in innovative and valuable forms (i.e., through dashboards) (T. Martin & Sherin, 2013; Reyes, 2015). The most important aspect of learning analytics is providing valuable information to improve learning and teaching processes by modeling and making predictions on student profile, performance, and engagement, promoting actionable intervention based on profiling and making predictions, and monitoring the outcome (Francis et al., 2020; Lockyer et al., 2013; Mah, 2016; Zilvinskis et al., 2017). Based on the metrics and indicators presented by learning analytics methods, both students and instructors are informed about their pedagogical choices and strategies (Broughan & Prinsloo, 2020). Thus, learning analytics contributes to educational decision-making by optimizing and personalizing the learning and teaching experience (Clow, 2013; Ifenthaler, 2015; T. Martin & Sherin, 2013; Reyes, 2015; Wise, 2014).

Despite EDM and LA being interrelated fields that use exceptional data analysis tools and methods to improve learning, the core differences between them can be explained by their positions on the continuum of objectives for the process (analysis vs. analytics), the data analysis (human vs. automated), operationalizing the phenomena (system vs. structure) and intervening (automated vs. improvement). For the process, analysis refers to EDM, whereas analytics refers to LA since analysis is focused on uncovering the hidden links and patterns within data, and analytics is concerned with presenting and communicating that information (Şahin & Yurdugül, 2020). For the data analysis, EDM relies on developing new algorithms and models using data mining techniques to automatically look for new patterns in large amounts of data and process that data (Marcu & Danubianu, 2019; Piety et al., 2014; Romero & Ventura 2020; Siemens, 2013; Vieira et al., 2018). On the other hand, learning analytics is more oriented toward human sense-making and interpretation of existing data in educational settings and data-driven decision-making by applying methods such as business intelligence (Marcu & Danubianu, 2019; Piety et al., 2014; Romero & Ventura, 2020; Siemens, 2013). EDM focuses on organizing and reducing educational data into individual constituents (specific constructs) and how they are interrelated by embracing a reductionist approach; LA aims to understand the entire system of learner data with full complexity within the holistic perspective (Czerkawski, 2015; Papamitsiou & Economides, 2014). Finally, EDM models are often used for automated interventions within the computer-based system, such as an intelligent tutoring system. In contrast, LA models empower the informed decision-making of instructors and learners (Siemens & Baker, 2012).

Both fields contribute to improving the quality of education by developing specific tools and applying data science methods, such as predictive models, despite differences in their origins, standard methods for analysis, and primary goals. Technological challenges in education are of interest to EDM, with origins in the Data Mining domain, while LA, with origins in Business Intelligence and the Semantic Web domain, is concerned about the educational and pedagogical challenges (Marcu & Danubianu, 2019; Romero & Ventura, 2020). Learning and academic analytics are sometimes interchangeably used in literature, even with different objectives. Unlike learning analytics, academic analytics aimed attention at the political/economic challenges of educational practice to provide solutions at institutional (meso) or national (macro) levels (Ferguson, 2012; Piety et al., 2014). The following sections will introduce the techniques borrowed by Learning Analytics and Educational Data Mining, which assist in how learner data can provide helpful information to advance the learning process.

2.3 Learning Analytics Techniques

Learning analytics employs various data science techniques for analyzing educational data. Before digging into these standard techniques, it should be noted that the choice of different learning analytics techniques depends on the objectives of the analytics task (Chatti et al., 2012). Three main categories of learning analytics applications are *descriptive*, *predictive*, and *prescriptive*. Descriptive analytics interprets static data to understand better changes in student behavior and performance within digital learning systems (Yau & Ifenthaler, 2020). Current score, time spent, and frequency of access are typical examples of data measures for descriptive analytics techniques (F. Martin & Ndoye, 2016).

On the other hand, predictive analytics aims to predict unknown future events, such as student behavior, skill, and performance, by analyzing educational data (Clow, 2013; Sin & Muthu, 2015; Yau & Ifenthaler, 2020). Prescriptive analytics is related to both descriptive and predictive analytics. However, it primarily informs interventions designed by monitoring student data to improve learning outcomes, such as suggesting immediate feedback (Clow, 2013; Yau & Ifenthaler, 2020).

Learning analytics applies various techniques from different domains to perform the analytics described above, such as data mining and machine learning, statistics, social network analysis, and web mining (Romero & Ventura, 2007). Siemens

(2013) describes these techniques as the algorithms and models necessary for conducting analytics, which reflect machine learning and Artificial Intelligence techniques. He differentiates learning analytics applications by highlighting that they are used to promote teaching and learning. Klašnja-Milićević and Ivanović (2018) state that there are four stages of a learning analytics application as follows: Awareness, Reflection, Sensemaking and Impact. This section will illustrate standard techniques, the objectives, and their applications within sample cases. The most common algorithms and models used in learning analytics can be categorized as follows: prediction, clustering, relationship mining, distillation of data for human judgment, discovery with models, and social network analysis (SNA) and so on (Baker, 2010, 2013; Baker & Yacef, 2009; Calvet Liñán & Juan Pérez, 2015; Papamitsiou & Economides, 2014; Romero & Ventura, 2010, 2013).

2.3.1 Prediction

As discussed above, prediction algorithms and models are used to infer an individual aspect of the data by analyzing some other aspects (Romero & Ventura, 2013). In education, the predicted variables are usually students' performance, knowledge, score, or grade. The critical application of this technique in learning analytics is to predict student performance and detect student behaviors to provide an early intervention. An excellent example of this can be found in the Purdue Signals Project, which aims to predict the probability of a student's failure or dropping out of a course in a semester and inform instructors about these students. This very unique project showed that this prediction application has significantly improved student retention and performance outcomes at Purdue University (Arnold & Pistilli, 2012). Broadly, the three methods for inferring predicted variables from predictor variables are classification, regression, or density estimations (Romero & Ventura, 2013). Classification (supervised learning) is used when the predicted variable is binary or categorical, while regression is preferred for continuous variables. Decision trees, neural networks, and Bayesian classifications are some classification methods. For instance, Keržič et al. (2019) used and compared many classification methods to predict the final performance and grade of students, including the naïve Bayesian classifier, logistic regression, k-nearest-neighbors (kNN), support vector machines (SVM) with a linear kernel, and random forest. In another study, Strang (2017) used multiple regression to examine the hypotheses associated with the predictive factors of student online activities such as Moodle engagement analytics, reading and quiz activities, and quiz scores. Density estimation, on the other hand, is helpful if the predicted value is a probability density function. Valuable information about a large dataset can be gained from the data of previous students in the courses by applying sophisticated techniques (Clow, 2013).

2.3.2 Clustering

Clustering methods find data points that naturally group together and split the entire dataset into the detected clusters. This method uses distance measures to identify groups of similar observations in a dataset (Chatti et al., 2012; Romero & Ventura, 2013). In the educational context, the learning and interaction patterns detected by clustering algorithms and models help to group similar students or course materials. Clustering algorithms are practical when no prior information about categories exists in the data (unsupervised learning). Clustering methods may be divided into three main categories: partitioning methods, hierarchical methods, and density-based methods (Chatti et al., 2012). In partitioning methods (e.g., k-means), an initial random partitioning is constructed, where data objects are iteratively relocated to reach the most representative clusters. Hierarchical methods, however, form a tree of clusters by merging or splitting data objects.

On the contrary, in density-based methods, clusters are seen as dense regions of objects—for instance, Romero et al. (2009) used the k-means algorithm to cluster students based on the knowledge level and frequency of page visits. Another example would be that Klašnja-Milićević et al. (2011) benefit from data clustering methods to break students into groups based on their learning style and provide related learning materials to their profiled groups.

2.3.3 Relationship Mining

Relationship mining techniques discover the relationships between various variables in a dataset. As a learning analytics application, relationship mining supports identifying relationships between learner behavior patterns and diagnosing their difficulties in the learning process. There are four main types of relationship mining algorithms: association rule mining, correlation mining, sequential pattern mining, and causal data mining. Association rule mining aims to find if-then rules in the data. For example, Merceron and Yacef (2008) exemplified how association rule mining can determine the relationship between student use of the resources and their exam results by stressing two measures of interestingness, cosine, and added value and lift. However, correlation mining seeks (positive or negative) linear correlations between variables, while sequential pattern mining looks for temporal relations between events. Finally, causal data mining aims to discover whether one event has caused another event or not.

2.3.4 Distillation of Data for Human Judgment – Learning Analytics Dashboards

The distillation of data intends to represent complex data using intelligible methods such as summarization, visualization, and interactive interfaces. This method utilizes statistics and visualization techniques to help students and teachers to comprehend data analytics. As digital platforms provide reports on complex educational data, they become more challenging to understand. The distillation of data helps instructors analyze the visual representations and summary of current student activities and the use of course content. When presenting analytics data, traditional statistical visualization strategies such as bar plots, pie charts, scatter plots, concept maps, heat maps, and word clouds can be used, as well as novel approaches like interaction matrices, circular graphs, and spiral timelines (Vieira et al., 2018). For example, the Social Networks Adapting Pedagogical Practice (SNAPP) tool visualizes the patterns of student behaviors in online discussions (Bakharia et al., 2009).

Learning Analytics Dashboards serve as a distillation of data, providing students with opportunities to enhance their awareness, reflection, sense-making, and decision-making skills (Francis et al., 2020; Grann & Bushway, 2014; Kim et al., 2016; Klašnja-Milićević & Ivanović, 2018). Learning analytics dashboards provide valuable information to not only students but also teachers. They found that learning analytics dashboards are potentially useful in supporting their teaching and learning practice (D. T. Tempelaar et al., 2015).

Numerous researchers have dedicated their efforts to investigating the design and structure of learning analytics dashboards in various contexts. Jayashanka et al. (2022) developed a learning analytics dashboard aimed at visualizing learning data and supporting time management for higher education students. Their findings revealed that the system enhances student motivation, engagement, and grades in both online and blended learning. Similarly, Broos et al. (2020) found that using self-service dashboards to learn and practice study skills early on is associated with higher academic achievement later in the academic year.

Moreover, Han et al. (2021) conducted a study that demonstrated that implementing learning analytics dashboards resulted in significant improvements in group study processes, group achievement, and individual learning within collaborative study environments. Additionally, Akçapınar and Hasnine, (2021) examined how gamification could enhance the use of learning analytics dashboards and discovered that it increased students' motivation and engagement with the dashboard.

However, there is a lack of evidence regarding the effectiveness of Learning Analytics Dashboards in improving learner outcomes (Matcha et al., 2020; Susnjak et al., 2022). Further research is needed to understand their impact on student behavior, learning strategies, and performance. This lack of evidence may be attributed to several factors, such as the dashboards not being based on theoretical foundations, not being user-oriented, failing to incorporate indicators of learning processes and effective feedback (Matcha et al., 2020) or student's low level of dashboard usage (Bodily et al., 2018).

For instance, a study by Kaliisa and Dolonen (2023) suggests that involving teachers in the design and implementation of learning analytics dashboards aligns dashboard metrics with relevant theoretical constructs, enabling teachers to monitor learning designs and make course design changes in progress. Additionally, the study highlights the need for learning analytics dashboards to provide actionable insights and move beyond simply reporting on the current state to desired outcomes. Moreover, the visual appeal and usability of learning analytics dashboards significantly impact learner comprehension, which affects perceived usefulness, influencing potential behavioral changes (Y. Park & Jo, 2019)Another aspect of learning analytics dashboards that would increase their effectiveness is giving students control over customizing them. Providing students with control over the learning analytics dashboard can enhance self-regulated learning and academic achievement (Roberts et al., 2017).

2.3.5 Discovery with Models

This technique uses a previous model of a phenomenon validated by other techniques, such as prediction and clustering techniques, in another related analysis (Baker & Yacef, 2009). Discovery with models aims to identify relationships among student behaviors and characteristics or learning environment-related phenomena. For instance, Hershkovitz et al. (2013) applied discovery with models to investigate the relationship between student carelessness as a form of disengaged behavior in computer-based learning activities and their attributes. First, they modeled the construct of "carelessness" by employing a machine-learned decision tree. Then, using that validated model, they used cluster analysis to discover the relationship between carelessness and motivation. In another study by Pardos et al. (2014), they trained and validated metrics related to effect and behavioral engagement constructs using a couple of classification algorithms, such as J48 decision trees, step regression, JRip, Naive Bayes, K*, and REP. Trees. This model was then used to explore and predict students' performance in state tests.

2.3.6 Social Network Analysis

Social network analysis (SNA) aims to analyze the connections between entities in networked information rather than variables (Clow, 2013; Romero & Ventura, 2007). The structure and content of online education communities are studied using data mining and social networks. It mainly studies interactions between students and facilitators and interaction among students. SNA, as a learning analytics application, enables interpreting the structure and relations of students in collaborative activities such as discussion boards and how they interact with the communication tools used in those activities. Interaction measures such as frequency of posts, length of posts, and themes are examples of interaction measures for this technique (F. Martin & Ndoye, 2016). For instance, Macfadyen and Dawson (2010) used network analysis to identify disconnected students in discussion forums of a course and patterns in student-to-student communication and instructor positioning within the network by integrating the SNAPP (Bakharia et al., 2009) as an extension to the current LMS. Clow and Makriyannis (2011), on the other hand, take advantage of network analysis techniques in the iSpot that enable social interaction in a scientific mode to discover a social picture of activities taking place on this platform. Another example of how SNA is used as learning analytics can be found in the study that aimed to explore student participation and social connections within the Massive Open Online Course (MOOC) by clarifying relationships between nodes on the network (Fournier et al., 2011).

As described in this section, learning analytics applications contribute to the prediction and personalization of learning by using sophisticated techniques and models. In the following section, the promises of learning analytics that employ these data science techniques and sophisticated data analysis tools will be presented in detail.

2.4 Promises of Learning Analytics

Learning analytics data provides many opportunities to improve productivity and effectiveness in learning and teaching practice (Archer & Prinsloo, 2020; Baker, 2013; Durall & Leinonen, 2016; Verbert et al., 2012). Learning analytics can provide significant information to learners and teachers about their educational performances by using adequate methods and data analytics software mentioned above (Klašnja-Milićević & Ivanović, 2018). Although learning analytics is a relatively emerging field of research, its promises for improving education are impressive.

2.4.1 Understanding the Learning Process

In general, learning analytics applications and tools help instructors better understand student learning by providing formative data (Baker, 2013; F. Martin & Ndoye, 2016). Learning analytics offers insights about student learning based on the analysis of data combinations of students' behavioral traces within digital platforms and other sources of data (e.g., demographical and prior learning) (Archer & Prinsloo, 2020). This information on learners and learning processes provided by analytics data can potentially improve the quality of the learning experience (Long & Siemens, 2011). This potential influence can be seen in the case of ASSISTment, an online tutoring system that provides students with instructional assistance while they work on specific questions (Feng et al. (2009) used learning analytic techniques to evaluate students' experience in this system and to understand better the time spent solving a problem and the number of attempts to finish a problem.

2.4.2 Tracking

Another promise of learning analytics is tracking students' online traces to analyze their behavior and engagement by seeking factors that may indicate the risk of failing or dropping out (Baker, 2013) and responding to the changes in their behavior and engagement (F. Martin & Ndoye, 2016). It provides methods for predicting learner performance and modeling students, which informs teachers about students with specific learning needs. In recent online learning systems, assessment of student engagement and even emotion has become increasingly archivable. As mentioned above, the Purdue Signals Project tracks students' progress, predicts potential student failure or dropout, and finally informs instructors (Arnold & Pistilli, 2012).

2.4.3 Feedback

The information obtained by monitoring the student learning process supports the practice of the key stakeholders, who are closely associated with educational processes. The information provided by learning analytics advances teachers' awareness and reflection on their professional practice (Francis et al., 2020). Teachers can also identify the learning topics that are more complicated for students by utilizing reports generated by recent learning platforms (Baker, 2013). Information about the achievement of learning objectives in a course provides opportunities for teachers to redesign the pedagogical approaches and materials related to that part of the curriculum. Thus, teachers can understand and improve the effectiveness of teaching practices.

A significant example is LOCO-Analyst, a generic feedback provision tool for teachers (Jovanović et al., 2007, 2008). Learning analytics also provides personalized feedback for other stakeholders and students, empowering them to better understand their data. In this sense, J. Aguilar et al. (2018) conducted a study on utilizing Learning Analytics in the context of smart classrooms. They proposed integrating cloud and multi-agent paradigms to create a knowledge feedback loop within the smart classroom to improve learning. This approach, tailored to students' teaching and learning requirements, aimed to enhance the overall learning experience in a smart classroom.

Learning analytics helps students make sense of their learning data through sophisticated visualization of their progress (Durall & Leinonen, 2016; Francis et al., 2020). This visualization supports students' competencies for self-directed and self-regulated learning (Clow, 2013).

2.4.4 Personalization

Finally, learning analytics have the potential to provide personalized learning experiences by suggesting relevant learning resources to individual students (Durall & Leinonen, 2016). The learning analytics systems analyze learner data to suggest learning materials, peers, or specific learning paths. According to Aguilar (2018), learning analytics prompts the design of a learning experience for an actual student rather than an average student who is no one. In this sense, Khribi et al. (2009) have attempted to develop a recommendation system that provides students with personalized educational resources and links embedded in e-learning platforms. Similarly, the AHA! system provides students with tailored navigation in a general-purpose adaptive hypermedia platform based on their knowledge level (Romero et al., 2009). Another outstanding example of personalization of the learning experience would be suggestions made by *Protus,* which is a recommendation module of a programming tutoring system, on online learning activities and materials based on students learning characteristics, knowledge, preferences, and purposes within (Klašnja-Milićević et al., 2011). The *STACK* system, which originated at Aalto University in 2006, is another software that offers personalized exercises, instant feedback, dynamic images, interactive visualizations, and a programming environment for e-learning games. It enables flexibility and timesaving benefits for students and delivers personalized and interactive learning experiences in mathematics (Rasila et al., 2015).

As discussed above, the objectives of learning analytics are promising. However, researchers agree that those theoretical foundations are significant bases for learning analytics practice and research (Gašević et al., 2017). The following section outlines some learning analytics frameworks that conceptualize learning analytics practice and research.

2.5 Learning Analytics Frameworks and Learning Design

As Aguilar (2018) stated, data-driven educational technologies employing learning analytics are not silver-bullet solutions to educational problems. Several scholars highlight the importance of the theoretical framework to lead the best application learning analytics to successfully establish indicators of teaching quality and student performance (Dawson & Siemens, 2014; Gašević et al., 2017; Lockyer et al., 2013). Regarding theoretical orientation, learning analytics involves identifying connections, guiding data collection and analysis, interpreting results, developing strategies, validating patterns, informing theory and instructional design, and establishing a conceptual framework (Mangaroska & Giannakos, 2019). Correspondingly, Nistor and Hernández-Garcíac, (2018) have presented a comprehensive conceptual model known as "observed process-data-transformation-analysis-output" for analyzing diverse learning analytics studies. This model consists of cognitive and social processes, various types of data used, data transformation processes, analysis methods, and outcomes. The framework facilitates the understanding and comparison of research studies in learning analytics research and practice, considering observed processes, data types, analysis methods, and outcomes.

By contrast, learning analytics initiations are mainly urged by already collected data rather than pedagogical theories (Chatti et al., 2012). Although there are infinite possible patterns in learner data, a theory guides researchers' attention to specific variables to include data mining models (Wise & Shaffer, 2015). A learning analytics practice operationalized by a theory becomes more functional in learning design by validating the assumptions of theory in various contexts (Rienties et al., 2016; Yau & Ifenthaler, 2020). For example, prediction models may overlook the reason for student failure while successfully calculating its probability.

On the contrary, explanatory models rely on theories to operationalize concepts and test causal explanations. For the effectiveness of learning analytics in finding patterns and making sense of the noise in data, the models should be established based on a theory (Archer & Prinsloo, 2020). Thus, learning analytics studies offer guidelines for planning the optimal design of instruction with the correct set of variables that promote better learning outcomes. In addition to the contributions of theory in developing models, it provides a framework for interpreting the results and justifying the actions for improved learning (Wise & Shaffer, 2015). In this section, a couple of learning analytics frameworks will be discussed.

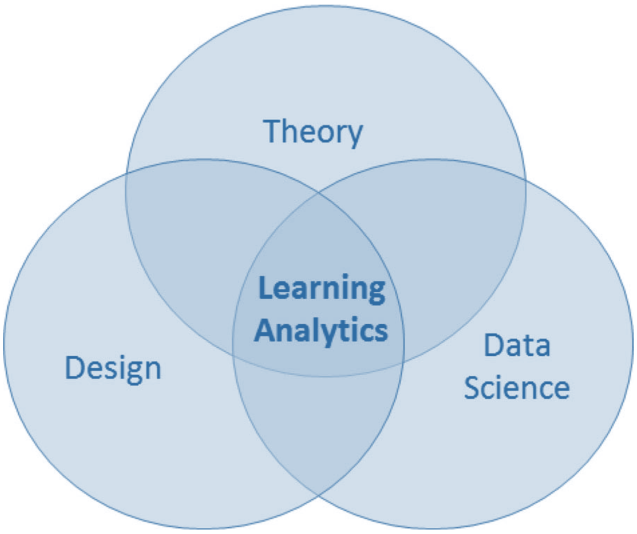


Figure 2 Consolidated Model of Learning Analytics (Gašević et al., 2017)

Gašević et al. (2017) presented a consolidated model that shows how learning analytics practice and research interact with different disciplines (see Figure 2). They argue that the professional lenses of the following fields: theoretical foundations, design, and data science inform learning analytics processes. For example, Rienties and his colleagues (2016) proposed a framework in which the premises of the Community of Inquiry as a theory suggest teachers' choice of interventions. A similar framework presented by Greller and Drachsler (2012) provides detailed guidelines for setting up learning analytics services. This framework presents six essential aspects of appropriate and beneficial learning analytics practice: stakeholders, objectives, data, instruments, and external and internal limitations. According to this framework, the team responsible should address the following questions about the dimensions to achieve maximum efficiency from learning analytics before carrying out learning analytics projects. It is crucial to distinguish between stakeholders who are interested in (e.g., teachers) or impacted (e.g., students) by analytics to understand better the influence of learning analytics on individual users. The purpose of learning analytics integration should be pedagogically oriented. Learning analytics uses data students generate in learning systems, leading to context-specific results. Therefore, selecting specific data from available datasets is critical to evaluate the learning process properly. Learner analytics teams should also select the optimal methods, tools, and algorithms to support educational stakeholders' objectives.

Similarly, Chatti et al. (2012) classified learning analytics solutions based on these four dimensions: data and environments, stakeholders, objectives, and methods and techniques. Davies et al. (2017) presented another framework that outlines the process of integrating learning analytics into digital learning systems. They point out five critical steps to consider in effectively integrating learning analytics into an instructional system: data selection, data capture and storage, data visualization and reporting, data use, and system refinement. In brief, they emphasize the processes: the selection of data with specific, theory-driven, and pedagogical purposes, well-planned data capture and storage solutions, providing stakeholders with visually comprehensive and intuitive data representation, employing valid algorithms to interpret the data and recommend for intervention, and finally refinement of the system over time.

Greller and Drachsler (2012) incorporate other dimensions that need to be considered, such as potential limitations such as ethical and legal issues, managerial and organizational problems, and competency and acceptance level of stakeholders, which would affect the expected efficiency of learning analytics. For example, in a comparison study, Wise et al. (2018) concluded that required and specified policies and visions of learning analytics aligned with stakeholders' needs, training sessions, and sophisticated analytic tools should be provided for an appropriate practice of learning analytics. In particular, communication and engagement among stakeholders are fundamental to supporting intended behavioral change (Prieto et al., 2019). More importantly, O'Donoghue (2023) stressed prioritizing student awareness, autonomy, and data ownership in policies and ensuring fairness and justice in using learning analytics. Likewise, Seufert et al. (2019) developed a framework with similar dimensions. However, the starting point in this framework is pedagogical theory and learning design in order to improve the learning process and outcomes. Greller and Drachsler (2012) made an analogy for the learning process as "boiling water" and learning analytics as "thermometers." They argue that learning analytics translates learning into numbers that encapsulate the pedagogic behavior of users, and these numbers inform the stakeholders to determine specific interventions to accomplish pedagogical results. According to Mokhtar et al. (2019), diagnostic, predictive, and prescriptive analysis, in addition to descriptive analysis, are required for a data-driven practice. Several types of data about learners, learning environments, and contexts have been studied in learning analytics. However, the objectives of an event using data science methods should also be identified.

Most importantly, the data provided by learning analytics should direct stakeholders such as instructors and students for future actions in their practice. Scheffel et al. (2014) validated the assumptions discussed above by proposing a framework of quality indicators for learning analytics with the results of a group concept mapping study. This study supports the criteria for successful learning analytics use, which considers all data aspects, including algorithms, transparency, privacy, necessary learning support for stakeholders, learning measures and output, privacy, and organizational issues.

Similarly, De Freitas et al. (2015) present the Learning Analytics Model (LAM), particularly for higher education, as a set of principles that institutions can use to implement learning analytics processes. Their goal is to enhance decision-making and practices related to teaching, learning, and student support services. The LAM uses data analytics to comprehend student behaviors, monitor their progress, and offer personalized support and interventions to enrich their experience and increase retention rates. These principles also stress the significance of a learner-centered approach, integrating various data sets, adaptive user behavior modeling, and ethical considerations in data usage.

As explained earlier, learning analytics intervention should be designed to improve teaching and learning practice by integrating theories and considering some essential dimensions. Learning design, which provides models for educational processes, aims to promote practical learning experiences with theory-informed practices (Gašević et al., 2017). According to Wise (2014), if a direct and immediate impact on teaching and learning processes is desired, learning analytics should be justified by considering the following situations. Learning analytics designers and developers should examine potential stakeholders, their goals, the frequency of use, and the learning context in which learning analytics provides actionable intervention.

In conjunction with his conceptualization, he developed a model for designing pedagogical learning analytics intervention to support the productive use of learning analytics by students (stakeholders) with four principles and three processes, which subsequently evolved into a process model —the Student Tuning Model (Wise et al., 2016). The first principle, Integration, supports students in relating analytics with pedagogical intent. The Agency principle aims to help students develop self-regulated learning skills by helping them set individual goals, interpret their analytics, and make personal decisions about changes. In the Reference Frame, students are expected to reflect on their performance and participation by noticing differences and using this reflection to guide their future practices. The last principle, Dialogue, allows instructors and students to interpret the analytics collectively. These principles conceptually outline how students engage with analytics as a part of the learning process and guide the integration and use of analytics as a prescriptive framework in a learning environment (Wise, 2014; Wise et al., 2016).

Bakharia et al. (2016) proposed a learning analytics conceptual framework for learning design, whose dimensions emerged from teacher interviews. They categorized five significant analytics teachers value in their practice: temporal analytics, tool-specific analytics, cohort dynamics, comparative analytics, and contingency. Temporal analytics provides information about the course statistics, content, and tool access within the LMS during the course. Comparative analytics shows the patterns or relations among aspects of a course in order to compare the impact of learning activities on student participation. Cohort Dynamics is used to see student access patterns to a specific content item or tool to access the cohorts of successful and unsuccessful students. Tool-specific analytics is mainly related to analyzing quiz scores, quiz attempts, and counts for discussion forum posts. In the final category of analytics, Contingency, and Intervention Support Tools, teachers expect to identify and intervene if a student is detected to be potentially at risk. They categorized essential learning analytics data as valuable for improving teaching quality and learning efficiency.

2.6 Theoretical Framework

In order to effectively select the specific variables from available datasets, analyze that learning analytics data, and interpret the results, as explained above, there is a need for a theoretical framework. Learning theories and instructional design theories have guided instructional practices for ages, apart from the current need for learning analytics applications. Each learning theory has attempted to explain the nature of human learning from different perspectives and find ways to support it. As Mayer (2019) illustrated, human learning has been conceptualized in three major phases: behaviorist, cognitivist, and constructivist. In the first phase, learning has been seen as strengthening and weakening associations to responses through rewards and punishments (Schunk, 2012; Driscoll, 2005; Gredler, 2009; Reigeluth & Carr-Chellman, 2009). In the second "cognitivist" phase, adding information to memory has been considered learning (Schunk, 2012; Driscoll, 2005; Gredler, 2009; Reigeluth & Carr-Chellman, 2009). In the final phase, the constructivists have viewed learning as an active knowledge construction in which a mental representation of working memory is personally built (Schunk, 2012; Driscoll, 2005; Gredler, 2009; Reigeluth & Carr-Chellman, 2009).

Although these learning theories have evolved over time, their instructional strategies should still be adapted and blended to suit the needs of the students. According to Ertmer and Newby (1993, 2013), the instructional strategies of three learning theories—behaviorism, cognitivism, and constructivism—should be customized based on the student's prior knowledge level and the level of cognitive processing required for the task. All the theories are consistent within their own boundaries, and their notions describe different aspects in different learning settings.

Kirschner and van Merriënboer (2013) stated that there is no one-size-fits-all approach to education. They have still influenced the practice of learning and teaching. However, the transition to computer-based platforms has created a need for a fresh perspective on the concept of learning (i.e., cognitive theory of multimedia learning). Migrating the learning process into multimedia environments requires sophisticated students to have specific skills such as monitoring and controlling their learning processes (R. A. Bjork et al., 2013; Mayer, 2019). Therefore, instructional designers must strive to find the most effective method to enhance learning. It's crucial to select the most practical approach from various theories. Thus, we must recognize and deal with several learning variables within learning analytics.

2.6.1 The New Theory of Disuse

Some contemporary learning theories distinguish between performance and learning to optimize the conditions of learning. Performance is described as what can be observed and measured during instruction, whereas learning is the practically permanent change in the knowledge or understanding of instructed content (E. L. Bjork & Bjork, 2009; R. A. Bjork & Bjork, 2019b; Soderstrom & Bjork, 2015). The relation between performance and learning is not bidirectional. Learning can be inferred from learner performance; however, current performance can be unreliable in assuming that learning has occurred (R. A. Bjork & Bjork, 1992, 2019b). In this context, the new theory of misuse (E. L. Bjork & Bjork, 2009;

R. A. Bjork, 1994, 1999; R. A. Bjork & Bjork, 2006), which is a modification of Thorndike's (1914) original law of disuse has formulated this distinction between learning and performance in terms of storage strength and retrieval strength. Storage strength indicates how well information is rooted in the memory, which is more related to long-term retention and transfer and is assumed to be permanent. On the other hand, retrieval strength refers to the measure of how well information is recalled from the memory, which corresponds to current performance. This theory implies that storage strength can increase, but a decrease in current storage strength is never expected. However, retrieval strength is limited since it depends on more retrieval cues and regular adjustments in the retrieval strength of related memory traces.

Conditions of learning that rapidly improve performance (increase in retrieval strength) and support long-term retention and transfer (gain in storage strength) are remarkably different. In order to optimize long-term learning, the conditions of learning should create some challenges that result in a slow performance rate. The desirable difficulties framework suggests that those conditions with desirable difficulties trigger encoding and retrieval processes for more durable and adaptable learning (E. L. Bjork & Bjork, 2009; R. A. Bjork, 1994). Desirable difficulties might be ensured with several retrieval practices or elaboration activities with the following structures: the distribution of practice (the spacing effect), variability of practice, and interleaving the practice (E. L. Bjork & Bjork, 2009; Zepeda et al., 2020). In brief, they prompt forgetting, meaning losing retrieval strength, which opens the way for increasing the storage strength of targeted information (E. L. Bjork & Bjork, 2009; R. A. Bjork & Bjork, 2019a, 2020; Storm et al., 2014). In general, it is claimed that aspects of tasks or situations leading to short-term learning difficulties are favorable if they enhance long-term performance.

The spacing effect occurs when repetitions of learning points are distributed over time, and it claims that it supports long-term learning, but massing practice supports short-term performance (E. L. Bjork & Bjork, 2009; Mödritscher et al., 2013; Nazari & Ebersbach, 2019). It supports learning since it requires more cognitive effort, which strengthens memory representations with multiple retrieval routes and produces more forgetting, which triggers more effective encoding strategies. Spacing lessons apart in time also promoted elementary school students' generalization performance for both simple and complex concepts (Vlach & Sandhofer, 2012).

Several researchers have studied the optimal number of spacing intervals, and most of them suggest that expanding spacing intervals may be helpful when no feedback or relearning is provided (Carpenter, 2020; Cepeda et al., 2008; Rawson & Dunlosky, 2011; Thalheimer, 2006). For example, Carpenter (2020) suggested that the best way to schedule spaced learning opportunities depends on how long the information needs to be retained in the future. Longer intervals between repeated learning opportunities lead to better retention over longer periods of time. Rawson and Dunlosky (2011) suggest that if students practice recalling information with three times the correct response criteria and in three widely spaced intervals, they may reach more durable and efficient learning. According to some scholars, on the other hand, the optimal spacing interval should approximately match the retention interval, which is the period between the last time of exposure to information and testing the retention of that information (Cepeda et al., 2008; Thalheimer 2006).

Variations during learning in terms of context (i.e., environment) have more benefits for long-term retention rather than short-term performance (E. L. Bjork & Bjork, 2009). Imundo et al. (2021) provide evidence for studying in varied environmental contexts rather than one fixed location enhanced recall of studied content. Another beneficial practice that results in superior learning is interleaved practice, in which topics or tasks are separated rather than blocked. Kornell and Bjork (2008) showed that students could recognize new paintings of an artist when the paintings of this artist are interleaved with other artists' paintings. In other words, interleaving the content rather than presenting it consecutively would support inductive learning and long-term recall. Carvalho et al. (2022)found that when students completed different types of practice activities instead of the same activity multiple times, this was associated with improved learning outcomes, supporting the interleaving practice aspect of desirable difficulties.

These learning strategies might generally slow or prevent improvement during the learning process, but they often produce superior long-term retention and transfer.

2.6.2 Testing as Learning Events

As discussed above, the learning events in which students are involved in more retrieval efforts support learning. In other words, retrieving information from the memory strengthens the retrieved information in the memory, making it more recallable in future events. Testing as a learning event is one of the most robust retrieval practices that creates desirable difficulties and consequently supports retention and transfer. The testing effect refers to the phenomenon where retrieving information from memory through testing or quizzing enhances long-term retention and learning. The testing effect emphasizes that taking an initial test rather than restudying the content before the final retention test improves the performance on the later tests (Karpicke & Roediger, 2007). Even if students have not recently studied the targeted information, it produces the testing effect (Marsh et al., 2007).

Researchers have acknowledged two distinct testing effects: the backward testing effect and the forward testing effect (Chan et al., 2018; Pastötter & Bäuml, 2016; Yang et al., 2017, 2018, 2021). The backward testing effect involves the retrieval practice of previously studied information, enhancing its long-term retention. It indicates that testing yourself on the information you have already learned improves your memory. On the other hand, the forward testing effect indicates that testing on studied information can also aid in acquiring new information. In other words, testing yourself on previously learned material can improve your ability to learn new information presented afterward. The forward testing effect, also known as test-potentiated new learning, refers to the phenomenon where testing on previously studied information facilitates the acquisition of new information. When learners are tested on material they have previously learned, it enhances their ability to learn and remember new information. This effect has been observed in various educational contexts and with different materials, such as word lists, line drawings, face-name pairs, and lecture videos. The forward testing effect highlights the benefits of incorporating testing as a learning strategy, as it helps consolidate previously learned material and promotes acquiring new knowledge by supporting the cognitive processes of students.

Many researchers have attempted to investigate under what circumstances testing-induced learning is beneficial (Yang et al., 2021). Yan et al. (2014) investigated the benefit of testing by trying to guess to-be-learned responses versus studying intact cue-response pairs. They found that activating knowledge by allowing students to make guesses with even incorrect trials can benefit correct recall even after long retention intervals. In a study conducted by Mulligan et al. (2020), it was discovered that the testing effect is superior in mixed lists consisting of both retrieval and restudy items compared to pure lists. The students also spent more time studying retrieval items in mixed lists and restudy items in pure lists, which aligns with the retrieval practice. Lantz and Stawiski (2014) also found that clicker questions with immediate feedback during a video lecture significantly increased test scores two days later. The timing of the clicker questions, whether during the lecture or at the end, did not significantly influence students' test scores. This study presents that retrieval practice, such as answering clicker questions, is also effective in an online learning environment featuring video lectures.

Cantor et al. (2014) found that multiple-choice testing was considerably more beneficial for accessing marginal knowledge (targeting real questions) than newly learned information (fictitious questions). In addition to multiple-choice tests, it is also found that even true-false tests with competitive clauses with more practical retention intervals are beneficial for recalling tested and related content (Brabec et al., 2021).

Some scholars indicate the importance of multiple-choice tests in which optimally constructed items can facilitate the recall of information on a later test (Little et al., 2012; Marsh et al., 2007). Little and Bjork (2014) suggest that multiple-choice questions containing competitive alternatives can boost the retrieval processes of memory traces for both tested and related information. The findings of a study by Sparck et al. (2016) suggest that confidence-weighted multiple-choice tests as retrieval practice activities can potentially improve students' performance on a later cued-recall test. In a similar study, Lipko et al. (2009) used standards like full-definition and idea units from each definition, which would reduce middle school students' overconfidence in evaluating the quality of recalls and consequently facilitate better learning. The findings of this study also apply to Dunlosky et al.'s (2011) investigation in which they explored whether idea-unit judgments would reduce the overconfidence of undergraduates. They additionally found that students overconfidently graded other students' responses as well.

A study conducted by Congleton & Rajaram (2012) studied how different learning methods and testing timing impact memory. They discovered that repeated retrieval led to better recall after a delay, whereas repeated study resulted in higher recall immediately after learning. Participants engaging in repeated retrieval also showed higher retrieval organization performance. They were able to quickly group related information, as opposed to those who repeated the study, showing a slower and steadier recall increase.

A similar result was found in a study by Leahy and Sweller (2019), which found that using tests during learning may reverse the testing effect, depending on the timing of the post-test. They suggest that the depletion of working memory resources may be a factor in reversing the testing effect on immediate post-tests. Nonetheless, these findings suggest that repeated retrieval improves conceptual retrieval organization, leading to stable recall of information. These studies, in general, support the combination of the retrieval effect and the spacing effect.

In a recent study, how mind-wandering and retrieval practices are related was explored (Wong & Lim, 2022). The researchers specifically examined whether retrieval practice helps reduce mind wandering compared to restudying and how this decrease in mind wandering would impact learning outcomes. The study revealed that students who did retrieval practice reported experiencing less mind wandering than those who restudied. Additionally, lower performance on the final test was observed if the level of mind wandering was high.

Storm et al. (2014) showed that the superiority of testing is not always warranted. If the initial testing is not challenging enough and provided along with feedback (Cantor et al., 2014; Hays et al., 2010; Kliegl et al., 2019; Pastötter & Bäuml, 2016), restudying would be more helpful in promoting performance on a delayed test. For example, Kornell and Rhodes (2013) found that receiving feedback after a test receiving feedback after a test decreases metacognitive accuracy. In other words, students' ability to predict their memory performance decreases with feedback. This result suggests that students may rely more on their prior test performance when evaluating their learning.

In another study where the testing effect was not supported, Davis et al. (2018) found no significant effects of the adaptive retrieval practice system in MOOC, which provides automated and personalized retrieval practice questions. This suggests that traditional instructional design practices for promoting retrieval in a face-to-face classroom or laboratory setting may not directly apply to an online context.

Furthermore, Moreira et al. (2019) reviewed applied research in which retrieval practice was compared to repeated study or "no-activity." However, they concluded that some studies found no advantage for tests compared to alternative control conditions. Retrieval practice did not show consistent benefits compared to concept mapping or activities involving the duplication of written materials, mainly when children took short-answer tests. Therefore, future research should verify whether these mixed results are consistent in various contexts, such as when using free recall and multiple-choice tests.

According to the distribution-based interpretation of testing effects, memory strength is assumed to be normally distributed after the initial learning session. After a restudy session, strength in memory increases. However, after retrieval practice, strength in memory has a 'bifurcated' item distribution. This means that the direction of strength in memory depends on the item's previous retrieval status. If information is successfully retrieved, it has more strength in memory, whereas information that is not successfully retrieved remains at its original memory-strength level. This has practical implications for the effectiveness of different learning strategies. (Kliegl et al., 2019)**.**

Rowland (2014) similarly discussed the contemporary theoretical explanations that specify the causal mechanisms of the testing effect in his review. The elaborative retrieval hypothesis suggests that the testing effect results directly from elaborating a memory representation resulting from retrieval operations. On the other hand, the mediator effectiveness hypothesis proposes that the testing effect is compelling because it makes more use of cue-target mediating information, which refers to information that provides a link between a cue and a target. The Transfer-Appropriate Processing (TAP) theory, in contrast, indicates that the effect of testing is related to the overlap in processing during initial and final testing.

Similarly, Su et al. (2021) investigated how different types of retrieval (semantic, which involves accessing and recalling the meaning and associations of a word, and phonemic, which involves accessing and recalling the sound-based information of a word) affect student memory compared to traditional encoding processes. They discovered that retrieval practice enhances subsequent memory more than restudying, showing the testing effect. However, they also found that the specific retrieval types, like the processing level during initial encoding, do not significantly impact student memory. Nevertheless, the testing effect remains robust and consistent across different retrieval types. On the contrary, Dang et al. (2022) observed that the re-encoding process, in general, significantly facilitates the forward testing effect.

Testing is more effective than other study strategies, such as restudying or concept mapping. It can lead to improved academic performance and overall learning achievement. Testing as learning events has been found effective for individuals of all age groups, including young children, older children, and adults (Dang et al., 2022; Vojdanoska et al., 2010). This indicates that the benefits of testing are not restricted by age and can be observed across different developmental stages. In addition to different levels of learners, testing as a study method can lead to better performance in learning various subjects such as science, chemistry, mathematics, second language, history, and medicine (Dirkx et al., 2014; Goossens et al., 2016; Kromann et al., 2010; McDermott et al., 2014; Todd et al., 2021).

Additionally, the research carried out by Jensen et al. (2020) showed that the testing effect is effective not only for lower levels of thinking, such as recall and comprehension but also extends to higher levels of thinking, including analysis and evaluation. This finding suggests that integrating testing as a learning strategy can significantly enhance students' abilities to engage in critical thinking and higher-order cognitive processes.

Furthermore, Vojdanoska et al. (2010) examined the impact of collaborative testing on student performance. The findings showed that collaborative testing resulted in higher performance on the initial test, but there was no difference in performance on the final test compared to individual testing. This intriguing result calls for further investigation to fully understand the interplay between collaboration and the testing effect and its potential to enhance learning outcomes. Despite this, several meta-analyses present compelling evidence supporting the effectiveness of test-enhanced learning in supporting academic achievement in the classroom (Adesope et al., 2017; Chan et al., 2018; Yang et al., 2021).

The use of learning analytics applications that incorporate desirable difficulties has the potential to support test-enhanced learning. For example, Nitu et al. (2018) developed an e-testing application with a personalized feedback system. This system tracks the progress of individual online learners throughout the assessment process. The system offers various levels of learning analytics - descriptive, diagnostic, predictive, and prescriptive tables to analyze each online learner's performance and progress. Case study results have indicated that this tool positively impacts student engagement, motivation, and academic performance.

A research study by Ifenthaler et al. (2023) suggests that students' active engagement in self-assessment during higher education is linked to improved exam performance. The study analyzed engagement levels to identify students who outperformed others in exams. The findings emphasize the importance of supporting self-assessment practices to enhance students' learning strategies. This can be facilitated by using learning analytics data to provide personalized feedback, ensuring students have the necessary support to succeed.

McHugh et al. (2021) emphasizes that using spaced retrieval practice with the Blank Slate software application incorporating learning analytics resulted in significantly higher quiz scores and better learning outcomes than non-spaced retrieval practice. The algorithm group, which used Blank Slate's spaced retrieval algorithm, achieved similar improvements in knowledge acquisition and retention as the sequential group but spent less time interacting with the application. This study not only underscores the effectiveness of spaced retrieval practice but also highlights the transformative role of technology-enhanced learning tools like Blank Slate in enhancing learning and preventing forgetting.

Similarly, the study by Rodriguez et al. (2019) revealed compelling findings related to spacing strategies and learning analytics. It found that students who consistently applied spacing strategies throughout the course achieved higher grades than those who relied on massed. Moreover, students who used spacing strategies accessed the Learning Management System (LMS) resources more frequently, albeit not earlier, before significant deadlines. The study also highlighted a general lack of engagement with LMS resources, underscoring the need to encourage students to utilize these resources when studying course material.

Despite these promising findings, there is limited research on test-enhanced learning integrating learning analytics applications. This study aimed to provide information on the association between desirable difficulties and learning analytics.

2.6.3 The Relation of Retrieval Practice with Self-Regulated Learning and Metacognition

The effects of retrieval practice have been shown to increase performance on meaningful learning assessment. Yang et al. (2017) observed that the forward-testing effect improves metacognitive monitoring, leading to better judgments of learning (JOLs). In other words, testing improves students' ability to track and review their learning by increasing their metacognitive awareness. However, many students still need clarification regarding the value of different learning strategies. This particularly applies to retrieval practice in which students are misinformed that different strategies, such as restudying or concept mapping, would benefit learning more.

Because students tend to overestimate their level of learning compared to their actual performance on later assessments. They often misinterpret their performance during acquisition when their retrieval strength increases (Lipko et al., 2009). This reliable guide to short-term performance but an unreliable guide to long-term learning may lead them to have an "illusion of mastery" (R. A. Bjork & Bjork, 2020).

These metacognitive illusions about the most effective strategies that lead them to higher learning may hinder long-term learning (Szpunar et al., 2014). For example, students consider massed studying more effective than spaced studying even though their performance is the opposite (Kornell & Bjork, 2008).

Thus, the students with these illusions have poor metacognitive evaluations of their performance and, consequently, inadequate judgments to regulate their learning processes (Yan et al., 2014). It is critical to provide students with opportunities to eliminate the illusion of mastery by providing ideal learning conditions. Managing the conditions of one's own learning is, therefore, essential in online learning settings. Students become more autonomous when their goal setting and time-management skills are prompted (Papamitsiou & Economides, 2019). In addition, Tullis et al. (2013) found that students can accurately recognize and appreciate the benefits of testing in enhancing long-term retention, particularly when supplemented with external assistance, such as feedback and performance monitoring. So, learning analytics applications might provide students with correct information about their progress in these activities and their learning styles by analyzing their behaviors for effective learning support. This means that a learning analytics application with retrieval practice opportunities can support students' self-regulated learning skills, including cognitive, motivational, and emotional processes. This empowers students to strategically plan, monitor, and adapt their learning approaches.

For example, Winne et al. (2019) showed that nStudy, which traces students' dynamic cognitive and metacognitive processes, would support improving their self-regulated learning skills. Similarly, Tempelaar (2020) found that actionable feedback was provided during assessment as learning was mostly demanded by maladaptive students who could not regulate their own learning.

McDaniel and Einstein (2020) found that incorporating effective learning-strategy training would support self-regulated learning. They highlight that such training requires acquiring knowledge, belief in the strategies, commitment to implementation, and creating an action plan, which can help students overcome the obstacles preventing them from successfully regulating their learning. So, supporting students' metacognitive awareness and judgments via learning analytics intervention might influence their choices when they regulate their own learning (Karpicke & Grimaldi, 2012).

2.7 Summary

Big data exploitation in online learning environments requires sophisticated data analysis methods and tools different than traditional ones to discover hidden patterns in learning processes within these environments. This need has led to many studies in the learning analytics field that aim to understand learning processes better. In learning analytics practice and research, several data science techniques and models have been used to accomplish its objectives, such as obtaining information about learners and the learning process, providing valuable feedback with the visually rich representation of analytics data to the stakeholders, and contributing to more personalized learning experiences. However, scholars in the field stress the importance of valid theoretical frameworks and models to guide learning designs for successful learning analytics applications. Therefore, this study aims to discover the learner analytics data strongly associated with student success and correspondingly provide an instructional design model that guides learning analytics implementation, which is namely, the new theory of disuse.

CHAPTER 3

METHODOLOGY

This chapter provides detailed information about the research methodology. It covers the research design, details about the participants and setting, materials used in the study, data collection instruments, procedures for collecting data, and data analysis techniques.

3.1 Design

This study uses the multivariate design, a mixed design in which researchers investigate repeated measures between groups as independent variables (Field & Hole, 2013). Students' progress in the learning environment will be studied as repeated measures, while students' success will be compared based on discriminant variables such as having actionable intervention and refreshing knowledge.

3.2 Setting and Participants

The data was collected in the context of the Entrepreneurship and Innovation in IT (ISE 432) course at a private university. In this course, Moodle and Pearson were the learning platforms that were mainly used. Moodle was used as a course management system. At the same time, the Pearson MyLab® platform, as a drill and practice system, provided customized course content, including homework and practice exercises, that offered unlimited opportunities to master the learning concepts. The study used the data collected from the students mainly within MyLab® Dynamic Study Modules (DSM), which included the content and activities from the coursebook Entrepreneurship: Successfully Launching New Ventures (Barringer & Ireland, 2012).

The study involved undergraduate students from the School of Engineering who had enrolled in this course. This multidisciplinary elective course is available to engineering students from various disciplines, such as Automotive, Chemical, Computer, Electrical-electronics, Energy systems, Industrial, Information systems, and Software.

The study utilized data from 226 students based on their use of Pearson MyLab and completion of DSM assignments. The cohort distribution for the semesters can be found in Table 1 below.

Table 1 The Distribution of Students Across Different Semesters

Cohort	Course	# of Students	Semester
1	Entrepreneurship and Innovation in IT	35	Spring 2019
2	Entrepreneurship and Innovation in IT	34	Spring 2020
3	Entrepreneurship and Innovation in IT	39	Summer 2020
4	Entrepreneurship and Innovation in IT	65	Spring 2021
5	Entrepreneurship and Innovation in IT	18	Summer 2021
6	Entrepreneurship and Innovation in IT	36	Spring 2022
Total		226	

3.3 Dynamic Study Modules

The Pearson MyLab® system provides drill and practice opportunities for students in parallel with the coursebooks. Students can practice concepts with *Dynamic Study Modules*, which utilize learning analytics technologies. It personalizes the learning content to reinforce concepts that students struggle with most by continuously assessing their performance and activity. It also provides opportunities to use and develop metacognitive skills by allowing students to reflect on their own learning processes. Students are required to evaluate their own knowledge and understanding and express it while responding to the questions, as shown in Figure 3 below. They must indicate whether they are certain or uncertain about their answers. Depending on their assessment or perception of their learning, they will proceed with personalized content in the subsequent assignment steps.

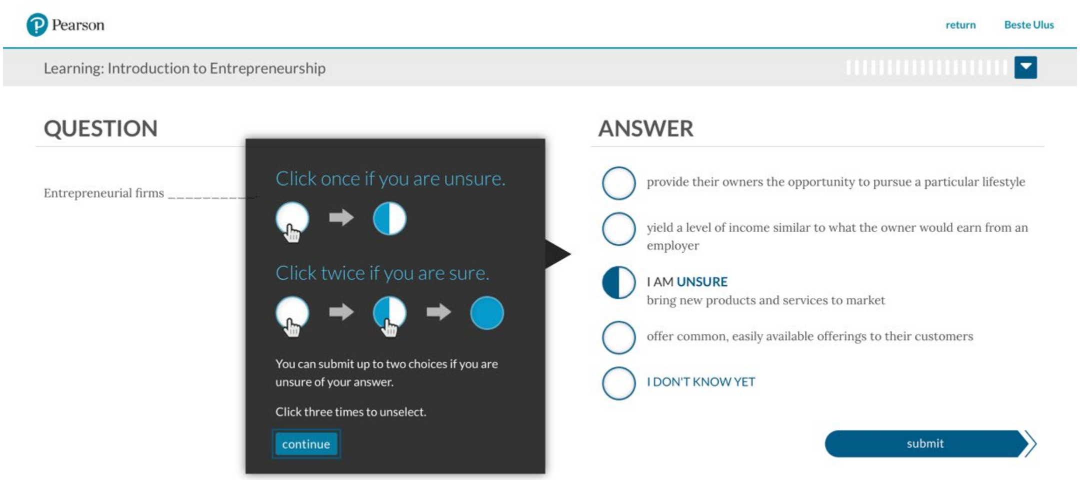


Figure 3 Question Screen of DSM Assignments

The Pearson MyLab® system is a comprehensive educational platform that offers quizzes and assessments to students and visualizes data in real time and post-assessment. The system allows students to monitor their progress during quizzes and see how well they are performing in real-time (see Figure 4).

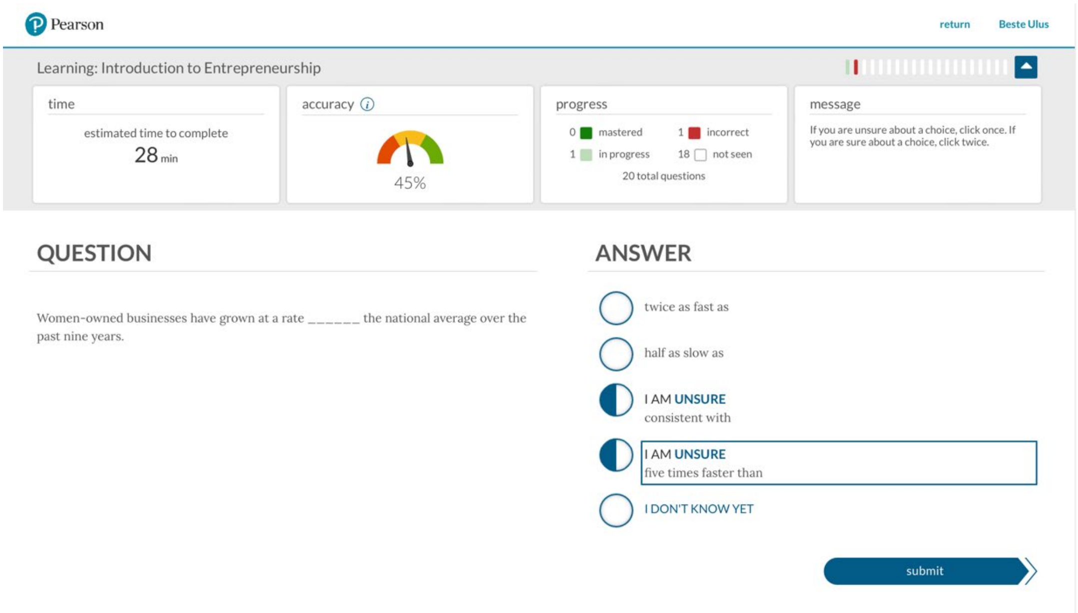


Figure 4 Progress Visualization During DSM Assignment

This study used student data collected through DSM assignments based on content from the textbook Entrepreneurship: Successfully Launching New Ventures (Barringer & Ireland, 2012). The textbook has chapters (known as modules) containing question groups, and a dynamic study module consists of about 40 unique questions (see Table 2).

Table 2 DSM Chapters of Entrepreneurship & Innovation in IT Course

No	Chapter	# of	Expected Time

		Questions	Spent
1	Introduction to Entrepreneurship	40	27 min
2	Recognizing Opportunities and Generating Ideas	40	27 min
3	Feasibility Analysis	40	35 min
4	Developing an Effective Business Model	40	32 min
5	Industry and Competitor Analysis	40	44 min
6	Writing a Business Plan	40	32 min
7	Preparing the Proper Ethical & Legal Foundation	40	28 min
8	Assessing a New Venture's Financial Strength & Viability	40	29 min
9	Building a New Venture Team	40	28 min
10	Getting Financing or Funding	40	30 min

Table 2 (continued)

Students are assigned to master DSM questions for each chapter to get credit as a part of the course requirements. In a DSM assignment, students practice entrepreneurship concepts and get actionable interventions based on their strengths and weaknesses. When students learn or master a study module for the first time, it is called “Learning,” which is compulsory. The other two assignment types are smart refresher and full refresher, which are optional in the study setting. In a smart refresher, students can practice only the questions they struggled with in a module to refresh their knowledge. In a full refresher, however, students can practice all the questions in a module to review their knowledge. Reviewing a completed learning module does not affect students' original score if they complete it before the due date. However, students have additional scores for each refresher activity they have completed.

Students begin a module by answering the first question set, which usually contains eight questions. At the end of the question sets, students see the correct answers and explanations (i.e., "WHAT YOU NEED TO KNOW") (see Figure 5).

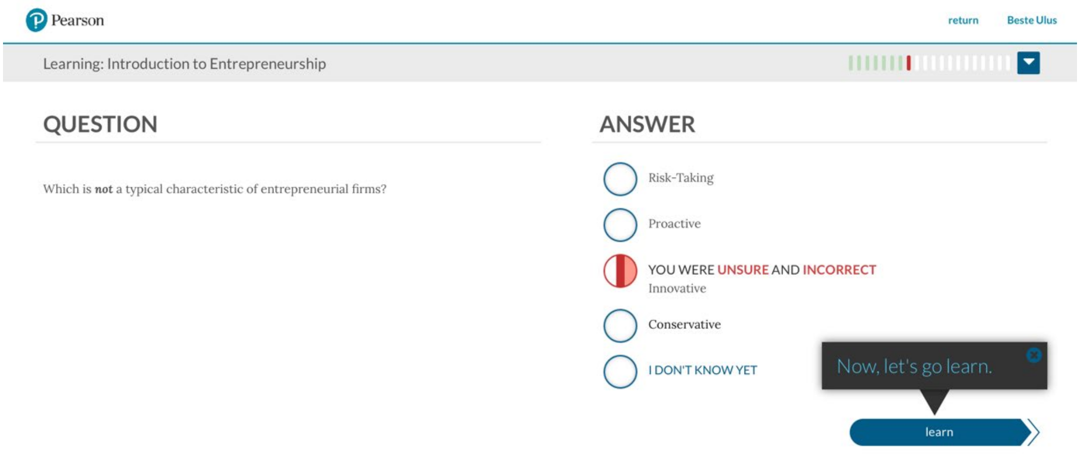


Figure 5 Progressing to Learn in the DSM Assignments

The system provides conceptual information about what students did not know earlier in the explanations. The questions that students see explanations for are repeated later in the module until students master each of them (see Figure 6).

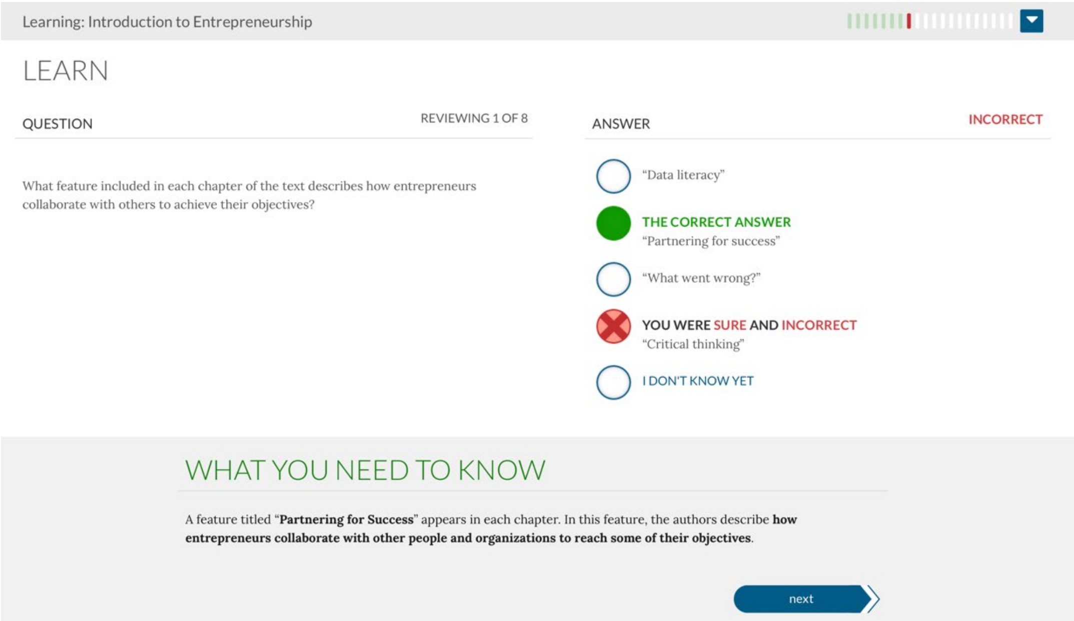


Figure 6 Explanations for Incorrectly Answered Questions

Students attempt to answer the questions in a module correctly and confidently (see Table 3) and receive scores based on their attempts. As students approach finishing the module, fewer questions appear in a question set.

Table 3 Description of the Attempts to the Question to Achieve Mastery

Icon	First Attempt	Following Attempts for Mastery
	Correct: The response is correct, and the student is confident.	Students will not see the question again.
	Unsure correct: Response is correct, and student is unconfident.	Students need to answer the question confidently and correctly ONCE.
	Partially correct: Students select two options, and one is correct.	Students need to answer the question confidently and correctly ONCE.
	I don't know: Students select the "I do not know" option.	Students need to answer the question confidently and correctly ONCE.

Table 3 (continued)

	Unsure incorrect: Response is wrong, and student is unconfident.	Students need to answer the question confidently and correctly ONCE.
	Incorrect: The response is wrong, and the student is confident.	Students will need to answer the question confidently and correctly TWICE.

The DSM reporting page enables instructors to track student performance based on various parameters, including modules, learning objectives, and individual students. The system generates a comprehensive report that displays detailed information on each parameter. The report is presented as a bar chart and a heatmap, allowing users to visualize the data and identify trends and patterns. The bar chart displays the performance of each module, while the heatmap shows the performance of each learning objective (see Figure 7). These dynamic visualizations are interactive and can be customized to show specific data points. They provide valuable feedback to students and instructors, enabling them to identify areas of strength and weakness and take appropriate action.

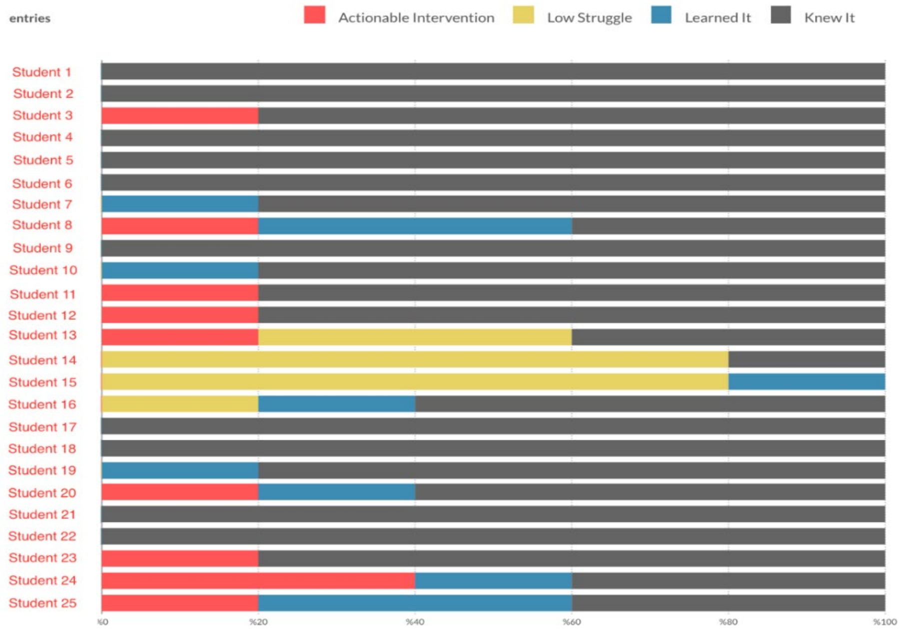


Figure 7 A Sample Bar Chart for a Learning Objective from DSM

3.3.1 DSM Metrics

There are two groups of metrics, knowledge and struggle, produced in the DSM platform. Knowledge metrics are about what students already know about the content. The metrics are produced following the students' initial attempts at the DSM assignments. Struggle metrics, however, are about how students struggle after seeing feedback or explanations. These metrics are calculated using the results from students' second attempt at the DSM assignments. The system provides these metrics for each learning objective, module, and student. The details about each knowledge and struggle metric can be found in the table below:

Table 4 DSM Metrics and Descriptions

Group	Metric	Description
KNOWLEDGE	**Misinformation:**	The student answered confidently, but his/her response was incorrect, which shows that the student had misinformation about the concept.
	Uncertainty:	The student answered correctly, but s/he was unsure.
	Mastery:	The student answered correctly and confidently, which shows that the student has conceptual knowledge and mastery of the concept.
STRUGGLE	**Actionable Intervention:**	Even if the explanation was presented more than twice, the student still could not answer confidently and correctly, which shows a high struggle level.
	Low struggle:	The student saw the explanation twice and did not answer correctly. However, upon the third try, the student mastered the question.
	Learned it:	The student answered incorrectly the first time the question was presented but answered confidently and correctly after seeing the explanation. This is a measure of efficient learning.
	Knew it:	The student answered confidently and correctly the first time, indicating prior knowledge of the concept. This metric corresponds to the Mastery bar in the Knowledge section.

3.4 Data Collection Instruments

The data for this study were collected through the DSM assignments in the Pearson MyLab® system. In addition to the DSM assignment data, students took the midterm exam in the middle of the semester and the final exam at the end. Fifty questions from the question bank offered by Pearson are included in the midterm exam, and each correct response is scored 2 points. The final exam consists of 80 questions from the same question bank, including all chapters, and each correct response is scored 1.25 points. In the final exam, each of the first five chapters had 5 questions, while each of the latter five chapters had 11 questions.

3.4.1 Semi-Structured Interviews

Semi-structured interviews were conducted to gather comprehensive insights into the students' experience with the DSM assignments. These interviews were designed to elicit detailed and nuanced responses from the participants. The questions were carefully crafted to ensure a thorough understanding of how the students interpreted the DSM assignments.

Questions

1- Do you think you benefited from the DSM assignments you actively used this semester?

If yes, how and why did the system help you?

If not, why do you think it was useless?

2- While doing DSM assignments, to what extent did you pay attention to the content on the dashboard, such as your progress, remaining time, and accuracy scale?

To what extent did this content contribute to your learning?

3- Did you repeat the same module after taking the DSM assignments?

If so, which type do you prefer? Full or smart refresher?

How often did you do this?

4- Did you take into account the information presented about your learning in the Pearson MyLab® system?

Have you compared yourself with your classmates based on this data?

5-How was it to take the assignments in a timely manner?

Can you compare the first 5 and last 5 modules?

3.4.2 Study Variables

As thoroughly discussed in the literature review, several key variables require careful consideration and analysis in learning analytics studies. Thus, taking a comprehensive and theory-oriented approach is essential to ensure that all relevant factors and variables are accounted for. At the same time, selecting the process variables associated with more cognitive activities within the system is crucial. Thus, each of these variables has the potential to impact the overall outcome of the research significantly since they are related to the metacognition processes within the system (see Figures 8 and 9).

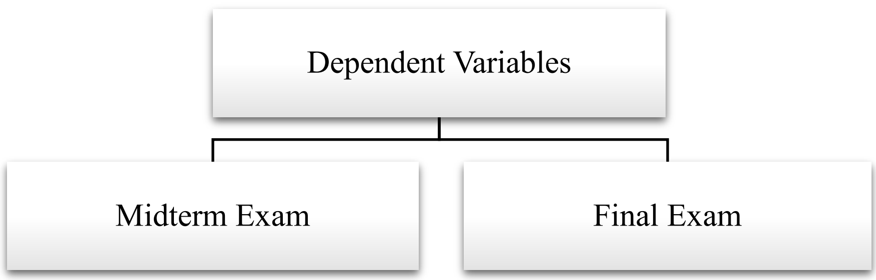


Figure 8 Dependent Variables

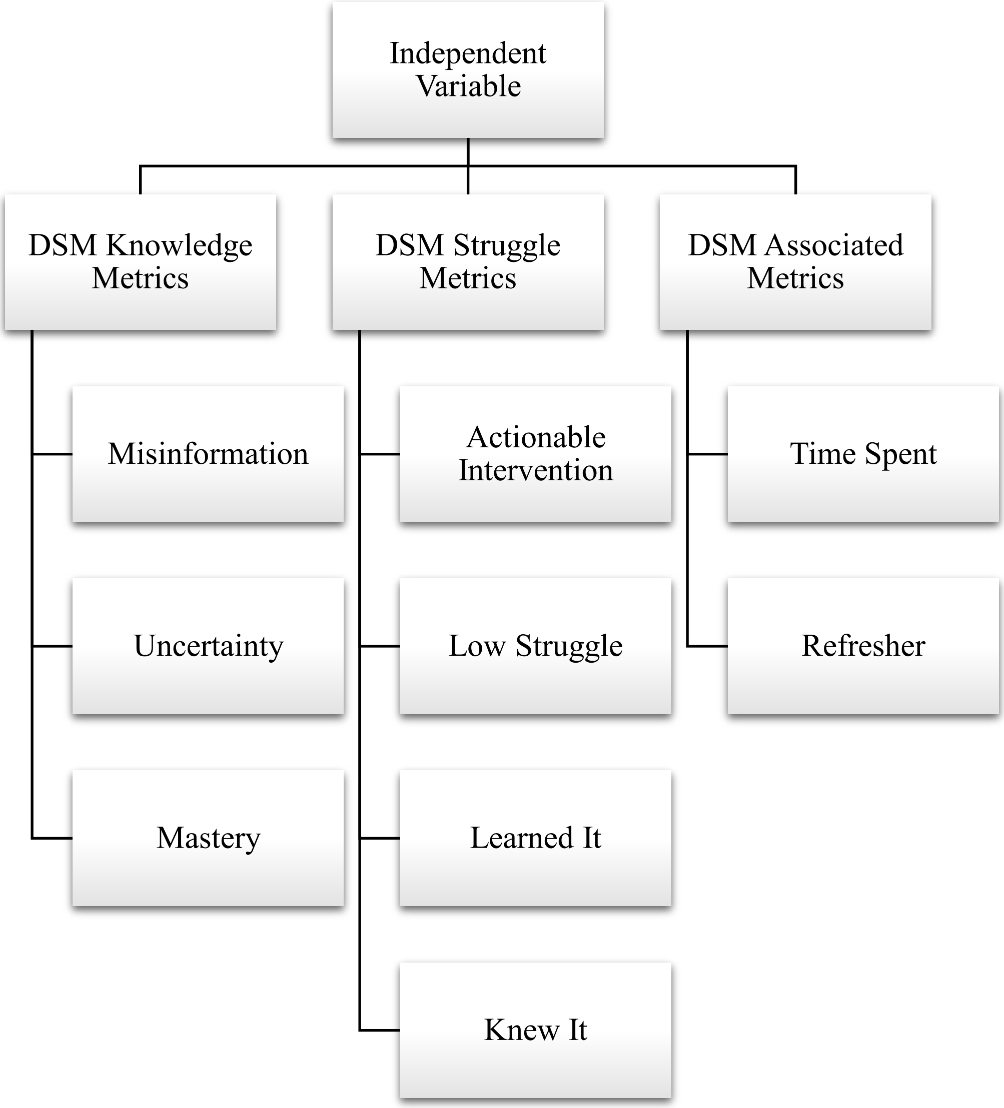


Figure 9 Independent Variables

3.5 Data Collection Procedures

At the beginning of the semester, the students were informed about the study and enrolled in the Pearson MyLab® system as a part of the course requirements. The data was collected during each academic semester the course was given. After completing each chapter in the course, the corresponding dynamic study module is released and assigned to the students with a specific due date. The students were expected to master ten DSM assignments. Besides, participants took the midterm exam in the middle of the semester and a final exam at the end of the semester. They lasted 55 minutes and 1 hour 20 minutes, respectively.

3.6 Data Analysis

All DSM data will be preprocessed for the following data analysis to answer research questions. Based on the DSM data related to knowledge, struggle, and knowledge refreshment, students will be categorized into different groups. Then, students' midterm and final exam scores will be calculated. The minimum and maximum scores that a student can have from the midterm exam and the final exam are 0 and 100, respectively.

While learning analytics techniques offer objective and real-time engagement data, it's important to note that they may only capture part of the complexity of engagement. This is because they primarily focus on students' interaction patterns, time spent on tasks, or frequency of logins, potentially overlooking other important aspects of engagement.

Regression analysis as a traditional data analysis method and cluster analysis, process mining, and sequence mining were used as learning analytics methods to investigate the association between DSM metrics and academic performance. Regression analysis was used to investigate how DSM performance predicts students' exam performance. Cluster analysis was used to group students based on their DSM scores, including knowledge and struggle scores and final exam performance. Process mining was applied using the Disco tool to understand better the entire process of students taking DSM Assignments. Finally, sequence analysis using TraMineR was performed to investigate the spacing effect.

3.6.1 Regression Analysis

Regression analysis is a statistical technique to understand the relationship between a dependent variable and one or more independent variables. The main objective is to examine how changes in the independent variables affect the dependent variable. In simpler terms, regression analysis helps in modeling and quantifying the nature and strength of the relationship between different variables (Field & Hole, 2013). Multiple linear regression is used when multiple factors affect the dependent variable, offering a more comprehensive understanding of variable relationships compared to the single linear regression alternative (Field & Hole, 2013).

This study used a multiple linear regression analysis to investigate the relationship between academic performance, specifically midterm and final exam grades, and various metrics obtained from the DSM assignments. These metrics include Knowledge Metrics (Misinformation, Uncertainty, Mastery), Struggle Metrics (Actionable Intervention, Low Struggle, Learned It, and Knew It), and other DSM metrics such as Refreshers Count and Total Time Spent. These DSM metrics calculated automatically based on student performance in the system were included as independent variables in the regression model. Considering all relevant DSM metrics, the analysis aimed to capture the multifaceted aspects of the DSM Learning Analytics application that could influence academic outcomes. The regression model assessed the extent to which these DSM metrics collectively predicted midterm and final exam grades.

3.6.2 Cluster Analysis

Cluster analysis is a statistical technique that groups objects or observations based on similarity and dissimilarity. One of the most popular and widely used clustering algorithms is K-means. K-means clustering is one of the best performers among partition algorithms (Navarro & Moreno-Ger, 2018). The algorithm divides a dataset into K clusters, where each data point belongs to the cluster with the closest mean. The K-means algorithm aims to minimize the sum of squared distances between data points and their assigned cluster centroids. It is an iterative optimization process that tends to converge to a solution but may only sometimes find the global optimum. The final result depends on the initial centroid selection.

This study used knowledge and struggle scores as features for clustering students. This helped to group students with similar knowledge levels and face similar challenges. The clusters formed by K-means can be interpreted as representing different student profiles or performance groups. Moreover, K-means clustering was also used to group students based on how they have refreshed their knowledge and the time spent on DSM assignments.

3.6.3 Process Mining

Process mining is a methodology that aims to extract knowledge from event logs generated during the execution of various processes. This approach helps analyze the chronological sequence of events and their relationships to provide valuable insights into how processes are carried out within a group. The process mining technique comprises three key steps: data extraction, process discovery, and conformance checking. Process mining has been used in varied domains such as marketing, healthcare, information and communication technology, education, finance, and logistics (Garcia et al., 2019). For example, a study by Stefanini et al.

(2016) showed that process mining can successfully identify and map patient-flow processes in healthcare settings.

Process mining was conducted using Disco, a process mining toolkit developed by Fluxicon (Günther & Rozinat, 2012) and available with an academic license for researchers and graduate students. Disco supports various process mining techniques, such as process discovery, conformance checking, and performance analysis (Günther & Rozinat, 2012). Out of all the options available, this would be the most user-friendly process mining tool (Çelik & Akçetin, 2018).

Disco by Fluxicon uses the Fuzzy Miner to visualize the outline of the individual processes and their connections, known as transitions (Saint et al., 2021). Fuzzy Miner helps researchers obtain the frequency and time of these micro-level process transitions (Saint et al., 2021). Fuzzy process models provide a human-centric approach to handling and understanding transitions for a more accurate classification (Pelekis et al., 1999).

Günther and Van Der Aalst (2007) point out the limitations of traditional process mining approaches with less structured processes ("spaghetti-processes") and introduce the Fuzzy Mining approach, which simplifies such processes based on multi-perspective metrics and abstraction while checking significance and correlation (Burattin, 2015; Günther, 2009). Inspired by cartography, it uses the idea of abstraction to show only highly significant behaviors like small routes in a city instead of entire city routes. This approach is recommended for use in scenarios where a more simplified process model is desired since it effectively cleans up confusing behavior, balancing precision and understandability in process mining. (Saint et al., 2021).

Therefore, this study used process mining to understand how students progress in DSM assignment activities during a semester. The primary objective of process mining is to identify blockages and optimize operational efficiency by providing a detailed understanding of how the DSM processes are executed in reality. The data was carefully prepared to meet the process mining requirements within Disco, which required an activity and at least one timestamp variable.

The DSM assignments consist of three activities: Learning, Full Refresher, and Smart Refresher. The system records each student's specific activities and their corresponding durations. The Last Activity time indicates when the students finish their DSM assignments, while the Time Spent represents the time they spent completing them. Using the Last Activity Logs and Time Spent, a Starting Activity log is computed, and the clusters, cohorts, and modules are established as attributes. These variables are essential components of the process mining analysis.

3.6.4 Sequence Analysis

This method has also been extensively used in various fields, including sociology, biology, psychology, and education (Macindoe & Abbott, 2012; Solomon et al., 2022). It has been used in sociology to study diverse phenomena such as occupational trajectories, dance rituals, and residential mobility. In sociology, Andrew Abbott has played a significant role in promoting sequence analysis and highlighting the significance of time and sequence in sociological theory (Halpin, n.d.).

Jovanović et al. (2017) used sequence analysis and clustering to analyze students' learning strategies in the education discipline. These analyses allowed them to identify student learning behavior patterns, detect different learning strategy profiles, and examine the association between learning strategies and course performance. Similarly, a study conducted by Ho and Yao (2018) utilized sequence analysis techniques to comprehend learner navigational behavior in a Digital Interactive Learning (DIL) environment. The study demonstrated that several navigational patterns detected by sequence analysis provide insights into how learners explore and navigate through different sections of the DIL environment. Moreover, the study recommends supplementing sequence analysis with memory recall tests to better understand learning outcomes associated with different identified behavioral patterns.

In another study by Monaghan (2020), four distinct groups of college students—marginal students, rapid completers, lifelong students, and delayed completers—were identified using sequence analysis. The study also revealed that social and academic background factors influence college trajectories. These findings deepen our understanding of college enrollment patterns and the endurance of inequality in higher education. These studies, in general, highlight the potential of sequence analysis techniques in educational research.

The Traminer Library of R Statistics is used for sequence analysis. The TraMineR library in R is a powerful toolkit for analyzing sequence data. It is especially useful for exploring and visualizing categorical sequence data, such as life course data, biological sequences, or any ordered categorical data. TraMineR provides a comprehensive set of tools for manipulating, rendering, and analyzing sequences of events or states (Gabadinho et al., 2011). Tasks such as sequence alignment, computing dissimilarities between sequences, and identifying patterns or clusters within the sequences can be performed (Gabadinho et al., 2011). The library also offers extensive plotting capabilities for visualizing sequences, state distributions, and other sequence-related characteristics (Gabadinho et al., 2011). TraMineR is particularly valuable in social sciences, biology, and any field where understanding the order and transitions of categorical events is important. TraMineR helps researchers gain deeper insights into their data's temporal structure and dynamics, which can facilitate more informed analyses and interpretations.

This study used sequence analysis to examine students' spacing patterns for DSM assignments throughout the semester. The categorical variable "spacing" was calculated based on the time interval between students completing the DSM assignment and taking the exams. If the period is less than seven days, it means students mass their study sessions. On the other hand, if it is more than seven days, it means they space out their study sessions. This new variable created spacing sequences for the semester-wide study habits. The spacing patterns between the assignments, the time intervals between each submission, and the similarities and differences among the students' submission patterns were investigated. The study aimed to explore whether there were any significant differences in the spacing patterns of students with different levels of achievement in DSM assignments and final exams.

3.6.5 Qualitative Analysis with Semi-structured Interviews

Semi-structured interviews were conducted to understand how students use the Pearson MyLab® system and engage with DSM assignments in the 2022 Spring semester. Twenty-one students were randomly selected based on their performance in the DSM assignments to represent all student profiles after they agreed to participate in interviews on the consent forms. The interviews were conducted in Turkish and took place online to provide convenience and accessibility for the students. A speech-to-text tool was used to transcribe all the recordings of these online sessions, ensuring accurate documentation of verbal responses without the delay and potential errors associated with manual transcription.

The transcriptions were then imported into MAXQDA Qualitative Analysis Tool, a qualitative and mixed-methods data analysis software. In MAXQDA, the transcriptions were carefully reviewed and analyzed. A systematic coding process was employed using specific codes to represent different themes, patterns, and categories identified in the data.

The coding process comprised multiple stages. Initially, open coding was conducted to generate broad, descriptive codes based on students' responses. Subsequently, axial coding was carried out to identify relationships between the codes and categorize them into higher-level categories, followed by constant comparison to ensure consistency and accuracy.

Finally, selective coding was used to integrate and refine the categories into core themes, providing a comprehensive understanding of how students use the Pearson MyLab® system and DSM assignments. This thorough qualitative analysis aimed to gain deep insights into the students' usage patterns, challenges, and perceptions regarding the Pearson MyLab® system and DSM assignment.

CHAPTER 4

FINDINGS

This chapter focuses on the detailed findings of the data analysis conducted. The analysis results have been presented comprehensively to provide a clear understanding of the explored research questions answered by analyzing the data.

4.1 The Descriptive Statistics of the DSM Metrics

The analysis of DSM assignments for 226 students from six different cohorts revealed knowledge and struggle metrics to measure student performance and learning behavior. Descriptive analysis was performed using SPSS to examine the metrics obtained from the system for each student, providing an overview of student performance within the system. Table 5 presents the results of descriptive statistics, indicating variability across different metrics.

Table 5 Descriptive Statistics of DSM Metrics

DSM Metrics	*N*	*Min*	*Max*	*Mean*	*Median*	*SD*
Misinformation	226	0.42	69	21.05	20.46	14.93
Uncertainty	226	0.00	91.50	11.46	4.87	16.54
Mastery	226	0.45	99.58	60.16	61.12	22.02
Actionable Intervention	226	0.00	52.50	5.91	3.50	7.54
Low Struggle	226	0.00	76.36	10.31	7.78	11.06
Learned It	226	0.00	39.23	13.95	14.00	7.64

Table 5 (continued)

Knew It	226	0.00	99.58	60.89	61.57	22.04
Time Spent	226	3.83	43.90	18.00	16.57	8.91
Refreshers Count	226	0.00	0.93	0.20	0.00	0.27

For instance, the 'Misinformation' metric has a mean score of 21.05 with a standard deviation of 14.93, while 'Uncertainty' has a mean of 11.46 and a higher variability (*SD* = 16.54). This indicates that students had low-level knowledge when they started to learn with DSM assignments. Metrics like 'Mastery' and 'Knew It' show higher average performance with mean scores of 60.16 and 60.89, respectively. Conversely, 'Actionable Intervention' and 'Low Struggle' metrics display lower mean values, suggesting areas where students might need additional support.

In addition, Table 6 illustrates the distribution of students' performance, with 51.8% of students performing below average in 'Misinformation' and a significant 69.9% performing below average in 'Uncertainty'. In contrast, 'Mastery' and 'Knew It' metrics have a slightly higher percentage of students performing above average (51.8% and 50.9%, respectively). These statistics provide a comprehensive overview of the student's learning dynamics, emphasizing both areas of strength and potential improvement. In short, most students initially had a low understanding of the concepts and struggled significantly.

Table 6 Percentage of Students for Each DSM Metrics

	Percentage of Students	
	Below Average	Above Average
Misinformation	51.8	48.2
Uncertainty	69.9	30.1

Table 6 (continued)

Mastery	48.2	51.8
Actionable Intervention	64.2	35.8
Low Struggle	63.3	36.7
Learned It	49.1	50.9
Knew It	49.1	50.9
Time Spent	55.3	44.7
Refreshers Count	62.8	37.2

4.2 The Overall Study Results

In this section, a detailed account of the findings of these analyses was provided. Numerous data analyses were conducted to explore the relationship between Dynamic Study Module (DSM) metrics and student success in the Innovation and Entrepreneurship in Information Technologies and Introduction to Management Information Systems courses. These analyses aimed to ascertain the degree to which DSM metrics can function as indicators of student achievement. This section presents a comprehensive account of the outcomes derived from these analyses.

4.2.1 The Relation between DSM Metrics and Course Achievement

The Shapiro-Wilk test was used to check if the DSM metrics and exam scores followed a normal distribution. The results, shown in Tables 7 and 8, indicated that neither of the scores were normally distributed. Consequently, the Friedman test was used to assess the relationship between DSM metrics and student course achievements.

Table 7 Shapiro-Wilk Result of the DSM Metrics and Exam Scores

	Shapiro-Wilk		
	Statistic	df	Sig.
Finalgrade	0.980	213	0.004
Midtermgrade	0.979	213	0.003
DSM_knowledge	0.721	213	0.000
DSM_struggle	0.691	213	0.000
DSM_all	0.737	213	0.000

Table 8 Descriptive Statistics of DSM Metrics and Exam Scores

	N	Skewness	Kurtosis	Min	Max	Mean	Median	SD
Final Grade	213	0.115	-0.665	28.57	98.75	64.43	62.86	16.80
Midterm Grade	213	-0.035	-0.700	26.67	100.00	68.86	66.67	16.10
DSM Knowledge	213	-1.887	4.122	12.08	33.33	30.87	33.33	3.69
DSM Struggle	213	-2.667	10.858	0.00	25.00	22.73	24.54	3.47
DSM All	213	-1.881	4.254	8.75	28.57	26.22	28.05	3.40

The analysis revealed a significant association between the DSM assignment scores and students' exam performance ($\chi 2(4) = 803.602$, $p = 0.001$), as seen in Table 9. Subsequent Dunn-Bonferroni post hoc tests confirmed that DSM knowledge, DSM Struggle, and DSM all scores were significantly correlated with both final exam grades ($p = 0.000$) and midterm exam grades ($p = 0.000$) (see Table 10). Kendall's W's substantial effect size of 0.94 further underscores the strength of these relationships.

Table 9 Related-samples Friedman's two-way analysis of variance by ranks

Related-Samples Friedman's Two-Way Analysis of Variance by Ranks Summary	
Total N	213
Kendall's W	0.943
Test Statistic	803.602
Degree Of Freedom	4
Asymptotic Sig.(2-sided test)	0.000

Table 10 Pairwise Comparisons

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
DSM_struggle-DSM_all	-1.009	0.153	-6.588	0.000	0.000
DSM_struggle-finalgrade	3.293	0.153	21.496	0.000	0.000
DSM_struggle-midtermgrade	3.664	0.153	23.917	0.000	0.000
DSM_all-finalgrade	2.284	0.153	14.908	0.000	0.000
DSM_all-midtermgrade	2.655	0.153	17.328	0.000	0.000
DSM_knowledge-finalgrade	1.261	0.153	8.228	0.000	0.000
DSM_knowledge-midtermgrade	1.631	0.153	10.648	0.000	0.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

4.2.2 The Predictivity of DSM Metrics on Course Achievement

A multiple linear regression analysis was conducted to investigate how DSM metrics can predict student performance in course examinations, including the final and midterm exams. The initial model consisted of various variables, including Knowledge Metrics (Misinformation, Uncertainty, and Mastery), Struggle Metrics (Actionable Intervention, Low Struggle, Learned It, and Knew It), and other DSM metrics (Refreshers Count and Total Time Spent). After the assumptions check, such as multicollinearity concern, the Knew It dimension was removed from the model since it showed a single multicollinearity problem with the Mastery dimension. Additionally, Uncertainty and Misinformation were removed from the model since their VIF values were greater than 10 and their Tolerance values were less than 0.1. Therefore, the final model only included the following dimensions: Mastery, Actionable Intervention, Low Struggle, Learned It, Refreshers Count, and Total Time Spent.

4.2.2.1 Regression Analysis for Final Exam

Multiple regression was conducted to see if students' DSM-related scores predicted their scores in the final exam. The data met the assumption of independent errors (*Durbin-Watson value* = 1.96). Based on the Collinearity statistics, it was found that multicollinearity was not a concern, indicating that the data met the assumption of collinearity (Actionable Intervention, *Tolerance* = .60, *VIF* = 1.66; Learn It, *Tolerance* = .57, *VIF* = 1.74; Low Struggle, *Tolerance* = .45, *VIF* = 2.19; Mastery, *Tolerance* = .28, *VIF* = 3.53; Refresher_Count, *Tolerance* = .75, *VIF* = 1.34; Time_Spent, *Tolerance* = .54, *VIF* = 1.86).

Using the enter method, it was found that DSM-related metrics explain a significant amount of the variance in the score of the final exam ($F(6, 207) = 3.853$,

$p < .05$, $R^2 = .10$, $R^2_{Adjusted} = .07$). However, none of the metrics added statistically significantly to the prediction, $p < .05$ (See Tables 11, 12 and 13).

Table 11 ANOVA Results – Final Exam

Model		*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
1	Regression	6108.283	6	1018.047	3.853	.001b
	Residual	54696.421	207	264.234		
	Total	60804.704	213			

a Dependent Variable: FinalGrade

b Predictors: (Constant), Refreshers_Count, LearnedIt, ActionableIntervention, TimeSpent, LowStruggle, Mastery

Table 12 Regression Analysis Model Summary – Final Exam

Model	*R*	*R Square*	*Adjusted R Square*	*Std. Error of the Estimate*	*Durbin-Watson*
1	.317a	0.100	0.074	16.255	1.960

a Predictors: (Constant), Refreshers_Count, LearnedIt, ActionableIntervention, TimeSpent, LowStruggle, Mastery

b Dependent Variable: FinalGrade

Table 13 Regression Analysis Coefficients – Final Exam

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
Model		*B*	*Std. Error*	*Beta*	*t*	*Sig*	Lower Bound	Upper Bound
1	(Constant)	57.54	9.30		6.19	0.00	39.21	75.87
	ActionableIntervention	-0.30	0.19	-0.13	-1.58	0.12	-0.67	0.07

Table 13 (continued)

LearnedIt	0.28	0.19	0.13	1.48	0.14	-0.09	0.65
LowStruggle	-0.03	0.15	-0.02	-0.22	0.82	-0.32	0.25
Mastery	0.11	0.09	0.14	1.16	0.25	-0.08	0.29
Refreshers_Count	7.78	4.74	0.13	1.64	0.10	-1.57	17.12
TimeSpent	-0.18	0.17	-0.09	-1.06	0.29	-0.51	0.16
a. Dependent Variable: FinalGrade							

4.2.2.2 Regression Analysis for Midterm Exam

Multiple regression was conducted to see if students' DSM-related scores predicted their scores in the midterm exam. The data met the assumption of independent errors (*Durbin-Watson value* = 2.07). Additionally, based on the Collinearity statistics, it was found that multicollinearity was not a concern, indicating that the data met the assumption of collinearity (Actionable Intervention, *Tolerance* = .60, *VIF* = 1.66; Learn It, *Tolerance* = .57, *VIF* = 1.74; Low Struggle, *Tolerance* = .46, *VIF* = 2.19; Mastery, *Tolerance* = .28, *VIF* = 3.51; Refresher Count, *Tolerance* = .75, *VIF* = 1.34; Time Spent, *Tolerance* = .54, *VIF* = 1.87).

Using the enter method, it was found that DSM-related metrics explain a significant amount of the variance in the score of the midterm exam ($F(6, 206) = 5.121$ $p < .05$, $R^2 = .18$ $R^2_{Adjusted} = .14$). Only learned it, mastery and refresher count added statistically significantly to the prediction, $p < .05$ (See Tables 14, 15 and 16).

Table 14 ANOVA Results – Midterm Exam

Model	*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*

Table 14 (continued)

1	Regression	7134.488	6	1189.081	5.121	<.001b
	Residual	47835.775	206	232.212		
	Total	54970.263	212			

a Dependent Variable: MidtermGrade
b Predictors: (Constant), Refreshers_Count, LearnedIt, ActionableIntervention, TimeSpent, LowStruggle, Mastery

Table 15 Regression Analysis Model Summary – Midterm Exam

Model	*R*	*R Square*	*Adjusted R Square*	*Std. Error of the Estimate*	*Durbin-Watson*
1	.423a	0.179	0.142	14.914	2.07

a Predictors: (Constant), Refreshers_Count, LearnedIt, ActionableIntervention, TimeSpent, LowStruggle, Mastery
b Dependent Variable: MidtermGrade

Table 16 Regression Analysis Coefficients – Midterm Exam

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
Model		*B*	*Std. Error*	*Beta*	*t*	*Sig*	Lower Bound	Upper Bound
1	(Constant)	52.985	8.722		6.075	0.000	35.790	70.180
	ActionableIntervention	-0.164	0.177	-0.078	-0.928	0.354	-0.513	0.185
	LearnedIt	0.450	0.178	0.217	2.524	0.012	0.099	0.802
	LowStruggle	0.088	0.137	0.062	0.642	0.522	-0.182	0.357
	Mastery	0.178	0.087	0.249	2.040	0.043	0.006	0.350
	Refreshers_Count	13.187	4.443	0.223	2.968	0.003	4.427	21.947
	TimeSpent	-0.209	0.160	-0.116	-1.305	0.193	-0.525	0.107

a. Dependent Variable: MidtermGrade

4.2.3 The Process of Students Taking DSM Assignments

In order to gain a more precise understanding of the students' processes while completing the DSM assignments, they were carefully grouped based on their knowledge and struggle metrics, as well as their final exam scores. K-means clustering was utilized in SPSS to categorize the students of the ISE 432 course. Then, process mining was conducted using Disco by Fluxion to comprehend better the DSM assignment processes for different groups of students each semester. The data was meticulously prepared to meet the process mining requirements within Disco, which necessitated an activity and at least one timestamp variable.

The DSM assignments consist of three distinct activities: Learning, Full Refresher, and Smart Refresher. The system records each student's specific activities and their corresponding duration. The Last Activity time indicates when the students finish their DSM assignments, while the Time Spent represents the number of minutes they spent completing them. Using the Last Activity Logs and Time Spent, a Starting Activity log is computed, and the clusters, cohorts, and modules are established as attributes. These variables are essential components of the process mining analysis.

4.2.3.1 Clustering Students based on Knowledge Metrics

Table 17 presents the initial cluster centers. These vectors have been calculated based on three knowledge metrics variables: Misinformation, Mastery, and Uncertainty. The clusters represent three groups of students with different performances on the first attempt to answer questions on a DSM assignment. These scores are at maximum index distance from each other.

Table 17 Initial Cluster Centers - Knowledge Metrics

	Cluster		
	1	*2*	*3*
Misinformation	0.417	69.000	1.818
Uncertainty	99.583	28.500	0.455
Mastery	0.000	2.500	88.636

Table 18 displays the number of iterations and the changes in cluster centers. The cluster centers are updated until the fourteenth iteration. After that, the redistribution of units stops because there are no further changes in the cluster centers. Although the number of iterations was set to 20, changes in the cluster center are shown only until the fourteenth iteration. There are no changes in the end, indicating that the value remained at 0.

Table 18 Iteration History - Knowledge Metrics

	Change in Cluster Centers		
Iteration	*1*	*2*	*3*
1	17.971	46.366	40.506
2	0.233	0.557	4.255
3	0.531	1.351	5.249
4	3.001	2.924	7.097
5	0.047	0.445	2.011
6	0.001	0.003	0.056
7	1.145E-05	2.674E-05	0.002
8	1.789E-07	2.073E-07	4.310E-05
9	2.795E-09	1.607E-09	1.197E-06
10	4.367E-11	1.246E-11	3.325E-08

Table 18 (continued)

11	6.750E-13	9.237E-14	9.237E-10
12	1.567E-14	7.105E-15	2.567E-11
13	0.000	0.000	7.004E-13
14	0.000	0.000	2.930E-14
15	0.000	0.000	0.000

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 15. The minimum distance between initial centers is 98.807.

Table 19 displays the final cluster centers, while Table 20 shows their distances. When examining Table 17 and Table 19, it becomes evident that the cluster centers have changed.

Table 19 Final Cluster Centers - Knowledge Metrics

	Cluster		
	1	*2*	*3*
Misinformation	6.822	28.647	19.050
Uncertainty	86.263	54.771	28.045
Mastery	3.995	7.114	45.343

Table 20 Distances between Final Cluster Centers - Knowledge Metrics

Clusters	*1*	*2*	*3*
1		38.443	72.448
2	38.443		47.622
3	72.448	47.622	

The dissimilarities in F-ratios provide insights into the significance of various mean variables in the clustering process. Table 21 presents the dispersion analysis results. They demonstrate that all DSM Knowledge metrics have the most significant effect on cluster formation.

Table 21 ANOVA - Cluster Analysis with Knowledge Metrics

	Cluster		Error			
	Mean Square	*df*	*Mean Square*	*df*	*F*	*Sig.*
Misinformation	10392.475	2	131.606	223	78.966	0.000
Uncertainty	40019.501	2	130.156	223	307.474	0.000
Mastery	20834.086	2	89.026	223	234.021	0.000

The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

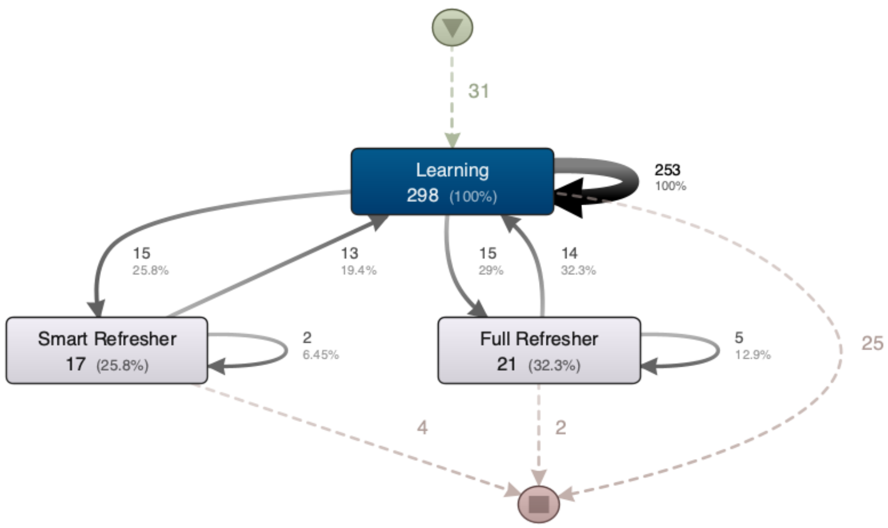
Table 22 presents the number of cases in each cluster. All cases were valid, and no cases were missing.

Table 22 Number of Cases in Each Cluster - Knowledge Metrics

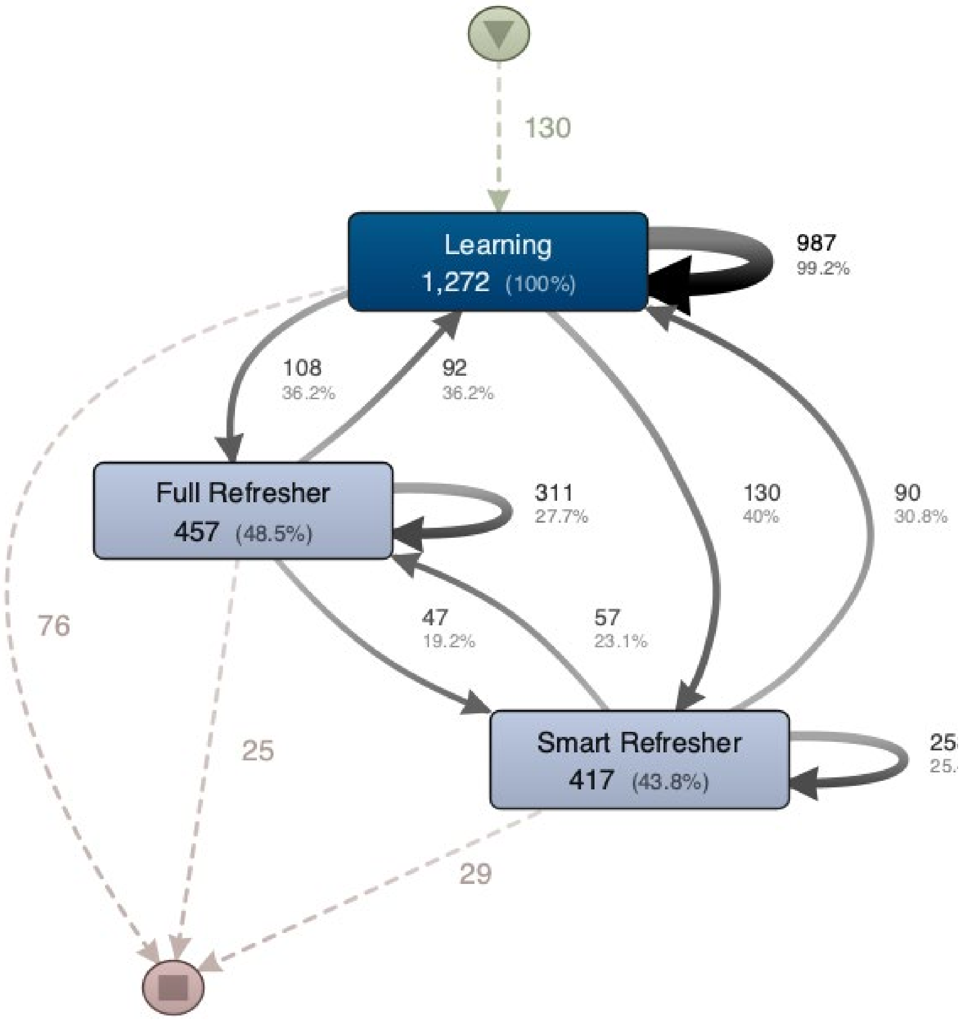
	Clusters	Cases
Cluster	1	65.000
	2	130.000
	3	31.000
Valid		226.000
Missing		0.000

Based on the F-ratio values, students in Cluster 1 appear to possess a significantly higher level of knowledge than those in Cluster 2, who have an average level of knowledge. On the other hand, students in Cluster 3 seem to possess a relatively lower level of knowledge based on their initial responses to DSM assignments.

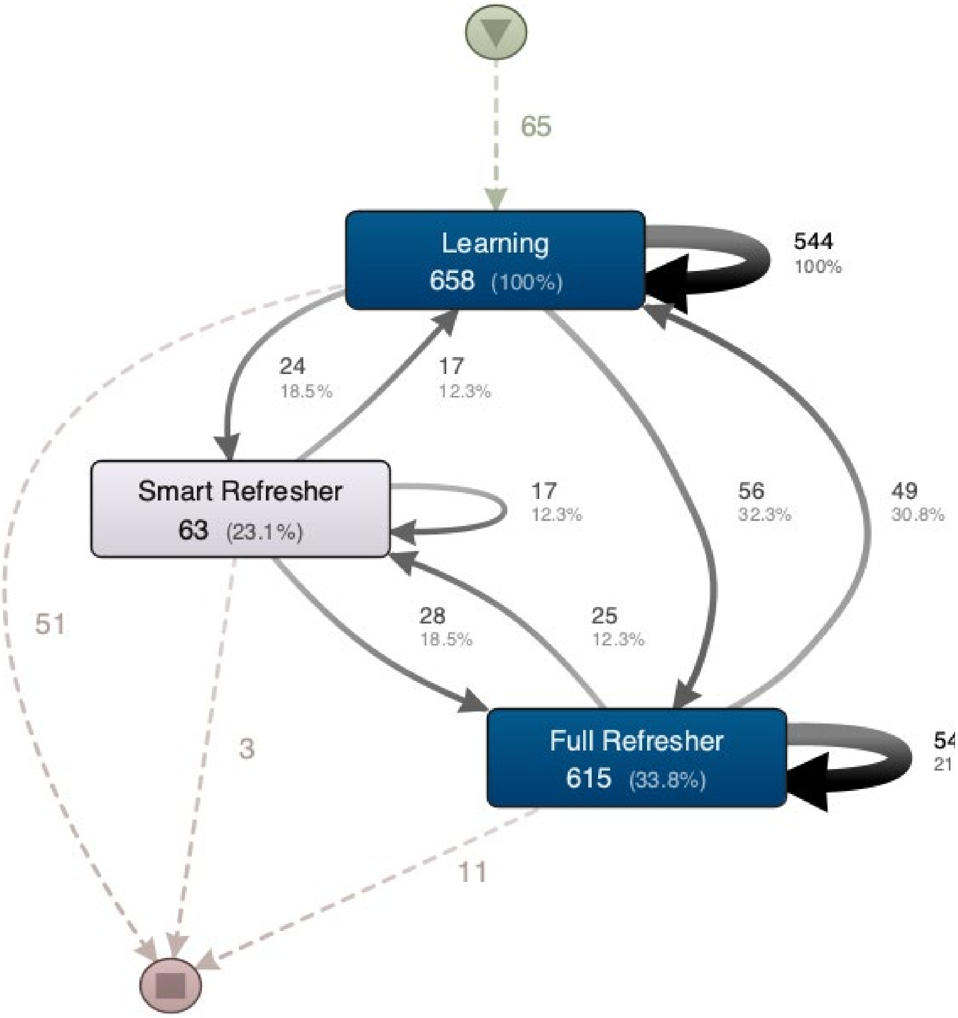
4.2.3.2 Process Mining for Knowledge Metrics Clusters



(A) Low Knowledge Cluster



(B) Average Knowledge Cluster



(C) High Knowledge Cluster

Figure 10 Process Map of Students the First Attempt of DSM Assignments

Figure 11 (A) visually represents the activities flow for students who did not perform well within DSM Assignments. There were 336 events and 31 cases, with a median case duration of 56.1 days and a mean case duration of 46.6 days. The analysis revealed 19 different process variations within the observed group. Below is a comprehensive overview of the process variants.

All students (298 events) began with compulsory Learning Activities, and nearly all (253 events) continued with Learning Activities. However, some students chose the Smart or Full Refresher Activities, with 25.8% (17 events) selecting Smart Refresher after completing a DSM Assignment. Of these students, 6.45% (2 events) took another Smart Refresher, while 19.4% (13 events) returned to Learning Activities. Additionally, 32.3% (21 events) opted for Full Refresher. Among this group, 12.9% (5 events) took another Full Refresher, while 32.3% (14 events) returned to Learning Activities.

Figure 11 (B) visually represents the activities flow for students who performed at an average level during their first attempt at DSM Assignments. The data is based on event logs, which recorded 2146 events and 130 cases. The median case duration was 56.3 days, and the mean case duration was 50.1 days. A total of 78 variants in this group's processes were observed. A detailed overview of these variants is provided below.

All students (1272 events) began with a Learning Activity, and 99.2% of them (987 events) went on to take a Learning Activity as their next step. A slightly different pattern emerged within this group regarding using Smart and Full Refreshers. Of the students in this cluster, 43.8% (417 events) engaged in Smart Refresher activities. Within this group, 25.4% (258 events) continued with another Smart Refresher, while 30.8% (90 events) returned to a Learning Activity. Among the students who took Full Refresher activities (48.5% or 457 events), 27.7% (311 events) moved on to another Full Refresher, but 36.2% (92 events) returned to a Learning Activity. Notably, students with average performance displayed a different pattern than those with low performance. Specifically, some students shifted between Smart and Full Refresher activities, with 23.1% (57 events) continuing with another Full Refresher activity after a Smart Refresher, while 19.2% (47 events) took another Smart Refresher activity after a Full Refresher.

Figure 11 (C) clearly represents how high-performing students progressed through semesters when attempting DSM Assignments for the first time. The data comes from their event logs, including 1336 events and 65 cases. The median case duration was 28.9 days, and the mean case duration was 39.9 days. The variants observed in this group's process were 26. A detailed sketch of these variants is represented below.

All students (1120 events) began with a Learning Activity, and 100% of them (880 events) continued with another Learning Activity. Interestingly, high-performing students showed a similar pattern to average-performing students. After Learning Activities, 23.1% of students (63 events) started with Smart Refresher activities, 12.3% (17 events) continued with another Smart Refresher, while 12.3% (17 events) moved on to another Learning Activity. Additionally, 33.8% of students (615 events) continued with Full Refresher activities. Conversely, 21.5% of students (540 events) moved to another Full Refresher activity, while 30.8% (49 events) of them transitioned back to another Learning Activity. There was also a move between Refresher activities, with 18.5% (28 events) continuing with another Full Refresher activity after a Smart Refresher and 12.3% (25 events) taking another Smart Refresher activity after a Full Refresher.

Upon analyzing the practices of the three groups based on the knowledge metrics, it was discovered that the ISE 432 students who excelled in their initial attempt invested a comparatively less expressive amount of time in comprehending the concepts and completing the tasks. Additionally, students with all knowledge levels took both refreshers. However, the frequency of these events was higher for the high-knowledge group. They chose to study by revisiting the material through supplementary activities, especially Full Refresher. This suggests that individuals with superior performance and elevated knowledge levels during DSM assignments managed their study sessions better. Essentially, they supplemented their studies with additional learning opportunities, namely refresher.

4.2.3.3 Clustering Students Based on Struggle Metrics

Table 23 presents the initial cluster centers. These vectors have been calculated based on three struggle metrics variables: Actionable Intervention, Low Struggle, Learned It, and Knew It. The clusters represent three groups of students who performed differently after the first attempt while taking the DSM assignments. These scores are at maximum index distance from each other.

Table 23 Initial Cluster Centers - Struggle Metrics

	Cluster		
	1	*2*	*3*
ActionableIntervention	0.000	2.727	52.500
LearnedIt	0.417	11.364	6.500
KnewIt	99.583	0.455	31.500
Uncertainty	0.000	88.636	4.000

Table 24 displays the number of iterations and the changes in cluster centers. The cluster centers are updated until the thirteenth iteration. After that, the redistribution of units stops because there are no further changes in the cluster centers.

Table 24 Iteration History - Struggle Metrics

Iteration	*Change in Cluster Centers* 1	2	3
1	23.901	32.939	47.491
2	5.078	11.057	5.745
3	4.763	11.423	4.822
4	0.073	0.346	0.037
5	0.001	0.010	0.000
6	1.734E-05	0.000	2.145E-06
7	2.668E-07	9.632E-06	1.637E-08
8	4.105E-09	2.919E-07	1.250E-10
9	6.314E-11	8.845E-09	9.648E-13
10	9.717E-13	2.680E-10	3.662E-15
11	2.925E-14	8.118E-12	0.000
12	0.000	2.474E-13	0.000
13	0.000	1.066E-14	0.000
14	0.000	0.000	0.000

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 14. The minimum distance between initial centers is 86.282.

Table 25 displays the final cluster centers, while Table 26 shows their distances. When examining Table 23 and Table 25, it becomes evident that the cluster centers for the clusters have changed.

Table 25 Final Cluster Centers - Struggle Metrics

	Cluster 1	2	3

Table 25 (continued)

ActionableIntervention	1.009	12.413	6.761
LearnedIt	6.992	19.348	16.077
KnewIt	87.574	28.425	55.536
Uncertainty	3.187	44.397	7.709

Table 26 Distances between Final Cluster Centers - Struggle Metrics

Clusters	1	2	3
1		74.024	34.096
2	74.024		46.083
3	34.096	46.083	

The dissimilarities in F-ratios provide insights into the significance of various mean variables in the clustering process. Table 27 presents the dispersion analysis results. They demonstrate that all DSM Struggle metrics have the most significant effect on cluster formation.

Table 27 ANOVA - Cluster Analysis with Struggle Metrics

	Cluster		Error			
	Mean Square	*df*	*Mean Square*	*df*	*F*	*Sig.*
ActionableIntervention	1471.582	2	44.238	223	33.265	0.000
LearnedIt	2297.386	2	38.343	223	59.916	0.000

Table 27 (continued)

KnewIt	40998.537	2	122.289	223	335.259	0.000
Uncertainty	19927.391	2	97.158	223	205.102	0.000

The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

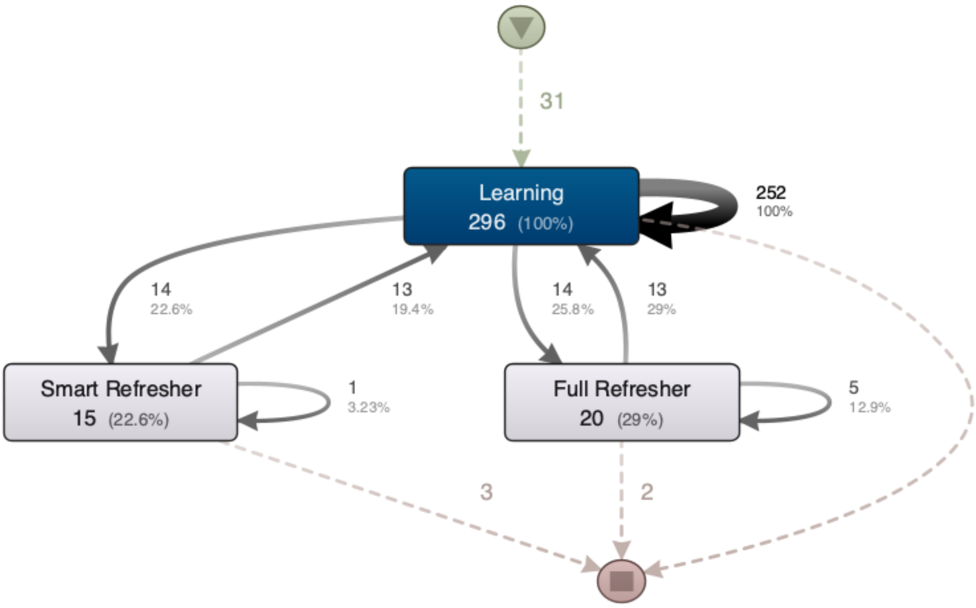
Table 28 presents the number of cases in each cluster. All cases were valid, and no cases were missing.

Table 28 Number of Cases in each Cluster - Struggle Metrics

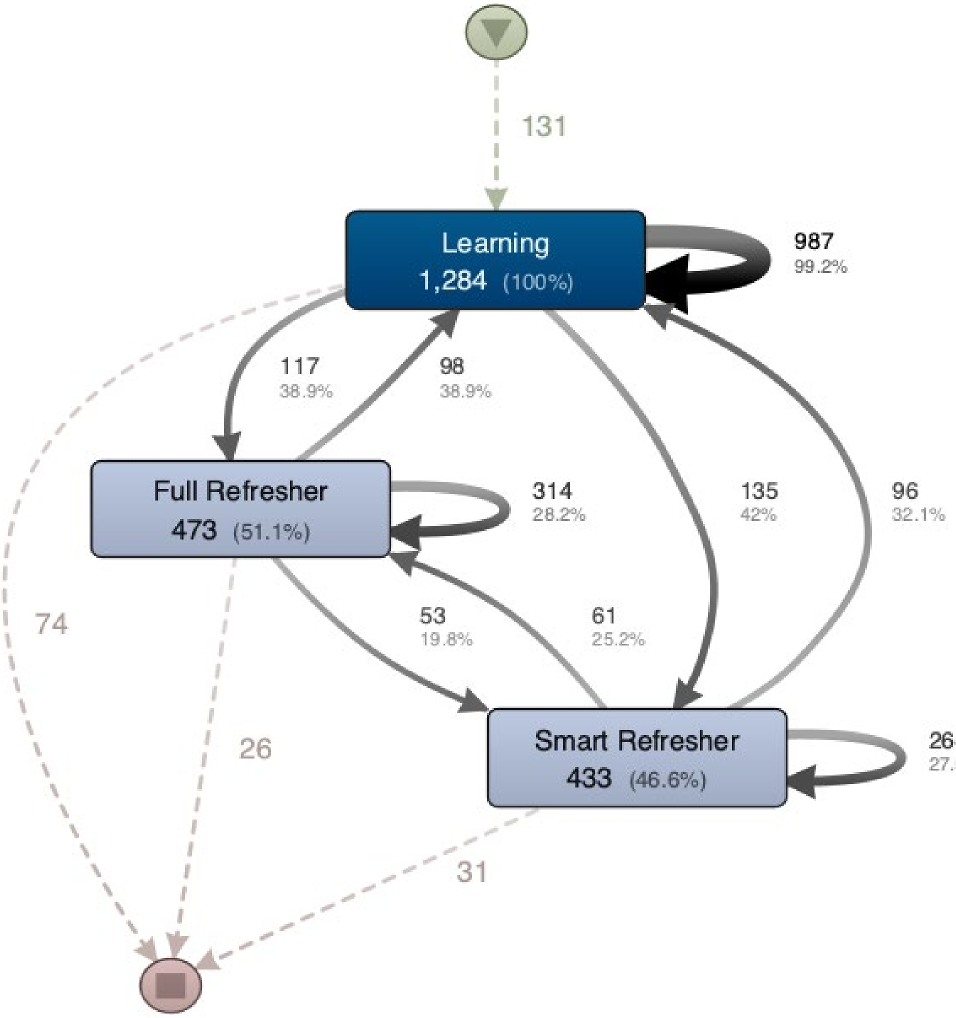
	Clusters	Cases
Cluster	1	64.000
	2	31.000
	3	131.000
Valid		226.000
Missing		0.000

Based on the significance of the F-ratio values, Cluster 1 comprises ISE 432 students with a high level of struggle, Cluster 2 comprises students with a low level of struggle, and Cluster 3 comprises students with an average degree of struggle.

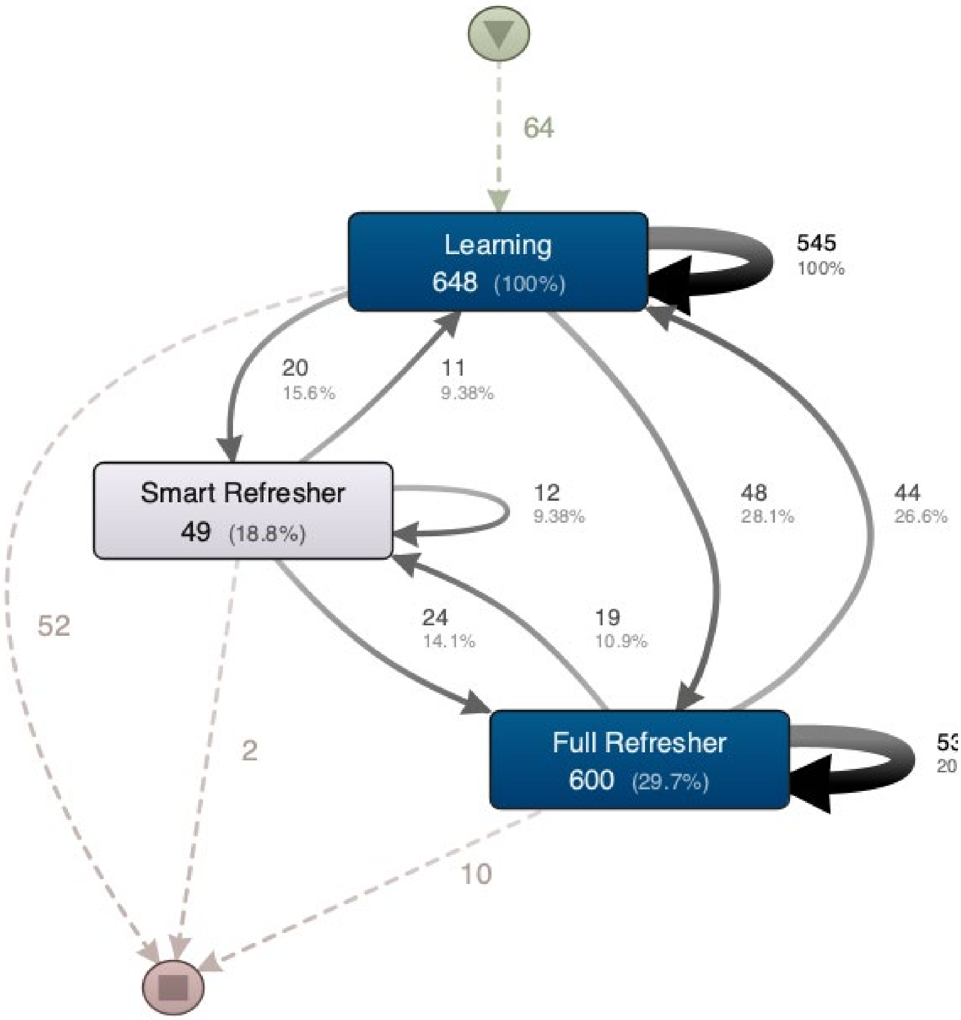
4.2.3.4 Process Mining for Struggle Metrics Clusters



(A) High Struggle Cluster



(B) Average Struggle Group



(C) Low Struggle Cluster

Figure 11 Process Map of Students After the First Attempt of DSM Assignments

In this process mining, a visual representation based on event logs was created to illustrate the process followed by students who performed poorly after their first attempt at DSM Assignments (Figure 12 (A)). The visualization consisted of 331 events and 31 cases, with a median case duration of 55.9 days and a mean duration of 44.9 days. Additionally, 19 variants in this group's process were pictured. A detailed portrait of the variants is described below.

All the students (296 events) started with compulsory Learning activities, and almost all of them (252 events) followed this with another Learning Activity. After the Learning Activities, the students could choose between two types of refresher activities: Smart or Full. Of the total number of students, 22.6 (15 events) chose to take a Smart Refresher after the Learning Activity. Among these, 3.23% (1 event) chose to take another Smart Refresher, while 19.4% (13 events) opted for another Learning Activity. Meanwhile, 29% (20 events) of the students chose to take a Full Refresher. Among these, 12.9% (5 events) continued with another Full Refresher, while 29% (13 events) of the students chose to move to another Learning Activity.

Figure 12 (B) displays a visual representation of the flow of activities within semesters for students who performed on average on their second attempt while taking DSM Assignments. These assignments were derived from their event logs. This visualization shows the process of students who struggled with a DSM assignment. A total of 2190 events and 131 cases were recorded. The median case duration was 56.9 days, and the mean case duration was 551.2 days. A total of 81 variants emerged in this group's processes. The text below presents how students have different processes.

All students (1284 events) started with a Learning Activity, and 99.2% (987 events) consistently took another Learning activity. The students who performed average showed a slightly different pattern to the low-performance students. A shift between refresher activities was observed. Also, more students continued with either Smart or Full Refresher activities. 46.6% of students (433 events) took the Smart Refresher activities after a Learning Activity. 27.5% of students (264 events) followed the Smart Refresher, while 32.1% of students (96 events) followed another Learning Activity. 51.1% of students (473 events) took the Full Refresher activities following Learning Activities. 28.2% of students (314 events) took the Full Refresher, while 38.9% of students (98 events) followed another Learning Activity.

Additionally, a move between refreshers was observed. 25.2% (61 events) continued with another Full Refresher activity after a Smart Refresher, while 19.8% (53 events) took another Smart Refresher activity after a Full Refresher.

Figure 12 (C) shows a visual representation of how students who performed well on their second attempt at DMS Assignments structured their semesters. This data was derived from their event logs, which showed 1297 events and 64 cases. The median case duration was 27.7 days, and the mean case duration was 38.5 days. This group's process generates 24 variants. The detailed specifications of these variants are illustrated below.

All students (648 events) started with a Learning Activity, and almost all of them (100% or 545 events) subsequently took another Learning Activity. The pattern for students with average performance was similar to that of the low and high-performance students. 18.8% of students (49 events) started with Smart Refresher activities after Learning Activities. 9.38% of students (12 events) moved to another Smart Refresher activity, whereas 9.38% of them (11 events) moved to another Learning Activity. 29.7% of students (600 events) continued with Full Refresher activities following Learning Activities. 20.3% of students (537 events) moved to another Full Refresher activity, whereas 26.6% of them (44 events) moved to another Learning Activity.

The data also showed that some students moved between refreshers. 14.1% (24 events) continued with another Full Refresher activity after a Smart Refresher, while 10.9% (19 events) took another Smart Refresher activity after a Full Refresher.

When comparing the processes of the three clusters of struggle metrics, it was discovered that they showed a similar pattern with clusters of knowledge metrics. Students who performed better on their second attempt spent relatively less time completing activities and understanding the concepts. Similar to knowledge metric clusters, less-struggled students also took more studying opportunities by refreshing their knowledge with refresher activities. In other words, they tend to take more full refresher activities. This suggests that students with higher performance and knowledge levels regulated their study sessions better and chose to study more with additional learning activities (refreshers).

4.2.3.5 Clustering Students Based on Final Exams

Descriptive analysis was conducted on SPSS to classify students according to their exam performance levels. The results of the Kolmogorov-Smirnov Test, which assesses normality (see Tables 29 and 30), indicated that final exam scores with skewness of .110 (*SE*= 0.166) and kurtosis of -.671 (*SE*=0.331) are normally distributed. Because of the normal distribution, the students were categorized into three groups based on their z-score statistics (see Table 31). The group below the -1 z-score was classified as the low-performance group, the group above the +1 z-score was classified as the high-performance group, and the group between the -1 and +1 was classified as the average performance group. The categories were calculated using the "Recode into Different Values" tool in SPSS.

Table 29 Descriptive Statistics of Final Exam Scores

	N	*Skewness*	*Kurtosis*	*Min*	*Max*	*Mean*	*Median*	*SD*
Final Exam Scores	214	0.110	-0.671	28.57	98.75	64.28	62.86	16.89

Table 30 Kolmogorov-Smirnov Test Results of the Final Exam Scores

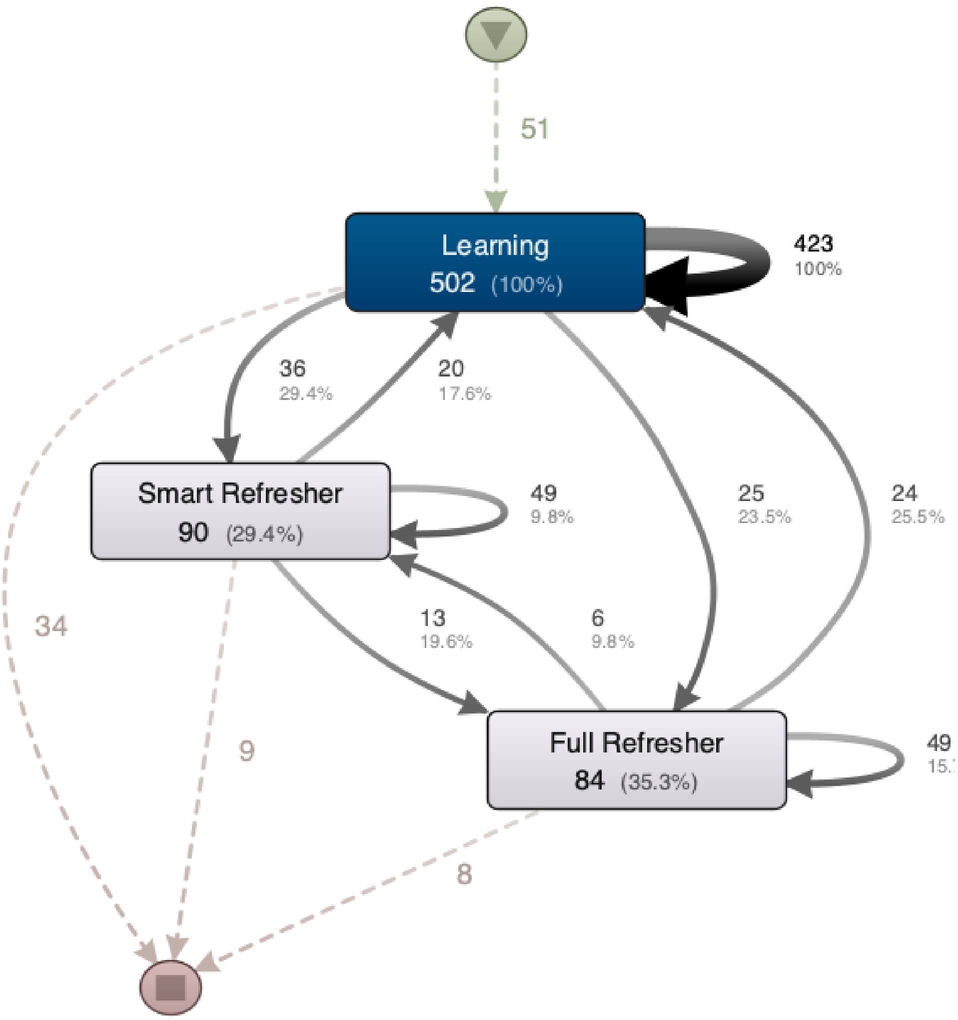
	Kolmogorov-Smirnov[a]		
	Statistic	df	Sig.
Final Exam Scores	0.055	214	.200*

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

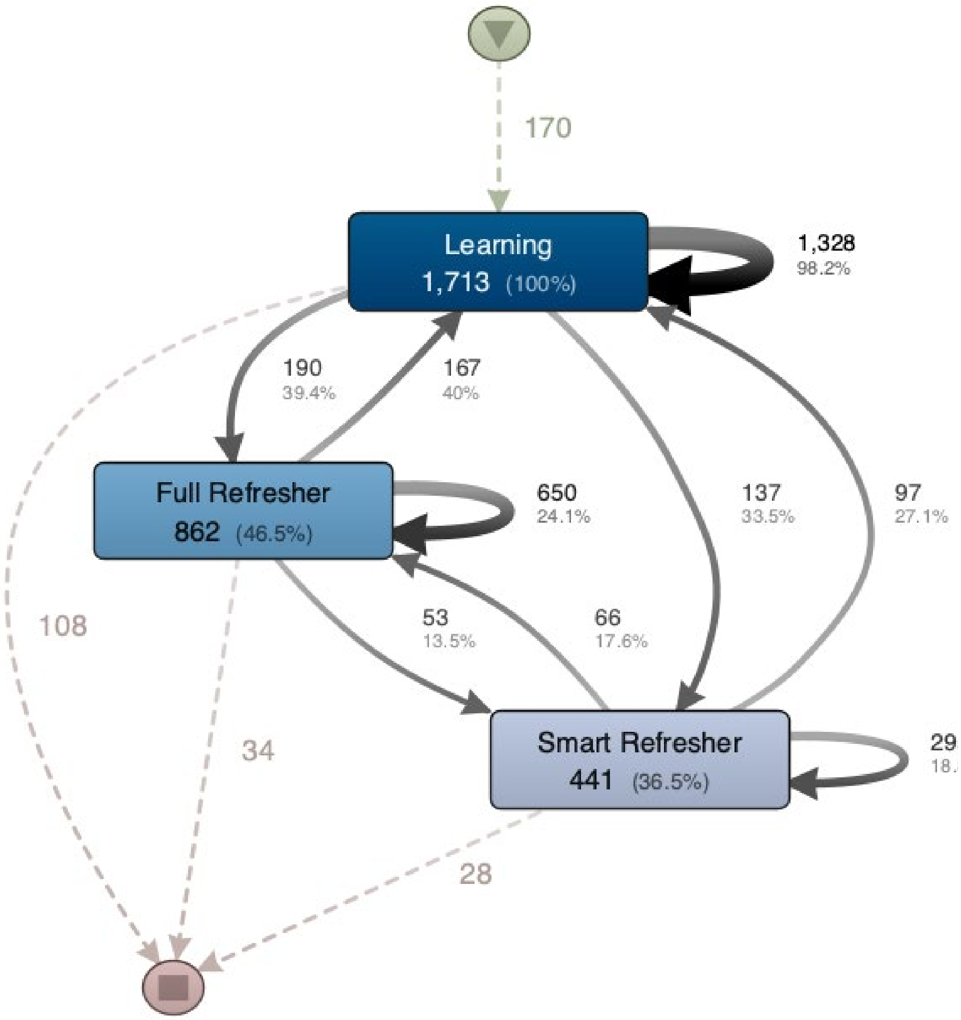
Table 31 Number of Cases in Each Cluster – Final Exam Scores

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	36	15.9	16.8	16.8
	2.00	135	59.7	63.1	79.9
	3.00	43	19.0	20.1	100.0
	Total	214	94.7	100.0	
Missing	System	12	5.3		
Total		226	100.0		

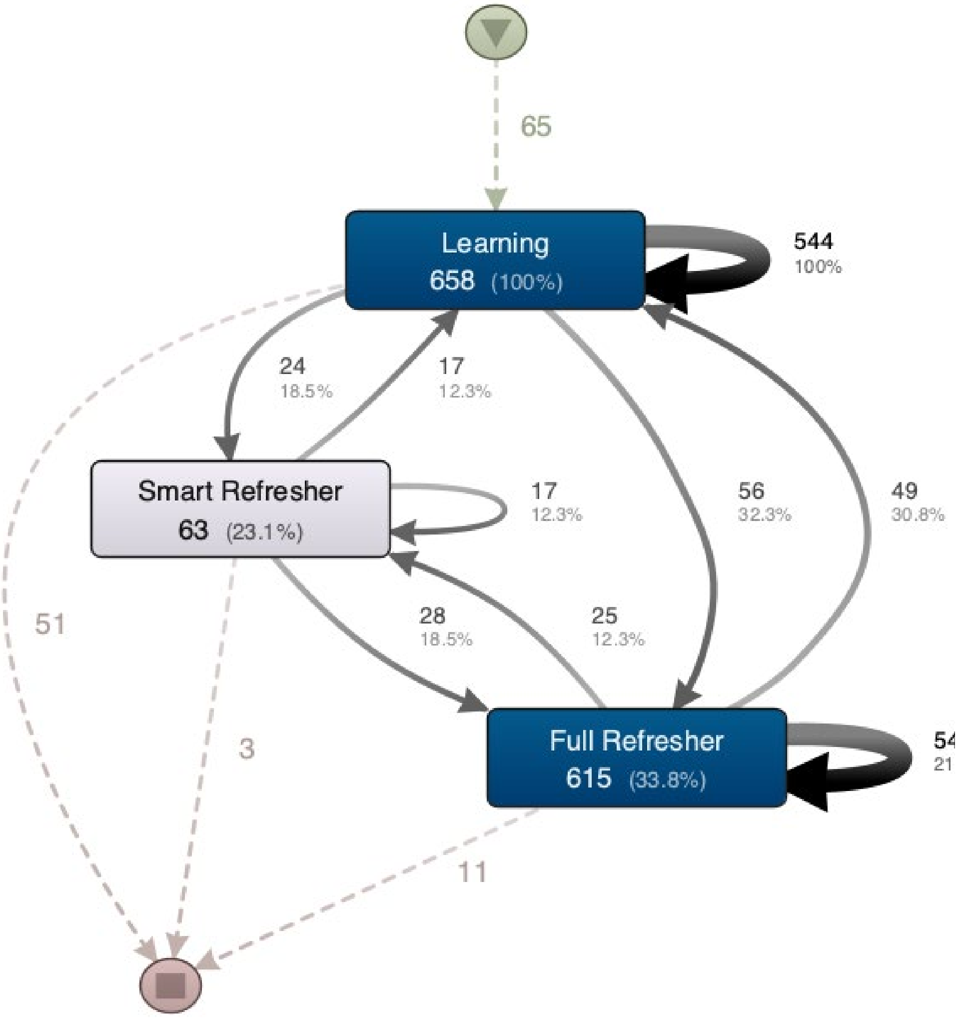
4.2.3.6 Process Mining for Final Exam Clusters



(A) Low Exam Performers



(B) Average Exam Performers



(C) High Exam Performers

Figure 12 Process Map of DSM Assignments for Students based on their Exam Performance

This visual representation, shown in Figure 13 (A), depicts the activities flow for students who performed poorly on their final exams. A total of 676 events and 51 cases were recorded, with a median case duration of 30.1 days and a mean case duration of 39.2 days. Below is an overview of the 25 discovered variants within this group's processes.

All students (502 events) began with compulsory Learning Activities, and almost all (423 events) continued with additional. Learning Activities. From there, students followed two paths: Smart or Full Refresher activities. Of the students who chose Smart Refreshers, 29.4% (90 events) took them after completing a DSM assignment; 9.8% (49 events) took them successively. However, 17.6% of the students (20 events) followed another Learning Activity. Meanwhile, 35.3% of students (84 events) chose Full Refreshers, with 15.7% (49 events) taking them successively and 25.5% (24 events) moving to another Learning Activity. Some students also switched between refreshers: 19.6% (13 events) continued with Full Refreshers after a Smart Refresher, and 9.8% (6 events) took another Smart Refresher after a Full Refresher. This pattern aligns with previously discovered knowledge and struggle metrics cluster patterns.

Figure 13 (B) visually illustrates activities flow throughout semesters for students who scored average on the final exam. The visualization presents the process followed by students who received an average performance. The data set consisted of 1709 events and 102 cases, with a median case duration of 35.6 days and a mean case duration of 41 days. In this group's process, 52 variations were detected, which are described below.

All students (1004 events) began with a Learning Activity, and 99% of them (809 events) continued with Learning Activities. The pattern of students with average performance was like that of low-performance students.

Of the students who scored an average, 32.4% (222 events) went on to take the Smart refresher activities after the Learning Activities. Out of these, 18.4% (148 events) took Smart Refreshers successively, while 23.5% (47 events) moved to another Learning Activity.

On the other hand, 41.2% (483 events) of students took the full refresher activities. Out of these, 23.5% (378 events) took Full Refreshers successively, while 34.3% (76 events) moved to another Learning Activity. A transition between refreshers was also observed, with 14.7% (29 events) continuing with another Full Refresher activity after a Smart Refresher and 12.7% (29 events) taking another Smart Refresher activity after a Full Refresher. This process was similar to that of the low-performance cluster, with the only difference being that the frequency of refresher activities was higher.

Figure 13 (C) visually represents the flow of activities during semesters for students who performed well on final exams. There were 1281 events and 61 cases. The median duration of a case was 67 days, and the mean duration was 58.3 days. In this group's processes, a total of 37 variants were discovered, and the details are presented below.

All the students (602 events) started with a Learning activity, and 100% of them (457 events) continued with Learning activities throughout the semester. Students with higher performance followed a similar pattern to those with lower performance. However, 45.9% of the students in this group (171 events) continued with Smart Refreshers. Of these students, 26.2% (76 events) took Smart Refreshers successively, while 29.5% (46 events) switched to another Learning Activity. On the other hand, 45.9% of students (508 events) continued with Full Refresher activities after Learning Activities. Among these students, 31.1% (421 events) took Full Refreshers successively, while 37.7% (49 events) moved to another Learning Activity.

Additionally, a move between refreshers was observed. 26.2% (42 events) continued with another Full Refresher activity after a Smart Refresher, while 23% (36 events) took another Smart Refresher activity after a Full Refresher. This process is like that of the low- and average-performance clusters, but the refresher activities are more frequent.

When comparing the processes of the three groups of students with exam performance, it was found that students who performed better on the final exam spent more time understanding the concepts and completing the activities. This finding slightly differs from the previous process mining based on the knowledge and struggle metrics clusters. However, as in the previous process mining results, they chose to study by refreshing their knowledge with refresher activities. This indicates that students with higher final exam performance managed their study sessions better. In other words, they chose to study more with additional learning activities (Refreshers).

4.2.3.7 Summary

The process mining analysis of DSM assignments showed consistent patterns among most students. Initially, students engaged in compulsory learning activities, after which they could choose between two refresher activities: Full Refreshers and Smart Refreshers. Only a few students opted to take both refresher activities in succession. The frequency and type of activities varied among low, average, and high-performance clusters.

Students in the low-performance group participated in fewer refresher activities than their higher-performing peers. The average-performance group frequently used both refresher activities, reflecting a more balanced study approach. High-performing students predominantly chose Full Refreshers over Smart Refreshers, indicating a preference for comprehensive review sessions.

Overall, most students began with mandatory learning activities before deciding between Full and Smart Refreshers. The frequency and nature of refresher activities differed across performance groups, with high-achieving students showing a preference for more frequent and thorough refreshers. These results highlight the significance of efficient study techniques, especially retrieval practice and self-regulated learning, in attaining academic success.

The table below summarizes event transitions. This study highlights the significance of retrieval practice and supports previous findings.

Table 32 Summary of Common Transitions Observed in Clusters

Transitions	*Clusters*		
	Low	*Average*	*High*
Learning ➞ Learning	100%[a] (253)	99.2%[a] (987)	100%[a] (544)
	100%[b] (252)	99.2%[a] (987)	100%[b] (545)
	100%[c] (423)	99%[c] (809)	100%[c] (457)
Learning ➞ Smart Refresher	25.8%[a] (15)	40%[a] (130)	18.5%[a] (63)
	22.6%[b] (14)	42%[b] (135)	15.6%[b] (20)
	29.4%[c] (36)	28.4%[c] (60)	39.3%[c] (64)

Table 32 (continued)

Smart Refresher ➞ Learning	19.4%[a] (13)	30.8%[a] (90)	12.3%[a] (17)
	19.4%[b](13)	32.1%[b](96)	9.38%[b](11)
	17.6%[c](20)	23.5%[c](47)	29.5%[c](46)
Smart Refresher ➞ Full Refresher	0%[a] (0)	23.1%[a] (57)	18.5%[a] (28)
	0%[b](0)	25.2%[b](61)	14.1%[b](24)
	19.6%[c](13)	14.7%[c](29)	26.2%[c](42)
Smart Refresher ➞ Smart Refresher	6.45%[a] (2)	25.8 %[a] (258)	12.3%[a] (17)
	3.23%[b](1)	27.2%[b](264)	9.38%[b](12)
	9.8%[c](49)	18.6%[c](148)	26.2%[c](76)
Learning ➞ Full Refresher	29%[a] (15)	36.2 %[a] (108)	33.8%[a] (615)
	25.8%[b](14)	38.9%[b](117)	28.1%[b](48)
	23.5%[c](25)	34.9%[c](95)	39.5%[c](50)
Full Refresher ➞ Learning	32.3%[a] (14)	36.2%[a] (92)	30.8%[a] (49)
	29%[b](13)	38.9%[b](98)	26.6%[b](44)
	25.5%[c](24)	34.3%[c](76)	37.2%[c](49)
Full Refresher ➞ Smart Refresher	0%[a] (0)	19.2%[a] (47)	12.4%[a] (25)
	0%[b](0)	19.8%[b](53)	10.9%[b](19)
	9.8%[c](6)	12.7%[c](29)	23%[c](36)
Full Refresher ➞ Full Refresher	12.9%[a] (5)	27.7%[a] (311)	21.5%[a] (540)
	12.9%[b](5)	28.2%[b](314)	20.3%[b](537)
	15.7%[c](49)	23.5%[c](378)	31.1%[c](421)

a. Knowledge Metric Clusters
b. Struggle Metric Clusters
c. Final Exam Clusters

*The values represent the case coverages

*The colors represent the ablolute frequencies

4.2.4 Comparison of Students' Final Exam Scores based on their Retrieval Practice

The results of the process mining showed the importance of the retrieval practice. Therefore, the course achievements of the students were compared based on the clusters of different retrieval practices.

4.2.4.1 Clustering Students Based on Retrieval Practice

In Table 33, the initial cluster centers were presented. These vectors have been calculated based on three struggle metrics variables: Refresher Counts. The clusters represent three groups of students with different retrieval practice levels while taking the DSM assignments. These scores are at maximum index distance from each other.

Table 33 Initial Cluster Centers - Struggle Metrics

	Cluster		
	1	*2*	*3*
TimeSpent	23.800	43.900	3.833
Refreshers_Count	0.000	0.000	0.167

Table 34 displays the number of iterations and the changes in cluster centers. The cluster centers are updated until the thirteenth iteration. After that, the redistribution of units stops because there are no further changes in the cluster centers.

Table 34 Iteration History - Struggle Metrics

Iteration	*Change in Cluster Centers* 1	*2*	*3*
1	2.267	9.013	6.659
2	0.123	1.451	0.289
3	0.691	0.815	0.240
4	0.009	0.020	0.002
5	0.000	0.000	2.055E-05
6	1.350E-06	1.183E-05	1.903E-07
7	1.687E-08	2.885E-07	1.762E-09
8	2.109E-10	7.036E-09	1.631E-11
9	2.636E-12	1.716E-10	1.511E-13
10	1.421E-14	4.164E-12	2.220E-16
11	0.000	1.208E-13	0.000
12	0.000	1.735E-17	0.000
13	0.000	0.000	0.000

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 13. The minimum distance between initial centers is 19.967.

Table 35 displays the final cluster centers, while Table 36 shows their distances. When examining Table 33 and Table 35, it becomes evident that the cluster centers for the clusters have changed.

Table 35 Final Cluster Centers - Struggle Metrics

	Cluster 1	*2*	*3*
TimeSpent	20.779	32.775	10.537

Table 35 (continued)

Refreshers_Count	0.160	0.029	0.303

Table 36 Distances Between Final Cluster Centers - Struggle Metrics

Clusters	1	2	3
1		11.996	10.243
2	11.996		22.239
3	10.243	22.239	

The dissimilarities in F-ratios provide insights into the significance of various mean variables in the clustering process. Table 37 presents the dispersion analysis results. They demonstrate that all DSM Struggle metrics have the most significant effect on cluster formation.

Table 37 ANOVA - Cluster Analysis with Struggle Metrics

	Cluster		Error			
	Mean Square	*df*	*Mean Square*	*df*	*F*	*Sig.*
TimeSpent	7544.991	2	12.484	223	604.397	0.000
Refreshers_Count	1.201	2	0.062	223	19.523	0.000

The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

Table 38 presents the number of cases in each cluster. All cases were valid, and no cases were missing.

Table 38 Number of Cases in Each Cluster - Struggle Metrics

	Clusters	Cases
Cluster	1	80.000
	2	39.000
	3	107.000
Valid		226.000
Missing		0.000

After analyzing the F-ratio values, it appears that students can be classified into three distinct clusters. The first cluster includes students who spend an average amount of time and complete an average number of refreshers. The second cluster consists of students who spend a high amount of time but complete a low number of refreshers. Finally, the third cluster is comprised of students who spend little time but complete a high number of refreshers.

4.2.4.2 Descriptive Analysis for Student Clusters Based on Retrieval Practice

The Kolmogorov-Smirnov Test results indicated that students' final exam scores with different retrieval practices were normally distributed (see Tables 39 and 40).

Table 39 Kolmogorov-Smirnov Test Results of the Final Exam Scores

		Kolmogorov-Smirnov[a]		
		Statistic	df	Sig.
Final	1	0.078	74	.200*
Exam	2	0.086	36	.200*
Scores	3	0.051	104	.200*

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Table 40 Number of Cases in Each Cluster – Final Exam Scores

	N	Skewness	Kurtosis	Min	Max	Mean	Median	SD
1	74	0.184	-0.849	34.29	96.25	64.21	61.83	17.16
2	36	0.118	-0.029	30.00	88.75	56.73	57.75	13.93
3	104	-0.062	-0.606	28.57	98.75	66.96	65.50	16.98

4.2.4.3 Inferential Analysis for Student Clusters Based on Retrieval Practice

There was a statistically significant difference between groups as determined by one-way ANOVA ($F(2,211) = 5092$, $p = .007$). A Tukey post hoc test revealed that the students with more retrieval practice scored statistically significantly higher on the final exam than those with less retrieval practice (p= 0.005, 95% *C.I.* = [2.66, 17.80). No statistically significant difference existed between the average and high groups ($p = .521$) and the average and low groups (p=.070).

4.2.5 The Spacing Pattern of Students Taking DSM Assignments

The study utilized sequence analysis to investigate students' spacing patterns for DSM assignments throughout the semester. The categorical variable "spacing" generated spacing sequences for the entire semester. The study examined the spacing patterns between assignments, the time intervals between each submission, and the similarities and differences among students' submission patterns. The aim was to determine if there were significant differences in the spacing patterns of students with varying levels of achievement in DSM assignments and final exams.

4.2.5.1 Descriptive of the Clusters of Students

The same clusters of students were used in the sequence analysis. Before conducting the sequence analysis on R using the TramineR library, a spacing metric was calculated based on the timing of students taking a DSM assignment compared to the midterm or final exam (see Tables 41 and 42). If they completed an assignment within one week of the exams, it indicated that they massed their study. It indicated a spaced study session if it took more than seven days. If students engaged in refresher activities for a module with varying spacing behavior, this was categorized as "both."

Table 41 The Number of Students in Each Cluster

Clusters	*N*
Low Knowledge Cluster	31
Average Knowledge Cluster	130
High Knowledge Cluster	65
High Struggle Cluster	31

Table 41 (continued)

Average Struggle Cluster	131
Low Struggle Cluster	64
Low Exam Performers	51
Average Exam Performers	102
High Exam Performers	65

Table 42 The Number of Events for Each Spacing Strategy in Each Cluster

Clusters	Both	Massed	Spaced
Low Knowledge Cluster	6	155	127
Average Knowledge Cluster	177	587	482
High Knowledge Cluster	63	263	322
High Struggle Cluster	4	158	124
Average Struggle Cluster	183	600	475
Low Struggle Cluster	59	247	332
Low Exam Performers	16	188	282
Average Exam Performers	108	487	379
High Exam Performers	110	294	198

A chi-square test was conducted to quantify the strength and significance of the association between each performance category and spacing variables. Cramer's V adapts the chi-square statistic to a 0-1 scale, providing a clear and interpretable measure of association for categorical data. The Chi-Square Test yielded significant results for knowledge clusters and spacing strategies ($\chi^2(4) = 53.00$, $p = .001$, $V = .11$), for struggle clusters and spacing strategies ($\chi^2(4) = 72.72$, $p = .001$, $V = .13$), and final exam clusters and spacing strategies ($\chi^2(6) = 122.59$, $p = .001$, V

= .17). These results imply a statistically significant, albeit small-sized, association between performance clusters and spacing strategy.

4.2.5.2 Sequences of the Clusters

A sequence was generated using the calculated spacing metric for each cluster. Initially, a repeated measures data frame was established for each cluster, followed by creating a sequence table for each DSM module (See Table 43). If a student did not complete all the modules and there was no activity for any sequencing, then this cell was automatically filled with "%." Subsequently, the following plots were generated, including sequence index, sequence frequency, and sequence density.

Table 43 Example Sequence Table for Low Knowledge Cluster

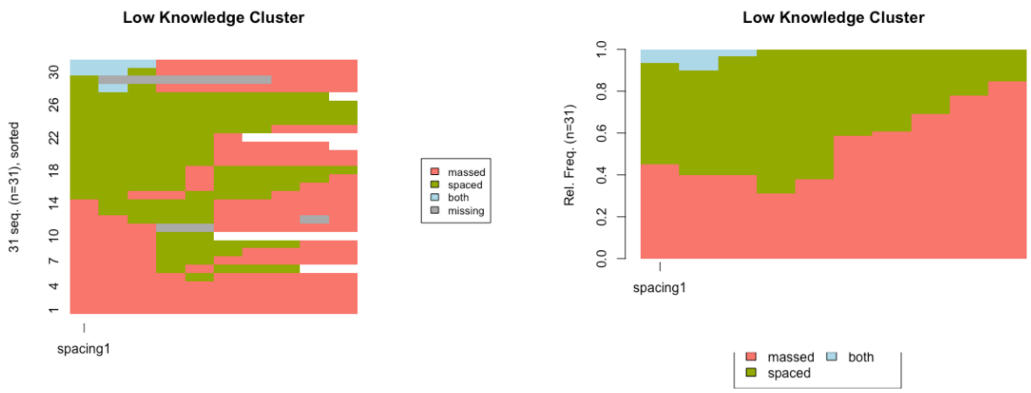
Student	Spacing									
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
X1	spaced	spaced	spaced	spaced	spaced	spaced	spaced	spaced	spaced	spaced
X2	spaced	spaced	spaced	spaced	spaced	massed	massed	massed	massed	massed
X3	spaced	spaced	spaced	spaced	spaced	spaced	spaced	massed	massed	massed
X4	spaced	spaced	spaced	spaced	spaced	spaced	spaced	spaced	spaced	%
X5	spaced	spaced	spaced	spaced	massed	spaced	spaced	spaced	spaced	massed
X6	both	both	both	massed	massed	massed	massed	massed	massed	massed
X7	massed	spaced	spaced	spaced	spaced	massed	massed	massed	massed	massed
X8	massed	massed	massed	massed	massed	massed	massed	massed	massed	massed
X9	massed	massed	massed	massed	massed	massed	massed	massed	massed	massed
X10	massed	massed	massed	massed	spaced	massed	massed	massed	massed	massed

The sequence index and density plots provide a visual representation of the spacing patterns observed among students as they progress through activities. The x-axis corresponds to each DSM module, while the y-axis represents the number of students. In the plot, green boxes represent spaced study behavior, red indicates massed study, and blue indicates a combination of both. The gray boxes indicate that students did not participate in a module, which suggests a lack of engagement. A white box at the end of a sequence represents an incomplete module that the student did not finish. The data depicted in the plots reveals that students, regardless of their achievement levels, initially tended to engage in spaced study sessions throughout the semester, particularly leading up to the midterm exam. However, as the final exam approached, there was a noticeable shift towards more concentrated massed study sessions, as seen in Figures 13, 14, and 15.

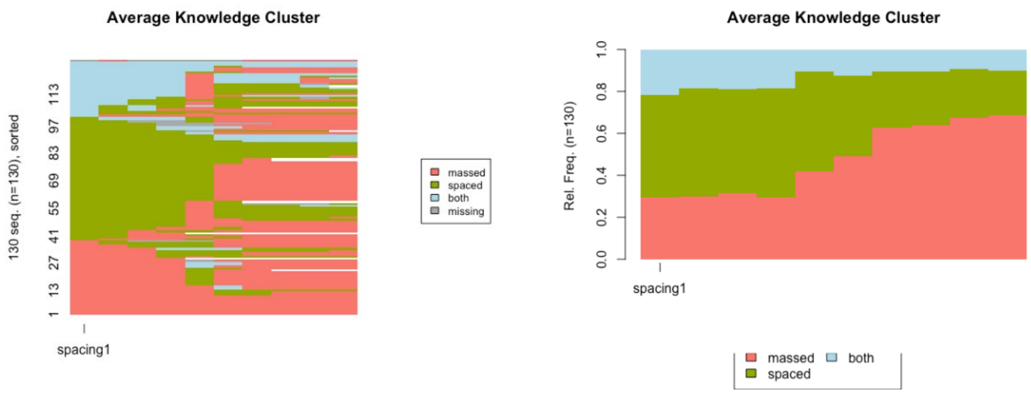
The "Low Knowledge Cluster" plot in Figure 13 (A) illustrates a high concentration of massed study sequences (red) with minimal representation of spaced study sequences (green), both types (blue), and missing data (gray). The sequences predominantly consist of spaced practice in the first half of the semester. However, students engaged in more massed practice in the second half of the semester. This indicates that towards the end of the semester, students in this cluster tend to utilize less effective study strategies.

According to Figure 13 (B), the "Average Knowledge Cluster" plot shows a well-balanced mix of massed (red) and spaced (green) study sequences, with both types represented (blue) and some missing data (gray). This suggests that students are using a combination of massed and spaced study strategies, indicating a moderate level of study effectiveness. The plot also reveals a similar pattern transitioning from spacing strategies to massed study strategies in a semester within this cluster.

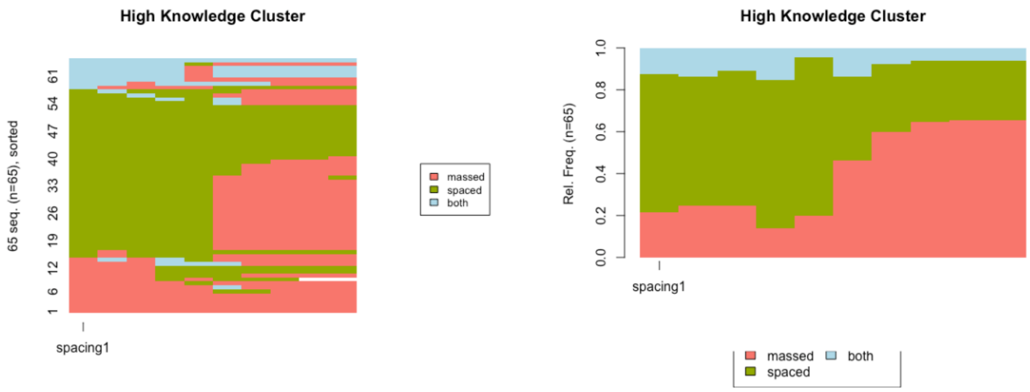
The "High Knowledge Cluster" plot, as seen in Figure 13 (C), shows a significant portion of sequences as spaced (green) and both types (blue), with massed sequences (red) being less dominant compared to the other clusters. Similar to the low and average clusters, as the semester draws to a close, it appears that some students are intensively cramming their studies. However, the presence of both types and spaced sequences indicates that students in this cluster are employing more effective study strategies, which are likely contributing to their higher knowledge levels.



(A)



(B)



(C)

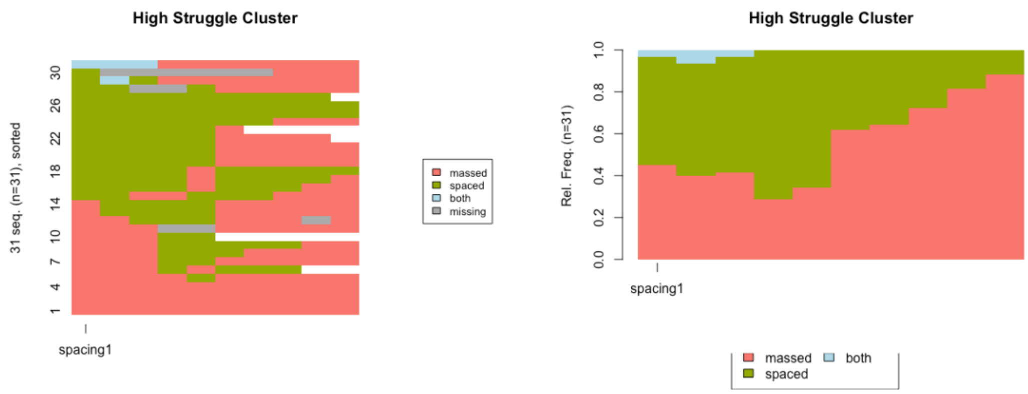
Figure 13 Index and Density Plots of Knowledge Clusters

In Figure 14 (A), the plots for the "High Struggle Cluster" display a high concentration of massed study sequences (red), accompanied by fewer spaced sequences (green) and mixed sequences (blue). Students in this cluster mainly rely on less effective massed practice, especially during the second half of the semester, which is linked to their high struggle levels. This finding indicates that their study methods do not assist them in overcoming learning challenges. The similarity between the sequences of the High Struggle Cluster and the Low Knowledge Cluster suggests that massed practice would lead to both increased struggle and decreased knowledge retention.

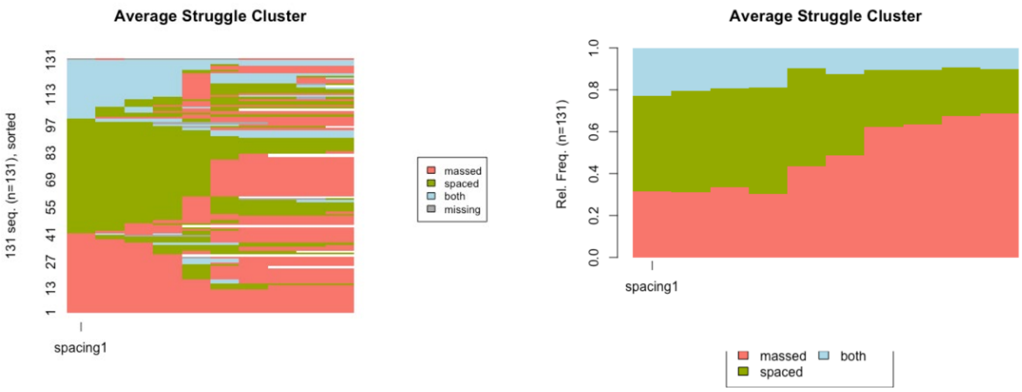
In the "Average Struggle Cluster" plots, as seen in Figure 14 (B), a more balanced distribution of massed (red), spaced (green), and mixed (blue) study sequences was observed. This cluster demonstrates a combination of effective and less effective study strategies, like study sequences of the Average Knowledge Cluster. The shift from spacing strategies to massed study strategies towards the end of the semester is also evident here, in this cluster. The similarity between the Average Struggle

Cluster and the Average Knowledge Cluster emphasizes that moderate use of spacing can lead to average performance and struggle levels.

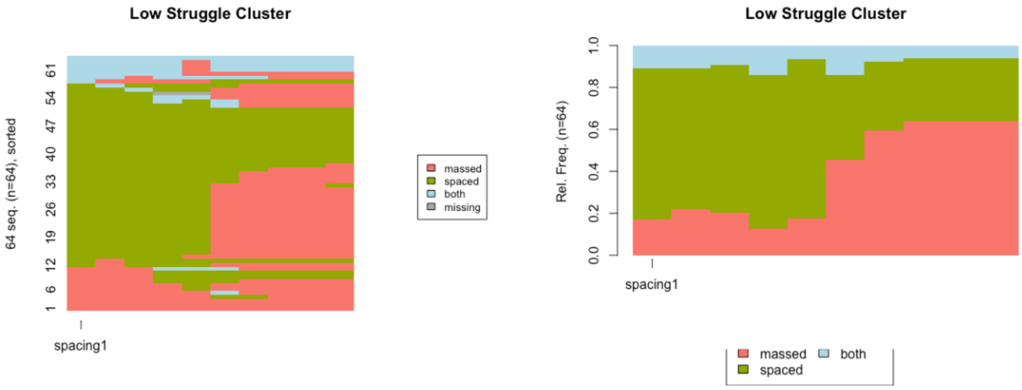
The plots for the "Low Struggle Cluster" reveal a significant presence of spaced (green) and mixed (blue) study sequences, with fewer dominant massed (red) sequences, as seen in Figure 14 (C). This trend closely resembles the High Knowledge Cluster, indicating that students employ more effective study strategies. Despite some massed study sessions towards the end of the semester, the consistent presence of spaced and mixed sequences suggests that these students possess better study habits, which help overcome struggles and contribute to lower levels of difficulty. The striking resemblance between the Low Struggle Cluster and the High Knowledge Cluster emphasizes that effective use of spacing strategies leads to both higher knowledge retention and reduced struggle.



(A)



(B)



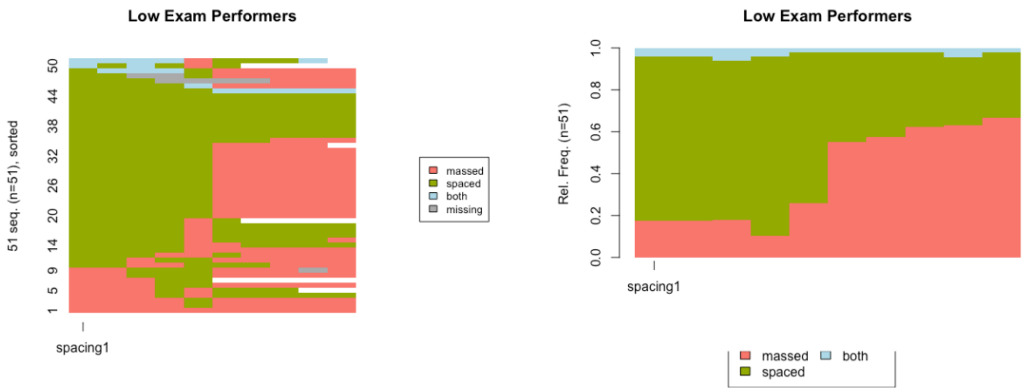
(C)

Figure 14 Index and Density Plots of Struggle Clusters

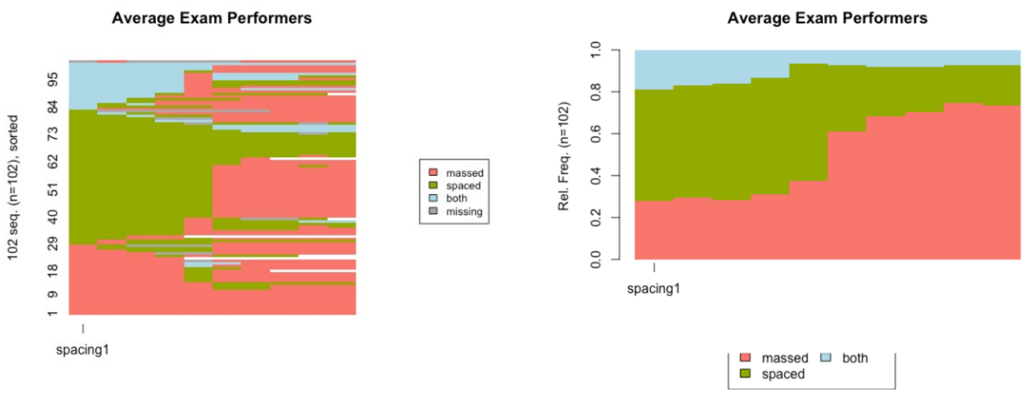
The "Low Exam Performers" plots, as seen in Figure 15 (A), shows a high concentration of spaced study sequences (green) with fewer massed (red) and mixed (blue) sequences. This pattern contradicts the High Struggle and Low Knowledge Clusters, where students predominantly use less effective mass study strategies, especially in the latter part of the semester. This suggests that these students may have performed poorly on the exam because they did not review their knowledge beforehand.

The plots titled "Average Exam Performers" in Figure 15 (B) depict a well-balanced mix of massed (red), spaced (green), and mixed (blue) study sequences, similar to the Average Struggle and Average Knowledge Clusters. It's evident that there is a shift from spaced to massed practice as the semester advances. This suggests that students in this category employ various study methods and tend to gravitate towards less effective massed practice as exams draw near. Their balanced approach leads to moderate exam performance.

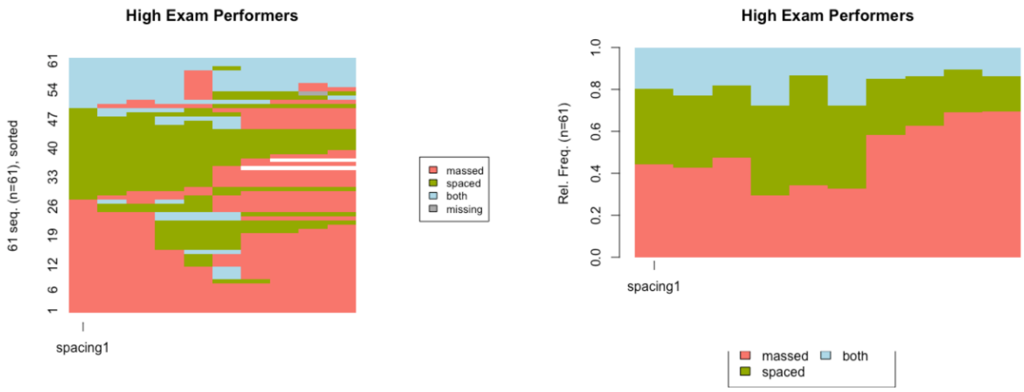
The "High Exam Performers" plots reveal a notable presence of spaced (green) and mixed (blue) sequences, with massed sequences (red) being less prominent as seen in Figure 15 (C). This trend is consistent with the Low Struggle and High Knowledge Clusters, where students employ more effective study strategies. Despite some massed study sequences at the end of the semester, the predominance of spaced and mixed sequences suggests that these students possess better study habits, contributing to their higher exam performance. The adept use of spacing strategies correlates with reduced struggle and improved knowledge retention, leading to better exam results.



(A)



(B)



(C)

Figure 15 Index and Density Plots of Exam Performance Clusters

The data depicted in the plots reveals that students who performed better in the DSM assignments tended to engage in spaced study sessions throughout the semester, while average performance clusters also adapted both study styles. However, the low-performance cluster showed a more concentrated engagement in massed study sessions. These results were slightly different for the achievement clusters of the final exam. The plots clearly showed that low exam performers were more engaged in spaced study sessions, while average performers chose to adopt both study styles. The high-performance cluster seemed to participate in fewer spaced activities and utilized both study styles. This finding is consistent with the process mining results, as high-achieving students often engaged in refresher activities. Therefore, in addition to focusing on spaced activities, they used massed study styles to review their knowledge before exams.

4.2.6 Interviews

Semi-structured interviews were conducted as part of this research study to gain insights into how students use the Pearson MyLab® system and DSM assignments. To ensure accuracy, speech-to-text tools were used to transcribe all the recordings of these online meetings. Once the transcriptions were obtained, they were added to the MAXQDA Qualitative Analysis Tool. The transcriptions were carefully analyzed and coded, resulting in several codes that provided a comprehensive understanding of how students utilize the Pearson MyLab® system and DSM assignments. The core codes found in the qualitative analysis are listed in Table 48.

All the students interviewed found DSM assignments practical and helpful. Several students stated they received help with exam preparation, while few found it helpful for following the course content. For example, one student highlighted how carefully crafted DSM questions helped students prepare for the exams and succeed in this statement: “The DSM assignments are generally helpful because the fundamental questions come directly from the topic. You know, we don't need to do extra work only after doing the DSM homework for the exam or preparation for next week's lesson next week. We don't need to do much preparation. Because it is entirely like the things that will come in the exam in the future, and because it asks a question in two different ways, what I did was like that, the question came in two different ways"

Most students reported learning the course material better with the help of DSM assignments. For example, this student emphasized the metacognition aspect of DSM assignments, forcing them to answer questions correctly until they became sure – "It is definitely helpful, first of all, because I solved tests in a way I had never experienced before. In the sense that, while answering the question, it asked us for options. Yes, are you sure? These were evaluated, such as sure or half sure. The following questions were organized accordingly. This is very important because if I got a question wrong, it means that I don't know that subject, and these DSMs don't say okay, you don't know; move on to the next question. It teaches the wrong answers first, in writing at the bottom, until you learn those questions... Until you know them. Then, it allows us to continue, and I can say that it has improved me a lot in this regard. I mean, it helped me a lot in the lessons, and if you go side by side with it, I can say that it helped me a lot."

Moreover, they found it easier to remember important concepts after studying with DSM assignments. For instance, this student found the DSM assignments helpful for practicing retrieval through testing, as opposed to restudying by reading slides or notes – "I had the opportunity to study the topics that would appear in the exam. In other words, we also have a method of studying by reading slides, but since this is a more interactive method, it was a click more useful for me than reading a slide or reading a note, and it helped me learn keywords."

Although most students were aware of the DSM analytics tools, not all used visualizations to guide their studies; almost half of the students did not benefit from the progress bar during DSM assignments. For instance, this student was confused about how they could use the progress information provided in the dashboard – "I actually paid attention to them as the questions progressed. I mean, I paid attention to how it happens. It is green; for example, it can be light green, red, etc., but I honestly could not understand precisely what it does."

Additionally, though the students were aware of the learning analytics visualizations on the assignment page, only half were aware of the reporting option and visualization page after completing the assignments. Only a few students found those pages helpful in identifying their weak points, and some did not use those charts to compare themselves with their classmates. As this student stated, the result pages were only used to access refreshers instead of taking advantage of the information provided there – "I never paid attention to those parts. In general, again... I think it just contributes directly to taking a refresher. I didn't look at those [result dashboard] parts much. I looked at my mistakes, thereby refreshing them again through the refreshes. Also, the question that we made the most mistakes is at the top. It goes down like that. In general, I looked at which ... topic I did wrong and where I did something wrong."

Only a few students did not take any refresher regarding the tendency for additional practice. Most students preferred a full refresher, while others preferred a smart refresher or both. The choice of which refresher to choose mostly depends on factors such as the structure of refreshers, time restrictions, and the individual's motivation to learn more. For example, this student had to give up taking full refreshers if he had limited time – "Except for one, I think I did full. I remember I did a full refresher on all of them. I didn't have time for that one. I had to go out. I only did smart refresh twice. I was doing it fully because I wanted to review what I did right again. Because it's different, sometimes, it can ask the same question in a different way. It's not always the same question. I want to see if I can do it when it is in a different way.” However, he was a self-motivated student who practiced with full refresher because he knew that it provided more opportunities for memory encoding.

Most participants preferred the spaced study method, while only many students preferred massed study sessions. Some students were unsure and acted contrary to their preferences. As stated by this student, time constraints from other responsibilities led to adjustments in both study styles – “Well, DSM assignments were usually due on weekends. I usually did it on the weekends and completed it, so I think it was due on Sunday night. I was doing it on Saturday. I was doing it on the weekend because I couldn't find much time during the week because of my other courses, so I was doing it on the weekend and completing the refresher on top of it.” It appears that students mostly chose to engage in massed study sessions with the use of refreshers.

Table 44 Core Codes Emerged from Qualitative Analysis

Code
Effectiveness of DSM Assignments in General
Tricked
Helpful
Getting Ready for the Exam
Following the Course
Learning the Subject
Remember the Subject
Useless
Leads to memorizing
DSM Interface and Tools
Unaware

Table 44 (continued)

Aware
Do not benefit from visualizations
Benefit from visualizations
Effectiveness of LA data and visualization
Aware
Beneficial for identifying weak points
Do not use for comparison with classmates
Unaware
Tendency for Additional Practice
Take refresher
Full refresher
Smart refresher
Both
Do not take refreshers
Evaluation for Spacing and Massed Study
Prefer Massed but Spaced
Prefer Spaced but Massed
Prefer Spaced
Prefer Massed

In summary, students found the DSM Assignments helpful due to their structured, actionable interventions and concise, keyword-based question format. They offer valuable practice opportunities for exam preparation, feedback on current progress, and memory strengthening. Students found that DSM assignments as retrieval practice helped enhance their learning.

However, most students do not fully utilize the visualization of the progress dashboard, typically only checking the progress indicators. Additionally, many were unaware of the course report page and avoided comparing their performance with that of their classmates.

Some students do not take refreshers or prefer either full or smart study modes. They have varied preferences for a refresher: some do them immediately after completing DSM, while others wait. This preference depends on their time restrictions, other responsibilities, and self-regulated study skills. Furthermore, despite most students finding spaced study sessions more helpful, they still need more motivation to implement this approach consistently

CHAPTER 5

DISCUSSION AND CONCLUSION

The current study aimed to investigate whether Dynamics Study Module (DSM) assignments could be a helpful tool for learning analytics and retrieval practice for undergraduate university students. The study explored the DSM variables that contributed to predicting students' success. A regression model was created that included all the DSM knowledge and struggle metrics alongside DSM-related metrics, such as the time spent on assignments and repeating the modules with the refreshers. The results revealed that this model significantly predicted students' midterm and final grades.

The study also used process mining to explore how students engage in DSM assignments as retrieval practices. It was found that students who performed well in DSM assignments tended to score better in their final exams, confirming the effectiveness of DSM assignments as retrieval practices to promote learning. Additionally, sequence analysis was conducted to discover how students distribute their learning sessions. The resulting sequences demonstrated that students with higher performance in DSM assignments and final exams spaced out their study sessions more.

Moreover, the study also conducted interviews, revealing that students found the DSM system helpful and supportive for their learning, confirming its effectiveness as a retrieval practice. However, students had varying perspectives on spacing out study sessions. While many preferred spaced studying, they found it challenging to manage when not forced. This finding suggests that students need support and guidance to develop effective study habits and strategies.

Overall, the study's findings suggest that DSM assignments as a learning analytics application effectively promote learning among undergraduate university students.

5.1 The Overall Effectiveness of the Drill and Practice System as a Learning Analytics Application

The study suggests that the multiple regression model, incorporating all DSM knowledge and struggle metrics and DSM-related metrics, could accurately predict students' final exam scores. This finding is significant because it indicates that DSM assignments, a learning analytics application, can effectively shape and enhance the learning experience. The study shows that instructors can use the drill and practice systems to help students identify their strengths and weaknesses and tailor their learning strategies accordingly. This personalized approach to learning effectively promotes student success, consistent with previous research highlighting the importance of interactive and adaptive learning technologies. These technologies foster student engagement, improve learning outcomes, and enhance the overall quality of the learning experience.

The selection of metrics for further analysis corresponds with the earlier findings since all the DSM assignment metrics are learning process data (Keržič et al., 2019; Papamitsiou & Economides, 2014; Strang, 2017; Svihla et al., 2015; Tempelaar et al., 2015). This research highlights that analyzing learning process data is pivotal in comprehensively understanding the learning phenomenon. Based on these findings, this study recommends selecting appropriate metrics for further analysis.

The positive feedback from students regarding the practicality and helpfulness of DSM assignments aligns with findings in the literature that suggest that digital learning platforms like Pearson MyLab® System, which offers DSM assignments, can significantly enhance student learning outcomes. These platforms often provide interactive content, immediate feedback, and personalized learning paths, contributing to a deeper understanding of the material (J. Aguilar et al., 2018; Arnold & Pistilli, 2012; Clow, 2013; Feng et al., 2009; Francis et al., 2020; Jovanović et al., 2007, 2008)

Additionally, students found DSM assignments helpful for exam preparation, and the following course content was consistent with the literature on adaptive learning technologies. Adaptive learning systems tailor educational experiences to individual learner needs, improving both retention and understanding of course material (Durall & Leinonen, 2016; Klašnja-Milićević et al., 2011; Klašnja-Milićević & Ivanović, 2018; F. Martin & Ndoye, 2016; Romero et al., 2009). This aligns with the finding that most students reported better learning and retention of course material through DSM assignments as a drill and practice system.

However, most students indicated they did not use analytics tools in the DSM System. Only a small percentage of students found analytics pages helpful in identifying weak points, suggesting better integration of these tools into the learning process. This lower usage of analytics tools within the DSM System reflects findings in other studies that indicate a gap between the availability and utilization of educational analytics dashboards (Matcha et al., 2020; Susnjak et al., 2022). While these tools can provide valuable insights into student performance and areas needing improvement, students often lack the training or motivation to use them effectively (Ifenthaler & Widanapathirana, 2014). The study conducted by Park et al. (2023) indicated that using an adaptive technology-integrated learning analytics dashboard provided real-time granularized information on learners' learning processes, enhancing their awareness. However, the study also revealed that learners still required a deeper understanding and more support to take meaningful actions towards achieving their learning goals and improving their metacognitive skills.

Additionally, DSM assignments, a learning analytics intervention, have been highly effective in supporting student learning because they are based on a learning theory called the "New Theory of Disuse" (R. A. Bjork & Bjork, 2006). This study analyzed only metrics related to this theory, demonstrating the effectiveness of learning analytics applications grounded in learning theories. By designing a learning analytics study that considers learning theories, it is possible to identify which data should be selected for further analysis. The study results correspond with the general opinion that learning analytics can only be effective when guided by theoretical frameworks, practical models, and pedagogical approaches (Gašević et al., 2017; Greller & Drachsler, 2012; Wilson et al., 2017; Wise & Shaffer, 2015; Yau & Ifenthaler, 2020).

The following sections discuss the relation between DSM assignments and the underlying principles of the desirable difficulties framework.

5.1.1 Retrieval Practices within the Drill and Practice Systems

This study examined how DSM assignments as retrieval practice affect student learning outcomes using process mining. The resulting patterns indicated that students who engaged in more retrieval practice performed significantly better on their final exams compared to those who did less retrieval practice. This finding supports existing literature on the benefits of retrieval practice for long-term retention and academic performance.

DSM assignments system can enhance students' learning by challenging them during the learning process, aligning with the desirable difficulties framework, thereby improving overall retention and recall of information. The concept of desirable difficulties, as outlined by E. L. Bjork and R. A. Bjork, suggests that introducing specific challenges during the learning process can improve long-term retention and recall of information (E. L. Bjork & Bjork, 2009; R. A. Bjork & Bjork, 2020). These challenges, such as spaced repetition, varied practice, and interleaved practice, create useful conditions that allow learners to experience moments where they may perceive a sense of forgetting. This temporary struggle to recall information reinforces storing and retrieving the targeted learning material.

DSM Assignments incorporate several desirable difficulty aspects, challenging students to promote their learning. First, if they struggle to answer a question correctly, they will repeatedly see similar questions in the following sets. When students are prompted to answer the questions that they struggle with, it creates a desirable level of challenge for students. Another challenging aspect of DSM Assignments is that there is no immediate feedback for incorrectly answered questions. When students cannot answer a question correctly, they do not receive correct answers or explanations immediately. This forces them to remember the explanations when answering those questions. This DSM aspect demonstrates another example of how desirable difficulties, i.e., spacing, would be introduced. DSM assignments include refresher activities, which come in two types: repeating the entire quiz or just the questions struggled with before. As a DSM feature, these refreshers align with the concept of forgetting curves, which show when and how students forget information they've learned. Using these refreshers, students can reinforce their learning before their memory fades. Regarding DSM refreshers, students might take them in their preferred order, which is also related to the interleaving principle of the desirable difficulties framework. Interleaved practice, where topics or tasks are separated instead of being grouped together, could also create desirable difficulties, leading to inductive learning and long-term recall. (Kornell & Bjork, 2008) .

The results of the regression analysis align with the proposed theoretical framework. Engaging with the drill and practice systems, which likely incorporate elements of desirable difficulties, helps reinforce learning and improve exam performance, especially in midterms, where the immediate application of learned material is tested. However, the absence of statistically significant predictors for the final exam suggests that the benefits of such a system might be more immediate and less pronounced over longer periods without continuous reinforcement. This result would be related to the fact that strength in memory decreases when retention intervals increase (Kliegl et al., 2019)**.** This also aligns with the desirable difficulties framework, emphasizing the need for continuous and varied practice to maintain the benefits over time. Additional research also supports the integration of retrieval practice as desirable difficulties into learning strategies (E. L. Bjork & Bjork, 2009; Zepeda et al., 2020).

In conclusion, the drill and practice systems can significantly support students' learning by incorporating the principles of desirable difficulties. These assignments create challenging conditions that enhance memory retention and recall, aligning with theoretical frameworks and empirical findings. By continuously engaging with the drill and practice systems, students will likely experience improved learning outcomes. Ongoing reinforcement and varied practice should be emphasized to maximize long-term benefits.

5.1.2 Testing Effect of the Drill and Practice Systems

Testing serves as one of the primary methods for retrieval practice. DSM assignments offer opportunities for testing, thus supporting the testing effect. DSM assignments, particularly well-designed multiple-choice questions, have the potential to challenge student's knowledge and skills. When students engage with carefully crafted quiz questions, they actively participate in mental processes such as encoding, which enhance long-term retention (Brabec et al., 2021; Cantor et al., 2014; Little et al., 2012; Little & Bjork, 2014; Sparck et al., 2016). Consequently, students are more inclined to remain focused on their studies rather than getting distracted (Wong & Lim, 2022).

DSM assignments as drill and practice systems stimulate learners to actively retrieve and apply their knowledge by creating desirable difficulties through the testing effect, thereby strengthening memory encoding, retention, and understanding (Yang et al., 2021). Therefore, the study's findings support the testing effect, indicating that a drill and practice system’s inclusion of retrieval practice in the learning process results in superior learning outcomes (Brabec et al., 2021; Cantor et al., 2014; Congleton & Rajaram, 2012; Dang et al., 2022; Karpicke & Roediger, 2007; Little et al., 2012; Little & Bjork, 2014; Marsh et al., 2007; Sparck et al., 2016; Su et al., 2021; Vojdanoska et al., 2010; Yan et al., 2014).

Many researchers have shown that testing enhances retention more effectively than other study methods, such as re-reading or note-taking (Congleton & Rajaram, 2012; Karpicke & Roediger, 2007; Marsh et al., 2007; Mulligan et al., 2020; Yan et al., 2014). These findings revealed that recalling information strengthens memory traces and fosters more enduring learning. Furthermore, several researchers explored the role of testing effect in diverse educational settings and discovered consistent benefits across different subjects and age groups (Dang et al., 2022; Dirkx et al., 2014; Goossens et al., 2016; Kromann et al., 2010; McDermott et al., 2014; Todd et al., 2021; Vojdanoska et al., 2010). Some studies have shown that the testing effect applies to higher-order skills as well (Jensen et al., 2020). Additionally, several meta-analyses reveal that the research supports the effectiveness of test-enhanced learning in academic achievement (Adesope et al., 2017; Chan et al., 2018; Yang et al., 2021).

According to many researchers, the forward effect of testing occurs when testing on previously studied information also helps in acquiring new information (Chan et al., 2018; Pastötter & Bäuml, 2016; Yang et al., 2017, 2018, 2021). The study provides support for the forward effect of testing by demonstrating that students who engaged in test-enhanced practices after learning each chapter in the classroom had better learning outcomes. The primary goal of these assignments was to support students' learning processes rather than focusing solely on retention. The study suggests that engaging students in retrieval practice through testing leads to better performance.

Thus, this study contributes to the existing literature by demonstrating that using the drill and practice systems as a testing practice can help university students understand entrepreneurial concepts. It underscores the universal applicability of the testing effect as an effective learning strategy.

5.1.3 The Spacing Effect of the Drill and Practice Systems

The study also explored how students spaced their study sessions with DSM assignments and provided valuable insights into students' spacing behaviors and their relation to their academic performance. The distinct study patterns were observed among students at different achievement levels in DSM assignments. High-performing students utilize both spaced and massed study methods and engage in refresher activities, which aligns with research indicating the effectiveness of spaced study strategies. Average performers adopted a combination of both study styles, which may reflect a flexible approach to learning, balancing the advantages of both methods. On the other hand, low performers relied mostly on massed study. These findings align with the existing literature on the spacing effect, suggesting that learning is more effective when studying is spaced out over time rather than being massed simultaneously (E. L. Bjork &

Bjork, 2009; Carpenter, 2020; Cepeda et al., 2008; McHugh et al., 2021; Mödritscher et al., 2013; Nazari & Ebersbach, 2019; Rawson & Dunlosky, 2011; Thalheimer, 2006; Vlach & Sandhofer, 2012).

However, students' study patterns slightly differed in terms of exam performance. It was found that students who performed poorly on exams tended to engage more in spaced study sessions, while those with average performance chose to use both study styles. Conversely, high-performing students participated in fewer spaced activities and utilized both study styles more. This aligns with the observation that high-achieving students often used massed study styles to review their knowledge before exams, in addition to focusing on spaced activities. Ifenthaler et al. (2023) identified engagement with self-assessments tends to peak in the weeks before exams, indicating that students primarily use self-assessments as a study tool to prepare for their exams. Similarly, Rodriguez et al. (2019) found that students who spaced their study sessions engaged more with course recourses but not earlier before major deadlines. This frequent use of recourses or massing the practices before the exams would also be related to the fact that massing practice supports short-term performance (E. L. Bjork & Bjork, 2009; Mödritscher et al., 2013; Nazari & Ebersbach, 2019).

The slightly different spacing patterns for DSM assignments and exam performance might be related to the fact that the research was not able to find the optimal interval for the spacing effect (Carpenter, 2020; Cepeda et al., 2008; Rawson & Dunlosky, 2011; Thalheimer, 2006). However, the time interval was fixed to one week in this study, which might have resulted in some variability in the spacing time. This variability could potentially have impacted the final results of the study.

This difference in findings may require further investigation into the specific conditions under which the spacing effect is most effective and whether it applies to various learning analytics applications. Future studies could delve into the variations in the design and implementation of spacing strategies within learning analytics tools to better understand their long-term impact on retention.

These findings support established educational theories and suggest practical approaches to improving learning outcomes. Educators can help students cultivate more effective study habits that lead to immediate and long-term academic success by promoting spaced practice and addressing misconceptions about massed study.

5.2 The Relation between the Drill and Practice Systems and Self-Regulated Studies

The study also investigated how students manage their studies with DSM assignments and discovered variations in additional retrieval practice participation based on students' performance levels. Initially, students participated in mandatory learning activities, after which they had the option to choose between two types of refresher activities: Full Refreshers and Smart Refreshers. Only a small number of students chose to complete both refresher activities in sequence. The frequency and type of activities differed among low, average, and high-performance clusters.

Students in the low-performance group participated in fewer refresher activities than their higher-performing peers. This observation is consistent with research indicating that lower-performing students often struggle with self-regulation and effective study strategies (Pintrich, 2004). These students may lack the metacognitive skills necessary to recognize when they need additional practice or review, leading to less engagement with supplementary learning activities (Schraw, 1998). Providing structured guidance and support could help these students develop better study habits and improve their performance.

The average-performance group frequently used both refresher activities, reflecting a more balanced study approach. This pattern is supported by literature suggesting that combining different study methods can enhance learning outcomes by engaging multiple cognitive processes (Dunlosky et al., 2013; Geng & Yamada, 2023). Both Full and Smart Refreshers likely provide a mix of broad review and targeted practice, which can help consolidate learning and improve retention (Brown et al., 2014).

High-performing students predominantly chose Full Refreshers over Smart Refreshers, indicating a preference for comprehensive review sessions. This strategy is in line with self-regulated learning (SRL) principles. Students establish specific learning objectives, track their progress, and utilize effective strategies to accomplish those goals (Zimmerman, 2002). High-performing students often exhibit solid metacognitive skills, allowing them to plan and manage their study time effectively (Jovanović et al., 2017; Papamitsiou & Economides, 2019; Winne & Hadwin, 1998; Zheng et al., 2022). Their frequent use of Full Refreshers suggests a deliberate effort to ensure a deep understanding of the material, contributing to their academic success. Research by Sun & Rueda (2012) has revealed that students with higher levels of self-regulation displayed increased levels of engagement.

The observation that high-performing students engaged more frequently in refresher activities, whether in DSM assignments or final exams, highlights the importance of retrieval practice. Retrieval practice, involving actively recalling information from memory, significantly enhances long-term retention and understanding of the material (Roediger & Butler, 2011; Storm et al., 2014). By incorporating Full Refreshers into their study routines, high-performing students likely benefited from the repeated retrieval of key concepts, leading to better assessment performance (Karpicke & Blunt, 2011).

As for the tendency for additional practice, most students preferred a full refresher, while a few preferred a smart refresher or both. In terms of study methods, most students preferred the spaced study method, while only 40% of students preferred massed study sessions. Most students prefer spaced study sessions over massed sessions, aligning with meta-cognitive psychology research. Spaced learning, or distributed practice, is more effective for long-term retention and understanding than massed practice (Cepeda et al., 2006). The observation that some students acted contrary to their stated preferences for study methods reflects findings in educational psychology that highlight a gap between students' knowledge of effective study strategies and their actual practices. This discrepancy often results from habits, lack of self-regulation, or misunderstanding of the strategies' effectiveness (R. A. Bjork et al., 2013).

According to a study conducted by Chen and Yeh (2017), students' cognitive styles impact their learning patterns within a learning application context. Based on the findings of the study conducted by Schumacher and Ifenthaler (2018), students expect a learning analytics application to assist with their learning planning and organization, offer self-assessment capabilities and provide adaptive recommendations derived from personalized analyses of their learning activities. Therefore, educators must equip students with practical strategies to enhance their self-regulation, especially in learning environments incorporating learning analytics (Sun & Rueda, 2012).

5.3 Summary

This study highlights the importance of using active learning strategies, such as retrieval practice, in learning analytics applications to promote meaningful learning. It also emphasizes the role of learning analytics studies in discovering how system data can provide insights into student learning. Educators can facilitate learning and better understand students' needs and progress by incorporating active learning strategies and analytics techniques. This approach can help identify areas where students may require additional support, enabling educators to provide personalized assistance, promote better engagement, and ultimately improve overall learning outcomes. This study aligns with established research and emphasizes the importance of integrating retrieval practice into educational strategies to enhance student learning outcomes.

5.4 Implications

The following two sections discussed the implications of integrating learning analytics applications, like DSM, as a drill and practice system into educational practices. The significant impact on enhancing student learning outcomes, strategies for boosting student engagement, the importance of practical learning analytics, and the use of well-designed supportive dashboards to facilitate informed learning decisions were explored.

5.4.1 Instructional Design Implications

This study's discoveries are significant for teachers, instructional designers, and policymakers. Integrating learning analytics tools like DSM into educational practices can significantly enhance student learning outcomes. Teachers should prioritize incorporating interactive and adaptable learning technologies, emphasizing retrieval practice, to foster deeper student engagement and understanding. Providing students with activities in drill and practice systems that incorporate desirable difficulties has the potential to increase their achievement level.

Utilizing testing for learning is one of the most effective methods to introduce the desirable difficulties. In order to enhance students' participation in the encoding processes, instructors can incorporate various testing activities into their curriculum. These testing activities may include various question types, which can encourage students to learn and remember essential concepts actively. Additionally, an important aspect of testing activities is offering students feedback to correct their misconceptions and the opportunity for self-reflection regarding their learning. This, in turn, allows students to refine their study strategies more effectively.

Another important aspect of desirable difficulties is using spaced study sessions instead of cramming. Students who struggle with self-regulation skills may find it challenging to space out their study sessions. Therefore, they require additional support and encouragement to help them regulate their studies with spaced sessions. Instead of leaving it optional, it should be included as a part of the course syllabus and made a compulsory course requirement.

5.4.2 Learning Analytics Implications

The research findings clearly indicated that incorporating testing and spacing effects into a learning analytics application significantly enhanced student learning outcomes. Based on these findings, it is strongly recommended that the following design principles be considered during the development of learning analytics applications.

The learning analytics application used in this study includes two types of interventions: assignments and a dashboard. The study demonstrated the effectiveness of the assignment intervention. However, the lack and ineffective use of a dashboard in the DSM system resulted in contradictory findings compared to the learning analytics literature, highlighting that learning analytics dashboards improve student learning.

Most students consistently turned to the progress dashboard when working on assignments, indicating a strong usability and relevance for this feature. However, the reporting dashboard was frequently overlooked, likely due to its location, which may have made it less accessible. Therefore, it is imperative to make developmental improvements to the dashboard intervention. One potential enhancement involves embedding the dashboard within the learning platform, which is prominently visible to students throughout their learning journey. This could help ensure that students can effectively utilize the reporting dashboard to track their progress and performance.

Concerning the spacing effect discussed in the previous section, students need support spacing out their study sessions. When designing learning analytics applications, it's crucial to integrate support mechanisms to encourage spacing strategies. Instead of providing unrelated trace data on the dashboard, students must be guided in their practice to space out their study sessions, mainly when engaged in testing practices.

Moreover, this study utilized a learning analytics application that incorporated metacognition data. Regrettably, the dashboard reports fail to outline this critical information. It is imperative to ensure the inclusion of this data in the report to empower students to make more informed decisions and effectively self-regulate their learning endeavors.

5.5 Limitations and Recommendations for Future Studies

It is important to acknowledge that this study has certain limitations that may impact the generalizability of the findings. Firstly, the DSM data from six different groups of students enrolled in the same course in different semesters were used. Other factors, such as students’ course load, group dynamics, and the instructor's experience over semesters, may influence students' interaction with DSM assignments.

Secondly, students were obliged to complete other assignments for the course during a semester, which could affect their performance in the final exam. In addition to DSM assignments, the Pearson MyLab system offers many learning activities, such as video activities, case studies, and Venture Capital (VC) writing exercises.

Thirdly, other aspects of the desirable difficulties framework might also affect the study design. DSM assignments are crafted considering all the pillars of the desirable framework: retrieval effect, spacing effect, and interleaving effect. For example, students were expected to take the DSM assignments after lessons. The location where they completed the DSM assignments was not controlled. This might trigger the influence of the variability of practice. Additionally, students took the DSM assignments after learning the subject. However, since some students did not follow the same spacing schedule, they also started learning new subjects. Learning other subjects might trigger the influence of interleaving of the practice.

Finally, it's important to note that the data obtained from the system underwent preprocessing within the DSM system, an advanced learning analytics intervention tool. This means that the data was not in its original raw format, which could potentially have impacted the study's outcomes.

Future research could address these limitations by replicating the study in various educational settings and exploring the long-term effects of DSM on learning outcomes. Furthermore, the spacing effect and the optimal interval between study sessions should be extensively studied, especially using other data analysis techniques. Furthermore, additional research is necessary to explore the intricate factors that impact the effectiveness of spacing effects in various learning contexts. Future studies could delve into the variations in the design and implementation of spacing strategies within learning analytics tools to better understand their long-term impact on retention.

In summary, this study adds to the growing body of research on learning analytics applications and their impact on student learning. The positive correlation between DSM and exam performance and the confirmation of the testing effect highlights the potential of incorporating interactive and adaptive learning technologies to create a more effective and engaging learning experience.

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APPENDICES

A. Consent Form - Turkish

Bu araştırma, ODTÜ Bilgisayar ve Öğretim Teknolojileri Eğitimi Bölümü doktora öğrencisi Beste Ulus tarafından Prof. Dr. Soner Yıldırım danışmanlığındaki ve Doç. Dr. Sacip Toker eş danışmanlığındaki doktora tezi kapsamında yürütülmektedir. Bu form sizi araştırma koşulları hakkında bilgilendirmek için hazırlanmıştır.

Çalışmanın Amacı Nedir?

Araştırmanın amacı, istenen zorluklar teorisini temel alan bir öğrenme analitiği uygulamasının akademik başarıyı ve öğrenmeyi ne ölçüde etkilediğini incelemektir.

Bize Nasıl Yardımcı Olmanızı İsteyeceğiz?

Araştırmaya katılmayı kabul ederseniz, anketlerde yer alan bir dizi soruyu derecelendirme ölçeği üzerinde yanıtlamanız beklenmektedir. İki anket dönem başında iki anket ise dönem sonunda uygulanacaktır. Anketleri doldurmak, yaklaşık 75 dakika sürmektedir. Ayrıca eğer gönüllü olmak isterseniz, sizden beklenen yarı-yapılandırılmış görüşmelerde dört açık uçlu soruyu kısaca cevaplandırmanızdır. Yaklaşık olarak 30 dakika sürecek bu görüşmelerde, daha sonra içerik analizi ile değerlendirilmek üzere cevaplarınızın ses kaydı alınacaktır.

Sizden Topladığımız Bilgileri Nasıl Kullanacağız?

Araştırmaya katılımınız tamamen gönüllülük temelinde olmalıdır. Çalışmada ve anketlerde sizden kimlik veya kurum belirleyici hiçbir bilgi istenmemektedir. Cevaplarınız tamamıyla gizli tutulacak ve sadece araştırmacılar tarafından değerlendirilecektir. Katılımcılardan elde edilecek bilgiler toplu halde değerlendirilecek ve bilimsel yayımlarda kullanılacaktır. Sağladığınız veriler gönüllü katılım formlarında toplanan kimlik bilgileri ile eşleştirilmeyecektir.

Katılımınızla ilgili bilmeniz gerekenler:

Bu çalışma ve kapsamındaki anketler, genel olarak kişisel rahatsızlık verecek sorular veya uygulamalar içermemektedir. Ancak, katılım sırasında sorulardan ya da herhangi başka bir nedenden ötürü kendinizi rahatsız hissederseniz anketleri cevaplama işini yarıda bırakıp çalışmadan çıkmakta serbestsiniz. Böyle bir durumda anketi uygulayan ve çalışmayı yürüten kişiye araştırmadan çıkmak istediğinizi söylemek yeterli olacaktır.

Araştırmayla ilgili daha fazla bilgi almak isterseniz:

Araştırma sonunda, bu çalışmayla ilgili sorularınız cevaplanacaktır. Bu çalışmaya katıldığınız için şimdiden teşekkür ederiz. Çalışma hakkında daha fazla bilgi almak için Bilgisayar ve Öğretim Teknolojileri Eğitimi Bölümü öğretim üyelerinden Prof. Dr. Soner Yıldırım (E-posta: soner@metu.edu.tr) ya da doktora öğrencisi Beste Ulus (E-posta: besteulus@metu.edu.tr) ile iletişim kurabilirsiniz.

Yukarıdaki bilgileri okudum ve bu çalışmaya tamamen gönüllü olarak katılıyorum.

(Formu doldurup imzaladıktan sonra uygulayıcıya geri veriniz).

İsim Soyad   Tarih   İmza

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B. Consent Form - English

This research has been conducted by Beste Ulus, a PhD student in the Department of Computer Education and Instructional Technology at METU. This research study is carried out within the scope of the doctoral thesis under the supervision of Prof. Soner Yıldırım and Assoc. Dr. Sacip Toker. This form has been prepared to inform you about the research conditions.

What is the Purpose of the Study?

The purpose of the study is to examine the effectiveness of a learning analytics application based on the desired difficulties framework on students' academic achievement and learning.

How Do We Ask You To Help Us?

If you agree to participate in the research, you are expected to answer a series of questions in the questionnaires. Two surveys will be administered at the beginning of the semester and two surveys will be administered at the end of the semester. Filling out the questionnaires takes approximately 75 minutes. Also, if you wish to be a volunteer, you are expected to briefly answer four open-ended questions in the semi-structured interviews. In these interviews, which will last approximately 30 minutes, your answers will be audio-recorded to be evaluated with content analysis later.

How Will We Use the Information We Collect From You?

Your participation in the research must be entirely voluntary. No identification or institution-identifying information is requested from you in this study and surveys. Your answers will be preserved completely confidential and will only be evaluated by the researchers. The information obtained from the participants will be evaluated collectively and used in scientific publications. The data you provide will not be matched with the identity information collected in the voluntary participation forms.

Here's what you need to know about your participation:

This study and the surveys generally do not contain questions or practices that may cause personal discomfort. However, if you feel uncomfortable with questions or any other situations during participation, you are free to stop answering the questionnaires and leave the study. In such a case, it will be enough to inform the person who conducts the study and surveys that you want to leave.

If you would like more information about the research:

At the end of the research, your questions about this study will be answered. Thank you in advance for your participation in this study. For more information about the study, you can contact Prof. Soner Yıldırım (E-mail: soner@metu.edu.tr) or PhD student Beste Ulus (E-mail: besteulus@metu.edu.tr) from the Department of Computer and Instructional Technologies Education (METU).

Name Surname	Date	Signature
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C. Approval of Human Subjects Ethics Committee

UYGULAMALI ETİK ARAŞTIRMA MERKEZİ
APPLIED ETHICS RESEARCH CENTER

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14 NİSAN 2022

Konu : Değerlendirme Sonucu

Gönderen: ODTÜ İnsan Araştırmaları Etik Kurulu (İAEK)

İlgi : İnsan Araştırmaları Etik Kurulu Başvurusu

Sayın Prof. Dr. Soner YILDIRIM

Danışmanlığını yürüttüğünüz Beste ULUS'un "Bir Öğrenme Analitiği Uygulamasının Öğrenmeye Etkisinin İncelenmesi" başlıklı araştırması İnsan Araştırmaları Etik Kurulu tarafından uygun görülmüş ve **0182-ODTUİAEK-2022** protokol numarası ile onaylanmıştır.

Saygılarımızla bilgilerinize sunarız.

Prof.Dr. Mine MISIRLISOY
İAEK Başkan

CURRICULUM VITAE

Surname, Name: Ulus, Beste

EDUCATION

Degree	Institution	Year of Graduation
MS	Boğaziçi University Educational Technology	2017
BS	Boğaziçi University Computer Education and Educational Technology	2013
High School	Atatürk Anadolu Vocational High School, Denizli	2008

FOREIGN LANGUAGES

Advanced English, Intermediate German

PUBLICATIONS

1. Ulus B., Öner D. "Fostering Middle School Students' Knowledge Integration Using the Web-Based Inquiry Science Environment (WISE)", *Journal of Science Education and Technology, 29*(2), 242-256 (2020).

2. Öner D., Akbulut MS., Ulus, B., and Umutlu, D. "Investigating Engagement and Achievement in an Online Teacher Education Course during the Compulsory Distance Education Period", *Hacettepe University Journal of Education, 37*(4), 1317-1328 (2022).