Doctoral Dissertation

Online Formative Learning Assessment in Higher Education: Integrating New Scoring Methods with Four-Multiple Choice Assignments

高等教育におけるオンライン形成的学習評価：

4 選択肢課題による新しい採点方法の統合

by:

SONEPHACHANH MALAYPHONE

Academic supervisors:
OHSHIMA NAOKI

March 2024

Graduate School of Sciences and Technology for Innovation,

Yamaguchi University

Table of Contents

List of Table

List of Figure

Abstract

The COVID-19 pandemic has significantly transformed higher education, shifting it from traditional classrooms to online platforms. This change requires reassessment and adaptation of educational methods, particularly student assessment. Online formative assessments have become essential for improving teaching and learning outcomes because they provide immediate feedback, enable interactive support, and encourage self-assessment, thereby playing a key role in the learning process.

The multiple-choice test is widely used to assess students. However, the inherent nature of multiple-choice questions poses the risk of obtaining correct answers, even without a genuine understanding of the content. To mitigate this issue, typical measures involve increasing the number of questions. To address this concern, this study implemented a new constraint aimed at enhancing the inherent characteristics of the multiple-choice format. This research objective focuses on investigating innovative scoring methods for formative assessments in online courses that can improve learning in higher education within the context of Yamaguchi University.

This study evaluated the effectiveness of this learning assessment method by employing multiple-choice questions, presenting a practical and efficient approach for online formative learning assessment designed to assess a large student cohort. The new scoring method in this study extends Ikebururo's concepts that introduce partial scoring systems in MCQ design, driving the creation of a new scoring system centered on the "degree of matching." This approach involved comparing the alignment between student responses and the instructor's design, resulting in a detailed five-level scoring system for

four-choice questions. This scoring method hinges on evaluating how closely students' answers align with the instructor's intended choices. Each question, with its four choices, is akin to a binary process, represented by a 4-digit binary number. Each digit in this comparison corresponds to a specific choice, allowing for a granular assessment of the match between student selection and the ideal answer. This innovative approach steps away from the conventional pass-fail binary system, offering a spectrum of evaluation outcomes. It provides a better understanding of students' comprehension by gauging the extent of the alignment between their choices and the instructor's design.

This method can enhance assessment accuracy by capturing the subtleties of student responses beyond mere correctness, earning partial points for partial knowledge or progress via multistep reasoning, promoting critical thinking, recognizing the importance of incremental progress, and capturing the depth of a respondent's knowledge.

Initially, an extensive literature review established a theoretical framework, identifying gaps in the current understanding of online formative assessments. Subsequently, the study examined data collected from graduate students in the 'Advanced Research and Development Strategies' course at Yamaguchi University. The data span two academic years, 2019 and 2020, and provide a comparative view of face-to-face and online Lecturer Formats.

Furthermore, the k-means clustering algorithm was used to analyze student performance using formative assessment scores. This method categorizes student performance into distinct clusters, revealing insights into individual learning behaviors. The k-means method, a popular technique in data mining and pattern recognition, efficiently groups data into 'k' clusters. It is effective for large datasets and versatile across various data types. The technique involves steps such as initialization, assignment, centroid updating, and convergence checking, and is instrumental in identifying performance patterns, enabling the development of more focused educational strategies.

The results demonstrate the potential of the four-choice multiple-choice scoring method to revitalize online formative assessments. The key contributions of this study are as follows:

- Innovative Scoring Method: This study shows how the four-choice method can lead to more dynamic and engaging online assessments. This approach captures student performance more accurately and encourages deeper engagement with the material.
- Enhanced Student Engagement and Understanding: The new four-multiple-choice scoring method significantly affected student engagement and understanding. This fosters an environment in which students are more actively involved in their learning processes, contributing to better comprehension and retention of material.
- Practical Implications for Educators and Institutions: The need to adapt assessment strategies for digital learning, focusing on continuous feedback and personalized learning.
- Educational Technology Contribution: Key insights into adapting assessment strategies for digital learning, emphasizing continuous feedback, and personalized learning.

This dissertation presents a comprehensive examination of new assessment techniques in the context of online learning. This provides a critical roadmap for educators and institutions to adapt to the digital educational environment for more effective and engaging assessment practices in online higher education.

Chapter 1 – Introduction

1.1 Background

The evolution of distance lectures over the past several decades has represented a significant transformation in the delivery of education, marked by technological advancements and changes in pedagogical approaches. This chronological summary outlines the key phases in the development of distance education, highlighting the innovative strides made to enhance accessibility, engagement, and quality of learning.

In the 1960s and the 1970s, the shift from radio-to television-based distance education marked the first significant evolution in distance learning, introducing an audio-visual experience that transcended the limitations of audio-only lessons. This period saw institutions like the University of Houston pioneering the use of television broadcasts to deliver courses, making education accessible to a broader audience, and adding a visual dimension to distance learning [1]. The 1970s and 1980s witnessed further democratization of education with the establishment of open universities and the expansion of distance learning courses [2]. This era emphasized breaking down barriers to higher education and making learning opportunities more flexible and accessible to diverse populations. Entering the 1980s and 1990s, the advent of the Internet revolutionized distance education, transitioning from static TV broadcasts to dynamic interactive online courses [3]. The late 1990s and 2000s saw the integration of digital technology into education becoming more sophisticated with the advent of Learning Management Systems (LMS) [4]. These platforms provide a structured environment for online courses, allowing the management, delivery, and tracking of learning processes. Moodle, introduced in 2002, emerged as a pioneering open-source LMS, enabling educators to create and administer courses online [5]. This flexibility and scalability have made it a popular choice for institutions worldwide, further enhancing the accessibility and quality of online education. This period was also characterized by the enhancement of online courses through interactive and multimedia content, making learning more engaging and effective [6]. The development and adoption of LMS such as Moodle facilitated this transition by providing the necessary infrastructure to support diverse learning activities, including video lectures, interactive exercises, and forums for discussion. As the 2000s progressed, online learning platforms and virtual universities offered a wide array of courses and degrees online. These developments were supported by LMS platforms, which became more sophisticated and offered features, such as mobile access, personalized learning experiences, and advanced analytics. The expansion of Massive Open Online Courses (MOOCs) in the 2010s further illustrated the potential of online learning to provide structured, high-quality educational experiences to massive audiences [9]. Platforms such as Coursera and edX have leveraged LMS technology to deliver courses from renowned institutions to learners around the globe [7]. The evolution of distance education culminates in the present focus on blended learning models that integrate the flexibility of online learning with the benefits of the traditional classroom experience [7]. LMS platforms, including Moodle, play a crucial role in facilitating blended learning by enabling the seamless integration of online and in-person activities. Through each phase of evolution, distance education has leveraged technological advancements to enhance accessibility, engagement, and quality of learning [8]. The development and adoption of Learning Management Systems, particularly Moodle, have been instrumental in this journey, providing the infrastructure needed to support the dynamic, interactive, and personalized learning experiences that define education today. The outbreak of the coronavirus pandemic in 2019 imposed unprecedented challenges on the traditional educational system, primarily because of the need to halt face-to-face classes to mitigate the risk of viral transmission. This situation catalyzed a swift pivot to online learning methods, not as a mere alternative but as a primary mode of instruction to maintain educational continuity while safeguarding health. The adoption of online lectures and digital platforms surged as educators and institutions sought to navigate the constraints imposed by the pandemic [9]. This section aims to elucidate the transformations in distance education precipitated by the pandemic, with a specific focus on technological accessibility and efforts to address the digital divide [10].

The rapid transition to online learning spotlighted the issue of the digital divide, a longstanding disparity in access to technology and internet connectivity among students [7]. The pandemic underscored how this divide could significantly impact educational equity, with students lacking reliable internet access or the necessary digital devices facing substantial barriers to participation in online learning. In response, educational institutions and government bodies have made concerted efforts to mitigate these challenges. Investments were directed towards providing students with the required technological tools and ensuring broadband access to facilitate remote learning [4]. Initiatives ranged from distributing laptops and tablets to students in need, to negotiating with telecommunications companies for affordable, even free, internet access for educational purposes. These interventions aimed to create a more inclusive distance-learning environment, recognizing the essential role of technology in enabling access to education amidst the pandemic. Consequently, a broader segment of the student population can engage with online learning platforms and resources. Despite these efforts, achieving a fully inclusive online learning environment remains an ongoing challenge. Not all students benefited equally from these measures, and disparities in access to high-quality internet connections and suitable learning environments at home continue to pose significant obstacles [11]. This reality suggests that while significant strides have been made in bridging the digital divide during the pandemic, achieving universal access to quality online education requires sustained efforts and innovative solutions to overcome persistent inequalities [12]. Prior to the global disruption caused by the coronavirus pandemic, online education was frequently viewed with skepticism, particularly in comparison to traditional in-person learning environments. Concerns were primarily centered on the perceived quality, rigor, and accreditation of online courses. The debate over the effectiveness of online learning vis-à-vis face-to-face instruction was a contentious issue, with many arguing that the former lacked the engagement and personal touch offered by physical classrooms [13]. This skepticism was partly due to the limited experience with or investment in online education methodologies by many institutions, which resulted in a general undervaluation of the potential of digital learning platforms. However, the onset of the pandemic and the consequent shift to online learning as a necessity rather than a choice led to a rapid reevaluation of these perceptions. With the increased allocation of resources towards enhancing the digital learning infrastructure, significant improvements have been made in the quality and delivery of online education. Educational institutions, driven by the urgent need to continue academic operations, have invested in the development of high-quality online courses [14]. This not only involved the digitization of learning materials but also the adoption of innovative pedagogical strategies designed to engage students remotely. The accreditation of online courses has received more attention, ensuring that they meet the same standards as their in-person counterparts, thereby increasing their credibility and acceptability among both educators and learners. Before the pandemic, one of the primary criticisms of online learning was the limited opportunities it presented for student interaction and networking. The traditional classroom setting was valued for its ability to facilitate direct engagement with peers and instructors, which was thought to be significantly compromised in online formats[15]. However, as educational technology has evolved rapidly in response to the pandemic, new tools and platforms have been developed to enhance interactions in virtual classrooms. Video-conferencing software, online discussion forums, and collaborative project tools have become integral components of the online learning experience, enabling real-time communication and teamwork among students and teachers. These technological advancements have addressed some of the initial concerns about the isolative nature of online education, showcasing its potential to foster a vibrant, interactive learning community despite physical distance [16]. The impact of the coronavirus pandemic on distance education has been profound, catalyzing a seismic shift in perceptions, methodologies, and infrastructures related to online learning. Although challenges remain, particularly in terms of achieving equitable access for all students, advancements made during this period have laid the foundation for a more resilient, inclusive, and high-quality educational system. As the world continues to navigate the implications of the pandemic, the lessons learned and innovations developed in response to it will undoubtedly shape the future of education, both online and in traditional settings [17]. Building upon the comprehensive evolution of distance education and the transformative shifts catalyzed by the coronavirus pandemic, this study delves into a specific critical aspect of online learning in higher education: formative learning assessment. The focus is on the integration of new scoring methods within the context of Four-Multiple Choice Assignments, a novel approach aimed at enhancing the effectiveness and accuracy of assessments in online learning environments. The transition to online learning necessitated by the pandemic underscores the importance of robust, reliable, and innovative assessment methodologies that can adapt to the demands of [17]. Traditional assessment techniques, often criticized for their limitations in accurately measuring student understanding and facilitating deep learning, are becoming increasingly inadequate in online education [18]. This has prompted a re-evaluation of assessment strategies, with a growing emphasis on formative assessments that support learning through feedback, rather than merely evaluating student performance. Formative learning assessment, characterized by its ongoing, interactive nature, provides students with timely feedback on their learning progress and identifies areas of strength and weakness[19]. This approach is particularly well suited to the online learning environment, where digital tools and platforms offer unique opportunities for implementing innovative assessment methods [20]. The integration of new scoring methods into the four multiple-choice assignments represents a strategic response to the need for more nuanced and effective assessment strategies in online higher education. These new scoring methods aim to leverage the capabilities of online learning systems and advanced analytics to provide a more personalized, engaging, and effective assessment experience [21]. By moving beyond traditional scoring mechanisms, these methods seek to recognize the complexity of learning processes and the diverse ways in which students engage with and understand course material. The adoption of four multiple-choice assignments, with their potential for nuanced scoring and feedback, aligns with the broader objectives of enhancing learning outcomes, promoting critical thinking, and fostering a deeper understanding of course content. This study explores the theoretical underpinnings of formative learning assessment, critically evaluates the potential of new scoring methods, and investigates the practical implications of implementing these approaches in online higher education settings [22]. By focusing on the integration of innovative assessment strategies with four multiple choice assignments, this study aims to contribute valuable insights into the development of more effective, equitable, and engaging online learning environments. This objective is not only timely, given the ongoing challenges and opportunities presented by the pandemic-induced shift to online education, but also essential for advancing the field of educational technology and pedagogy in higher education.

1.2 Factor in Online Formative Learning Assessment Effectiveness

The effectiveness of online formative learning assessments is contingent on several key factors, as the design and implementation of assessment tools play a crucial role. Effective formative assessments in online learning must be thoughtfully designed to align with learning objectives and course content. According to Imonje et al., assessments should be authentic, provide real-world relevance, and cater to diverse learning styles to ensure inclusivity [23]. The integration of multimedia and interactive elements can enhance engagement [24]. Additionally, these assessments must be adaptable, allowing for adjustments based on student feedback and performance [25].

The frequency and quality of feedback are integral to the effectiveness of formative assessments. Hattie et al. [4] highlighted the importance of timely, specific, and constructive feedback in promoting learning and student motivation[26]. In online settings, where immediate physical cues are absent, regular and clear feedback becomes even more vital. Technologies, such as automated feedback systems, peer-review platforms, and digital rubrics, as explored by Tan Alena, can facilitate efficient and effective feedback mechanisms [27]. This feedback should not only assess student performance but also guide them towards improvement and deeper understanding.

Therefore, the role of technology and its integration into the assessment process are not fully understood. The use of Information and Communication Technologies (ICT) in online formative assessment provides a range of tools and platforms that can enhance both the delivery and experience of assessment [28-30]. According to Mustapha et al. [31], effective technology integration involves not only the use of digital tools but also an understanding of how these tools can support pedagogical goals. These include the use of learning-management systems, interactive quizzes, and online discussion forums to foster an engaging and interactive learning environment. The challenge lies in ensuring that technology enhances the learning experience without becoming a barrier, a concern raised [32]. Meanwhile, the effectiveness of online formative learning assessment hinges on well-designed assessment tools that align with learning objectives, provision of timely and constructive feedback, and thoughtful integration of technology to support and enhance the learning process [13].

1.3 The Importance of Online Formative Assessments in Higher Education

Formative assessments have always played an important role in the educational sector, and their importance is reinforced in higher education environments. In contrast to summative assessments, which typically conclude at the end of teaching periods, formative assessments provide continuing evaluations that shape both teaching and learning throughout an academic journey [33].

The ability of formative assessments to offer fast and relevant feedback is a significant advantage [19, 34]. This feedback acts as a beacon for teachers, illuminating the efficacy of their educational practices and indicating areas that require more attention. For students, it offers a mirror that reflects their comprehension levels, enabling them to pinpoint knowledge deficiencies and recognize their strengths. This cyclical feedback system provides the basis for a culture of continuous improvement, ensuring that academic goals are met more effectively.

Formative assessments play an even more important role in higher education in a field that promotes self-directed learning. They serve as a link between teacher-led education and self-directed learning, ensuring that students are on the right track and assisting them in honing their academic skills [35].

Online formative evaluations have become important because of technological advancement [36]. The incorporation of novel digital technologies, ranging from online quizzes to immersive simulations, enables educators to administer these examinations more efficiently to larger cohorts. The multiple-choice question (MCQ) is a well-known instrument that has gained immense popularity, particularly in higher education. MCQs have cemented their place as a vital tool because of their ability to concisely assess a broad range of knowledge. Their collaboration with online platforms enables automated evaluation, quick feedback, and the extraction of data-informed insights into student achievement [37].

In today's digital era, formative assessments go beyond their conventional role as evaluation instruments [19]. They have developed as crucial builders in the educational process, forming a mutually beneficial and ever-evolving connection between educators and learners. As the landscape of higher education changes owing to technological advancements, the importance of these assessments in cultivating conducive learning environments remains evident.

1.4 Problem Statement

This study focuses on assessments in higher education, with a particular emphasis on online learning environments. At Yamaguchi University, the transition to online education has highlighted the need for effective assessment strategies that accurately measure student learning and performance. In this context, the reliability and validity of assessments, especially courses utilizing multiple-choice questions (MCQs), have become crucial. This study aimed to address the challenges inherent in current assessment methods, specifically in the context of four-choice MCQs, a common format in online formative assessments [38].

A significant problem identified at Yamaguchi University is the inadequacy of the current scoring methods for the four-choice MCQs in online formative assessments [11, 38]. The existing system struggles to provide a comprehensive evaluation of student learning, thus limiting students' ability to accurately assess their cognitive skills and knowledge retention. This issue is particularly pertinent because it affects educators' ability to effectively gauge and enhance student understanding, thereby impacting the overall educational quality and competence of graduates [39].

Thus, the significance of improving the scoring system for the four-choice MCQs cannot be overstated. Effective assessment is a cornerstone of educational quality, aligning closely with Bloom's taxonomy to ensure that students develop the necessary skills and understanding [40]. The current gap in the effective scoring of four-choice MCQs poses a barrier to accurately determining student performance, which is crucial for both students' learning trajectories and university reputation. Therefore, addressing this issue is imperative for maintaining high educational standards and ensuring that graduates are well equipped for their future endeavors.

This study proposes an objective scientific approach to address this problem. This involves investigating and developing an automated scoring system for four-choice MCQs to enhance the precision and efficiency of student assessments [41]. This study explores the potential of data-driven methodologies, possibly utilizing computational tools such as Excel or Python, to innovate current assessment practices. The anticipated outcome is a more effective, reliable, and scalable assessment tool that integrates seamlessly into the educational framework at Yamaguchi University, thereby significantly improving the quality of teaching and learning processes. Through this research, the goal is not only to advance the effectiveness of online formative learning assessments but also to contribute meaningfully to the broader field of educational assessment in higher education.

1.5 Objective of Study

The primary objective of this study is to investigate and enhance the scoring methods for Four-Multiple Choice within online formative learning assessments at Yamaguchi University. This study sought to implement these assessments through an online questionnaire platform, aiming to revolutionize the current approach to evaluating student performance in digital learning environments in higher education [42]. By introducing and analyzing a novel scoring method for Four-Multiple Choice, the study intends to substantially improve the effectiveness and efficiency of online learning assessments.

The research was guided by the following key questions:

RQ1: How did the evaluation scores in formative assessments change between 2019 and 2020, given the shift from conventional to online instruction?

RQ2: How does the introduction of a new Four-Multiple Choice scoring system impact the efficiency of online formative assessments in higher education?

RQ3: In what ways do students and educators perceive the efficacy of the Four-Multiple Choice scoring method in terms of its application in online formative assessments within the context of higher education?

RQ4: How does connectivity and technological infrastructure influence the effectiveness of online learning?

RQ5: What is the student learning outcome performance in higher education using k-means clustering as an analytical method?

1.6 Brief of Research Methodology

This study used empirical studies and qualitative methods. First, a comprehensive literature review was undertaken to formulate the researcher's problem, and the aim of the study, based on existing research questions, was made and verified to investigate formative learning assessments in the "Advanced Research and Development Strategy" course at Yamaguchi University. This study used data from formative assessments, attendance records, and student self-assessments. Utilizing methodologies such as conventional statistical techniques (regression analysis and t-tests) [43], this study offers a comprehensive understanding of the impact of transition on student learning outcomes. This integrative approach provides valuable insights into optimizing online education strategies and contributes to broader discourse on the efficacy of digital learning in higher education.

1.7 Significance of Study

The significance of this study lies in its potential to enhance the understanding of the effectiveness of online learning, particularly in the context of formative assessments at Yamaguchi University. By comparing face-to-face and online educational methods, this study provides insights into how the shift to digital platforms affects student learning outcomes. This is particularly relevant in the wake of the COVID-19 pandemic, which has necessitated a rapid shift to online education [19]. The findings could inform future educational strategies and policies, ensuring that they are adapted to maximize student engagement and learning efficacy in an increasingly digital academic world. This study not only contributes to the broader academic discourse on online education but also offers practical implications for institutions adapting to digital learning environments.

1.8 Organization of the Thesis

This thesis is organized into seven chapters as follows:

Chapter 1 Introduction: This chapter sets the stage for the dissertation by highlighting the transformative impact of online learning in higher education, accelerated by global crises, such as the COVID-19 pandemic. This emphasizes the need for innovative formative assessment methods in digital education. The introduction outlines the significance of formative assessments in enhancing learning processes and outcomes in online environments. It also identifies the challenges of implementing effective and adaptable assessment strategies in virtual settings, underscoring the importance of ongoing feedback and the role of information and communication technologies in formative assessments.

Chapter 2 Literature Review: This chapter delves into the critical examination of formative assessment, its theoretical underpinnings, its practical implementation, and its implications for pedagogy and learner achievement. It discusses the multifaceted role of formative assessment in enhancing learning processes and the significance of evidence in shaping instructional decisions. This chapter further explores the complexities of online formative assessment in higher education, highlighting the benefits of interactive feedback and the adaptability of assessment strategies across educational settings. This section acknowledges the need for further research to validate the effectiveness of formative assessments and examine the complementary roles of formative and summative assessments.

Chapter 3 Methodology: This chapter outlines the research design and approach adopted to evaluate new scoring methods for formative assessments in online courses. It begins with an extensive literature review to establish a theoretical framework, followed by a predominantly quantitative research approach encompassing several key statistical tools and techniques, such as comparative analysis of assessment scores, regression analysis, t-tests, and scatterplot matrices. This chapter also details the application of k-means clustering to categorize student performance, highlighting the research questions aimed at exploring the effectiveness of new assessment methods and the impact of technological infrastructure on online learning effectiveness.

Chapter 4 Development of the New Scoring Method: Leveraging Ikebukuro's innovative concepts, we developed a transformative scoring method that introduces a "degree of matching" principle for evaluating multiple-choice questions (MCQs). This approach diverges from traditional binary scoring models by implementing a five-level scoring system for four-option questions, effectively comparing student selections against the instructor's intended answers as if analyzing 4-digit binary numbers. This method not only recognizes correct answers but also identifies varying levels of comprehension, awarding partial credit to reflect a spectrum of student understanding. This significantly enriches student performance in online formative assessments, moving beyond the simplistic binary pass/fail paradigm to offer a more detailed and nuanced understanding of learning outcomes. This sophisticated scoring system is poised to revolutionize educational assessment, enabling a more granular and effective evaluation of student knowledge and reasoning processes in digital learning environments.

Chapter 5: Advanced Course of R&D Strategy Analysis: This chapter explores Yamaguchi University's strategic adaptation to the COVID-19 pandemic by focusing on the integration of digital technologies to transform teaching methodologies and learning environments. It specifically examines the shift in the Theory of Research and Development Strategy course to a fully online format and evaluates its impact on student learning and engagement. A key aspect of this transformation is an in-depth investigation of the use of formative assessments through four-option multiple-choice questions (MCQs) to understand their effectiveness in online education. This narrative not only highlights the university's efforts to navigate and excel in a rapidly changing educational landscape but also assesses the successes and challenges of implementing advanced digital learning tools and cloud-based conferencing services to enhance the quality of higher education in the face of global disruptions.

Chapter 6 Machine Learning in Online Formative Assessment Analysis: Chapter 6 explores the application of k-means clustering and the Elbow Method in analyzing student performance through formative assessments. It discusses the methodological underpinnings of these techniques, their effectiveness in revealing natural groupings within educational data, and the potential benefits of tailoring teaching methods to accommodate diverse learning behaviors. This chapter highlights a novel approach for utilizing unsupervised machine-learning algorithms to enhance educational analytics and contribute to the development of personalized learning experiences. Finally, Chapter 7 summarizes the dissertation's key findings, emphasizing the pivotal exploration of online formative learning assessments and the integration of innovative scoring methods with machine learning techniques. It discusses the contributions of this study to the domain of online assessments, highlighting the efficiency of the new scoring system, the role of formative assessment in enhancing learning outcomes, and the potential of machine learning to inform educational practices. This section also outlines the limitations of this study and recommends avenues for future research.

Chapter 2 – Literature Review

2.1 Formative Assessment

Formative assessment represents a pivotal element in the educational process, facilitating an interactive learning environment in which teachers and students engage in continual dialogue to enhance their learning outcomes. This literature review explores seminal and contemporary research on formative assessment and delineates its theoretical foundations, practical implementation, and implications for pedagogy and learner achievement.

In the exploration of formative assessment within educational contexts, a comprehensive analysis revealed its multifaceted role in enhancing learning processes. In [44], they offer a foundational framework for understanding formative assessment, positioning it within broader pedagogical theories, and linking it to self-regulated learning and classroom discourse. This approach provides a pivotal rationale for integrating formative assessments into teaching and learning strategies, suggesting their potential to significantly impact educational outcomes. Similar to [45], detailed the characteristics of formative assessment, emphasizing its responsiveness and the critical role of evidence in shaping instructional decisions. These studies underscore the process-oriented nature of formative assessment and highlight its importance in fostering an environment conducive to learning and engagement.

Further extension of the discourse in [46] addresses the complexities and ambiguities surrounding the definition and application of formative assessment, particularly in the context of its effectiveness and implementation challenges. According to [36], it contributes to this narrative by focusing on online formative assessment in higher education and identifying key features such as ongoing assessment activities and interactive feedback that enhance the validity and reliability of the assessment process. These perspectives are crucial for understanding the adaptability of formative assessment across various educational settings and its capacity to support personalized learning experiences.

The literature also engages with critical perspectives on the efficacy of formative assessments, as presented in [47]. These critiques emphasize the necessity of grounding claims of the impact of formative assessment in rigorous empirical evidence, advocating for a balanced approach that acknowledges its potential benefits, while recognizing the need for further research to validate its effectiveness.

The interplay between formative and summative assessments is another significant theme, with scholars exploring how these assessment types complement each other [48, 49]. This discourse highlights the importance of leveraging both forms of assessment to support a comprehensive understanding of student learning, thereby facilitating a more nuanced approach to educational evaluation.

2.2 Online Formative Assessment

Online formative assessments play a crucial role in today's education landscape, offering a powerful tool for teachers to gather real-time insights into students' understanding and progress [50]. By providing immediate feedback, online formative assessments help educators tailor their instruction to address students' specific needs, ultimately leading to improved learning outcomes [36].

One of the key benefits of formative online assessments is the opportunity to incorporate various traditional assessment methods into online platforms [28]. This approach allows for flexibility and adaptability in delivering assessments, making it easier for educators to implement a wide range of strategies [11]. Furthermore, online formative assessments have been shown to contribute to significant gains in students' academic performance while also fostering the development of essential cognitive processes such as self-regulation [51].

2.3 Impact of implementing an online learning system

The COVID-19 pandemic has caused global disruption, leading to a significant transformation in the education sector, particularly in terms of how graduate science and engineering students are taught. The abrupt transition from traditional face-to-face instruction to online lectures has not only challenged existing educational paradigms but has also catalyzed a rapid evolution in teaching methodologies [52, 53]. This study critically assessed the impact of these changes on students' learning outcomes and experiences, contributing to a better understanding of the efficacy and implications of online education in crisis contexts.

Owing to the COVID-19 pandemic, educational systems began online in educational institutions worldwide in 2019. As a result, many papers have reported the impact of the COVID-19 pandemic on educational systems and methods [54-58] and the impact of online learning [15, 55-63]. In the same period, many case studies discussing the need for literacy education in ICT and digital tools for university faculty and human resource development have also been published [30, 64-70]. These reports came not only from the United States and Europe but also from other regions including Bahrain [54], Jordan [55], Malaysia [56, 57], Indonesia [59], Nepal [60], the Philippines [64], and Algeria [65]. O. Al-Rawi et al. [54] discuss the impact of the COVID-19 pandemic on the educational environment in the Kingdom of Bahrain and the use of digital tools and technology to help overcome the problems. Fatima et al. detail the impact and problems of the COVID-19 pandemic in Jordan They report that COVID-19 had a negative impact on education in the form of disruption of on-site learning programs, closure and accessibility of educational and research institutions, and loss of economic activity, all of which increased the burden on students. Additionally, during the pandemic, educators and students primarily continued with internal-meteorology-based online learning. They also noted that factors such as inadequate infrastructure, network stability, and power supply capacity hampered the acceleration of online education [55]. I. Othman et al. [56] discussed the phased implementation of national education through the educational challenges of the post-Covid-19 pandemic in Malaysia. They discuss the operation of a phased-in national education system through the educational challenges after the Covid-19 pandemic in Malaysia. They also discuss the direct impact of school closures that resulted in huge learning gaps among Malaysian children, the restoration of the higher education system after the Covid-19 pandemic, and the promotion of digitization. Siti Aisyah Mohamad Zin et al. [57] describe the potential impact of online learning on students' mental health. The Malaysian Ministry of Education introduced a new platform to enable students to continue learning through an online learning system. However, the digital divide may affect students' mental health, such as stress, fear, anxiety, worry, and depression, due to their inability to learn adequately because they do not have adequate computer access and Internet speed to use while learning and completing assignments.

Helena Kovacs et al. examined the impact of the Covid-19 pandemic worldwide on various levels of the education system in terms of changes in educational practices. Interviews with 41 teachers at the primary, vocational, and higher education levels in the Swiss canton of Vaud revealed the challenges of acquiring competence in using digital tools, optimizing quality interactions, and ensuring presence in online education [58]. F. Hermanto describes the results of an online course on the theory and practice of the compass and steering system called "the Compass and steering system courses on theory and practice" at the Indonesian Police Academy. Courses are generally taught in the areas of navigation and direction finding. In general, online courses scored an average of 88 or higher, even though they were practical skills courses that included skills training in navigation and direction finding, theoretical lectures, and practical skills training in driving and maneuvering a vehicle or motorcycle [59]. The impact of this shift towards online education in Nepal was investigated. The main impacts of the paradigm shift to online education are access to quality education, adaptation to technology, emotional well-being, and acceleration of change, while simultaneously resulting in high dropout rates and a variety of responses [60].

G. Northey et al. use Facebook as a tool for asynchronous learning to complement face-to-face interactions and positively impact student engagement and academic outcomes. Using data from a longitudinal quasi-experiment, the authors showed that students who participated in both face-to-face on-campus classes and asynchronous online learning opportunities were more motivated to learn than those who participated only in face-to-face classes [61]. S. M. Obeidat et al. found that online during COVID-19 learning generally had lower academic performance than face-to-face learning, with mixed results for blended and asynchronous learning modes; they studied the impact of switching instructional formats with COVID-19 on student performance and whether online learning could provide students with academic performance comparable to face-to-face learning. The data for this study were collected from three engineering courses taught at the College of Engineering and Technology of a public university in Texas, USA. In general, student performance in the face-to-face mode is higher in these types of courses than in mixed face-to-face and online or asynchronous (online) groups [62].

J. Thiele et al. found that students studying online tended to be more autonomous and self-disciplined. They have more trust in their own judgment and can engage more deeply in content than traditional lecture-driven classes. Specifically, the online format fosters self-discipline because it allows students to work at their own pace. In addition, students could view the study material repeatedly online, thus deepening their understanding of the content. Interacting with other students through discussion forums also effectively enhances their thinking and expression. Online learning is effective in promoting students' autonomy and deep thinking. Compared to traditional classroom-centered teaching styles, it has been described as a point where learner patterns differ significantly [15]. J. Paulsen et al. found that while online learning has positive effects in terms of content difficulty, satisfaction, and study habits, when compared to face-to-face classes, collaborative learning and faculty interaction have positive effects. However, they found that online learning was disadvantageous in terms of collaborative learning and faculty interaction compared to face-to-face classes. Specifically, students in online courses have the advantage of focusing on learning content and deepening their understanding at their own pace. However, they have limited opportunities for discussion and group work with other students, which poses challenges for improving their cooperation and communication skills. Additionally, online communication with faculty members is more limited than face-to-face communication, and students have fewer opportunities to gain motivation and emotional support for learning. Although online learning has advantages depending on the learner's situation, it also has the advantages of face-to-face classes. It is believed that an appropriate combination of both is required [63].

C. Tolentino-De Leon described how blended learning during the COVID-19 pandemic did not have a positive impact on learner learning outcomes in a Purposive Communication course (aimed at developing communication skills). The study found no positive impact of blended learning on learner outcomes in a Purposive Communication course. Specifically, the combination of online and face-to-face instruction provided learners with some benefits, such as improved ICT skills, but was not sufficient for communicative skill development. One reason for this may be that the constraints of online learning limit opportunities for conversation, making it difficult to develop conversational skills by directly examining the reactions of others. The results showed that face-to-face teaching has unique advantages for language courses that focus on developing communicative competence. This should be considered in the future for blended learning [64].S

Haarala-Muhonen et al. examined the impact of teaching methodology and ICT training on teachers' online cheating approaches and the use of digital tools. A questionnaire was administered to 159 Spanish teachers. Trained teachers were more likely than untrained ones to conduct interactive online classes and use a wider range of digital tools, including educational apps and digital teaching aids. This study suggests that training to improve teaching methods and ICT skills can help teachers improve their online teaching skills. They concluded that ICT training should be emphasized in teacher education [30]. L. Hanane et al. showed the importance of ICT in the technology teaching skills of Algerian university teachers. A survey of university faculty members revealed that those who had received ICT-based training had better technological education skills than those who had not. Specifically, the ability to create e-learning content, use educational software, and develop new teaching methods using ICTs was significantly improved. The study concluded that it is extremely important to maximize the incorporation of ICT in the development of teachers' technical education skills. They recommended that this training be systematically implemented in the future [65].

M. Dooly analyzed the long-term impact of a teacher training project focused on the use of information and communication technology (ICT) in language teaching. Teachers who participated in the training experienced the long-term impact of promoting autonomous learning and collaborative problem-solving through ICT support. In the post-training interviews, participants reported using ICT tools to create teaching materials to support autonomous learning, facilitate ICT-based collaborative work, and share how to use ICT inside and outside the classroom. The skills and knowledge acquired during the training were also retained and used over time [66]. N. Pongsakdi et al. analyzed the impact of digital pedagogy training on ICT skills and confidence among preservice teachers. The findings indicated that teachers who received training had increased confidence in their use of ICT and decreased the extent to which they needed technical support. Teachers with higher initial ICT confidence reported greater benefits. Digital pedagogy training has been found to be effective in improving teachers' ICT literacy [67].

Magen-Nagar et al. analyzed the impact of an intervention program in which teachers and students collaborated to create digital games. They showed that participation in the program had the following impacts: decreased resistance to change, increased motivation, and the formation of positive attitudes towards collaboration in the classroom. Specifically, in post-program interviews, teachers and students reported that they had more opportunities to learn from each other and that a collaborative classroom climate was fostered. They also reported that students' digital literacy and problem-solving skills improved. This study suggests that collaborative digital game creation between faculty and students is effective in improving learning environments [68]. M. Daumiller et al. analyzed the impact of university faculty achievement goals on classroom perceptions, malaise, and learning outcomes during the transition to online teaching with COVID-19. They showed that learning approach goals (those that focus on learning and growth) are positively associated with cognitive challenges and competence development in online classes. By contrast, performance avoidance goals (those that focused on failure avoidance) were associated with higher faculty malaise and lower student learning outcomes. This study demonstrated the importance of faculty achievement goals in online classes during COVID-19 [69].

However, studies have been reported that discussed the adoption of technology in education and human resource development, regardless of the impact of COVID-19. m. Liesa et al. investigated the impact of ICT tools on student learning and 21st century skills development, as perceived by university faculty members. They found that university faculty members perceived ICT tools to have a positive impact on students' development of 21st century skills such as critical thinking, creativity, and communication skills. At the same time, however, they emphasized that proper integration of these ICT tools into teaching methods and digital skills training for faculty are essential for their incorporation into education [70]. K. Rosenbusch pointed out that while the expansion of online education has eased time and location constraints on learning and greatly expanded educational opportunities, faculty and university organizations need to adapt to these changes. Faculty members need to review their teaching methods and communicate with students using the latest technology, whereas universities need to respond to digital transformation by reforming their educational infrastructure and organizational structures. Therefore, it is essential to expand digital services to provide student support. This digitalization of higher education is also important from the perspective of social equity, and will play a major role in providing educational opportunities to learners from diverse backgrounds [71]. S. Joshi, et al. conducted an interview-based interview study on the use and effectiveness of AI technology in education from the perspectives of teachers and students. While teachers believed that AI could contribute to qualitative improvements in education through learning analysis and individual optimization, they also expressed the view that excessive reliance on AI could undermine learner autonomy. They noted that AI-based learning support systems are useful in promoting understanding, but that human factors remain important. Although AI has the potential to improve educational effectiveness, both teachers and students have indicated that proper implementation and monitoring are essential [72].

Previous studies on the implementation of online learning systems to avoid COVID-19 risks can generally be categorized into the following five categories. Table 2.1 shows the results of the categorization of references [15, 30, 55-72].

Table 2. 1 Impact of Introducing Online Learning Systems

Category	Target	impact	Research Overview	References
1	Student	Negative	Despite the introduction of an online learning system, students do not have adequate learning opportunities due to the digital divide and lack of communication due to inadequate infrastructure. This had a negative impact on students' mental health.	15, 57, 60,
2	Student	Positive	The students continued to learn at a high level after moving to the online learning system. Online learning is effective in encouraging student independence and deep thinking.	69, 61, 55
3	Student	Negative	Learning is more effective in the following order: face-to-face learning, combination of face-to-face and online learning, and online learning only.	62, 63, 64
4	Teaching staff	Positive	There is a correlation between high ITC literacy of academic staff (faculty) and high learning effectiveness of the online learning system.	58, 69, and
5	Teaching staff	Positive	ICT literacy for teachers to develop technology education skills is very important	30, 65, 66, 67, 68, 70, 71, 72

2.4 Item Response Theory and Latent Trait Theory

Item Response Item Response Theory (IRT) represents a significant evolution in the field of educational and psychological measurement, offering a sophisticated alternative to the limitations of Classical Test Theory (CTT) [73]. An et al. [74] traced the development and application of IRT, illustrating its theoretical foundations and broad-spectrum utility. Initially conceptualized to overcome the sample dependency and other constraints of CTT, IRT has provided a more nuanced framework for analyzing test responses. The theory posits that the probability of a test response is not merely a function of the test taker's latent traits but is also intricately linked to specific item characteristics

[75]. This dual focus allows for a deeper understanding of both the item and the respondent, facilitating the development of tests that are more adaptive, efficient, and reflective of diverse abilities and traits.

The advent of IRT introduced several models, such as the Rasch model, two-parameter logistic model, and graded response model, all of which address different types of data and measurement objectives. As discussed by Cai et al. [76], these models have not only enhanced the precision of educational assessments but have also found applications in health sciences, marketing research, and beyond. The ability of the IRT to provide detailed item-level information, such as difficulty and discrimination, without being tied to a specific sample of test-takers marks a clear advantage over the CTT. This feature is instrumental in creating reliable and valid tests across a range of ability levels, thereby maximizing the informativeness of each item included in the test.

Recent innovations within IRT, including Multidimensional IRT (MIRT) and response time modeling, have expanded its applicability even further. MIRT, for example, facilitates the assessment of complex constructs by simultaneously analyzing multiple latent traits, offering a richer and more comprehensive evaluation of test data. Similarly, incorporating response times into IRT models, as explored by Ranger and Kuhn [77], has opened new avenues for understanding the dynamics of test-taking behavior, providing insights that extend beyond correct or incorrect answers to include the strategies and processes employed by respondents.

The empirical application of IRT across various fields underscores its versatility and effectiveness. For instance, in health questionnaire development, IRT has been instrumental in refining instruments to ensure that they are psychometrically sound, capturing the full burden of disease or treatment impact with greater precision and efficiency, a point highlighted by Reeve and Fayers [78]. However, this practical utility is not without challenges. Addressing item bias and ensuring fairness in testing remain critical issues, requiring ongoing attention to statistical methods and qualitative analyses to detect and correct biases that may disadvantage certain groups of test-takers [79].

As IRT continues to evolve, it pushes the boundaries of measurement science, adapts to new challenges, and leverages technological advancements [80]. The exploration of nonstandard models for response processes and the application of IRT in digital learning environments exemplifies the theory's adaptability and potential for future growth. Through its development, IRT has not only enhanced the accuracy and fairness of tests, but has also contributed to a deeper understanding of the constructs being measured. Meanwhile, Item Response Theory has transformed the landscape of educational and psychological measurements. By addressing the shortcomings of Classical Test Theory and introducing a range of models to analyze test data more effectively, IRT has broadened the scope of what can be measured and how measurements are interpreted. Its application across diverse fields and its ongoing evolution reflect the dynamic nature of measurement science, underscoring its integral role in advancing our understanding of human abilities, traits, and behaviors [81].

2.5 Test Characteristics in Formative Assessment

In the context of learning environments, the application of multiple-choice questions to formative assessments is gaining traction. Analyzing its test characteristics through the lens of test theory provides a deeper understanding of its efficacy and wider implications [82].

2.5.1 Usefulness

Understanding the usefulness of a test goes beyond its ability to generate scores. It delves into how these scores can be interpreted and applied in an educational context. The true measure of a test's usefulness lies in the depth and actionability of the insights it offers [83]. When we speak of four-choice questions in formative assessments, the question of utility becomes more pertinent.

In educational assessment, the strategic crafting of multiple-choice questions elevates them beyond their conventional function as simple evaluative tools [84]. When carefully designed, these questions become powerful instruments that offer deep insights into various aspects of students' cognitive abilities. The effectiveness of these questions lies in their ability to balance challenge with accessibility, thereby serving not only as tools for assessment but also as facilitators for deeper learning and student engagement. This dual capacity is fundamental, as it extends beyond mere evaluation to actively contribute to the enhancement of students' understanding and involvement in the learning process. Recent studies [85] have highlighted the significant impact of this approach on question design, revealing the transformative nature of well-crafted four-choice questions. According to these findings, such questions transcend traditional assessment roles, acting as catalysts that bridge the gap between simple measurement and the advancement of comprehension and engagement.

The effectiveness of the four choice questions is not a static quality; they evolve significantly through the feedback mechanisms that surround them. Drawing upon the principles of Item Response Theory (IRT), research [86] indicates that the feedback derived from these questions can be uniquely tailored to each learner. This approach moves away from generic feedback, enabling educators to extract specific insights into learners'strengths, weaknesses, and growth. This personalized feedback approach, as underscored in another study [87], amplifies the transformative potential of this assessment method. According to this study, when feedback is intricately connected with IRT principles, it becomes a powerful tool that drives personalized instructional strategies. This ensures that teaching methods remain agile and adaptive, catering dynamically to each student's unique needs.

2.5.2 Practicality in Test

Practicality is a core concept of test theory. This denotes the feasibility and convenience of administering, scoring, and interpreting a test [73]. This idea covers various factors, including the duration necessary for conducting the test, resource demands, and related costs. At its core, a test that exhibits practicality demonstrates both time and resource efficiency.

Exploring the practicality of diverse test formats reveals the importance of four-choice questions. These questions present multiple benefits that bolster their practicality. One primary advantage is the ability to make the item-writing process more straightforward. This efficiency reduces the intricacy for educators during question development. As a result, a lessened cognitive load emerges for educators formulating questions and for students tackling them [11].

Advancements in contemporary test theory have introduced innovations, such as computerized adaptive testing (CAT) [88]. Through CAT, the potential of the four-choice format to transform test administration has become evident. CAT-designed tests can adjust dynamically based on a student's performance, thereby facilitating a tailored assessment experience. This design also permits instantaneous feedback, granting students immediate insight into their results. These characteristics underscore the capacity of the four-choice questions to optimize test administration in terms of efficiency and approachability [89].

2.5.3 Validity

Validity represents a foundational principle in test theory, serving as a metric for evaluating whether a test accurately assesses the intended construct [90]. Different dimensions of validity, such as content, construct, and criterion-related validity, collectively provide insights into the overall effectiveness of a test in terms of its measurement objectives.

In the context of classical test theory (CTT), validity focuses on a test's proficiency in gauging its specified construct. Four-choice questions, when meticulously aligned with curriculum goals and expected learning outcomes, demonstrated the potential to achieve accurate measurements. They highlighted the effectiveness of four-choice questions [91]. Their study revealed that questions anchored in both content specifics and cognitive processes can achieve validity coefficients comparable to or exceeding those of traditional test formats.

However, recognizing the evolving nature of validity is paramount. Rasch models indicate that validity does not remain constant and requires ongoing monitoring and adjustment. Tests, including those deploying four-choice questions, require periodic calibration and assessment. This continuous evaluation process ensured the sustained relevance and accuracy of the questions across varying periods and diverse student populations. Emphasis on this aspect underscores the necessity of regular scrutiny to maintain the test's integrity and applicability [92]. While validity operates as a measure of a test's precision in assessing its designated construct, achieving and maintaining it requires consistent effort, calibration, and evaluation to ensure applicability across different educational settings and timeframes.

2.5.4 Reliability

Reliability is a pivotal concept in test theory that addresses the dependability of test scores. Specifically, it emphasizes the extent to which test scores remain consistent or stable across different testing occasions or when different item sets measure the same construct.

Four-choice questions, when processed through rigorous item analysis and subsequent refinements, align favorably with the principles of reliability delineated by classical test theory (CTT). Although initial apprehensions existed regarding the likelihood of increased guessing owing to limited choices in this format, such concerns have been alleviated. Research employing item response theory (IRT) has shed light on this matter, demonstrating that the chances of guessing can be statistically managed and adjusted. This adjustment ensured that the reliability metrics derived from the tests using the four choice questions remained strong and trustworthy. Emphasis on this aspect underscores the necessity of regular scrutiny to maintain the integrity and applicability of the test [93]. They presented pivotal evidence that appropriate statistical considerations of the four-choice format can maintain robust reliability.

In essence, reliability not only represents the consistency of test scores but also underlines the importance of adopting meticulous analytical and refinement techniques, especially when deploying specific formats, such as four-choice questions. Ensuring that the scores remain consistent across varied conditions solidifies the reliability of the test, making it a reliable evaluation tool.

2.5.5 Authenticity in Testing

Authenticity in test theory evaluates how well a test mirrors a real-world situation [94]. A pivotal aspect of this is ecological validity, which determines the alignment of test behaviors with real-life actions. Although multiple-choice questions, especially the four-choice format, have historically been criticized for potentially lacking ecological validity, modern perspectives have challenged this notion. When these questions are embedded within genuine real-world scenarios, they can effectively simulate the actual cognitive challenges that learners may face.

In essence, the authenticity of a test is not solely about its resemblance to real-life situations, but also its ability to integrate real-world contexts within its items. Such integration ensures that the test offers a genuine representation of the challenges learners might encounter outside the testing environment.

The ripple effect in test theory describes the broader consequences of a test within an educational framework, extending its reach beyond direct outcomes. This concept suggests that the type and structure of assessments can profoundly influence various facets of education, from curriculum design to teaching methodology.

2.5.6 Ripple Effect

Four-choice questions are prime examples of this phenomenon. Their presence in assessments can drive changes in instructional techniques. This emphasizes that such test formats can lead to more direct and clear teaching methods, ensuring precision in conveying content [95]. Additionally, the nature of these questions can reshape students' attitudes towards learning. Research highlights that when confronted with assessments involving four-choice questions, students tend to prioritize deep comprehension over mere memorization [96].

Essentially, the ripple effect encapsulates the expansive impact of assessment tools on the academic landscape. It shows the intricate relationship between test formats, such as four-choice questions, and their influence on pedagogical strategies and student learning approaches.

2.6 Multiple-Choice Questions in Online Formative Assessments

Online formative assessments have emerged as indispensable tools in contemporary education. They provided real-time feedback adapted to individual learners to evaluate the impact of the transition from face-to-face to online lectures on graduate students' learning behavior in science and engineering by examining their formative learning and self-assessments. To achieve this, a four-choice question format was used for each class session. The use of multiple-choice format tests (MCQs) has proven to be an effective method for assessing the learning abilities of many students. Numerous studies have explored the optimal number of options and question types [11, 40, 97-102], and Ikebukuro et al. conducted an extensive study on multiple-choice question types in the medical licensing examination. The structure of multiple-choice questions is straightforward and consists of one question and four options. This type of question allows respondents to guess the correct answer and earn points, even if their knowledge is limited. To better understand this characteristic, a simple example of a multiple-choice question was provided. A straightforward multiple-choice question can be phrased as follows: "Select the appropriate topic from the options provided below. This sentence served to inform the respondent about the decision to be made and the manner in which to answer (the number of choices). In this instance, the option to choose is the "correct" one, and the predetermined number of correct answers is "*1*." If the respondent selects an option haphazardly, they have a "*1/N*" chance of choosing the "correct" answer (where N is the total number of options; in this case, $N=4$, and the probability is 20%). This score, not based on knowledge, is hereafter referred to as the "irregular score." Licensing examinations, such as the medical licensing examination, aim to minimize the percentage of irregular scores as much as possible. Strategies to reduce irregular scores include increasing the number of questions and complicating the structure of multiple-choice questions. In Japan's medical licensing examination, the percentage of simple multiple-choice questions is limited to 30% or less, while the remaining 70% consists of complex multiple-choice questions.

This method is effective in reducing irregular scores but also raises the burden and cost of question preparation. To ensure the quality of multiple-choice questions, they must be designed at three cognitive levels–recall, application, and analysis–based on Bloom's taxonomy [11, 40, 99-101]. The process of designing questions using Bloom's taxonomy becomes more challenging, depending on the complexity of the multiple-choice question structure. In the case of a large number of examinees, preparation of reserve examination questions is necessary as a risk hedge against unforeseen circumstances. In addition, hardware measures such as the introduction of a mark-sensing system may be required based on the number of examinees. These factors increase the burden and cost of administering examinations. Therefore, it is essential to have a system that can bear the cost of administering examinations, as is the case for national examinations. In this case, where the faculty member in charge of the subject is responsible for the entire process of designing and writing the questions, conducting the examinations, and marking and evaluating them, it is challenging to bear the cost of administering the examinations.

According to Ikebukuro, a common characteristic of multiple-choice questions with five answer choices is that it is impossible to distinguish the difference in knowledge levels between a respondent with a level of four and a respondent with a level of five when the two answers are correct [97]. A respondent's knowledge level was determined by their ability to identify one of the options. In this case, the knowledge level ranged from 0 to 5, depending on the number of correct answers. To overcome this limitation, Ikebukuro proposed a questioning method that does not indicate the number of correct answers, which allows the detection of differences between respondents with knowledge levels of 4 and 5 [97].

Multiple-Choice Questions (MCQs) have long been a foundational component of assessment in higher education. Originating in the early 20th century, MCQs were lauded for their ability to assess a wide range of contents in a short amount of time. Over the years, as pedagogical practices have evolved, so has the design and application of MCQs, making them more sophisticated and relevant to the changing educational landscape.

2.6.1 Optimal Number of Options

The structure of Multiple-Choice Questions (MCQs) has been a topic of academic interest for educators worldwide [103]. At the heart of this discussion lies a simple yet significant question: How many options should an MCQ have to be both effective and efficient?

A 2020 study by [104] brought a renewed focus to this debate. By employing a comprehensive mixed-methods research design, their findings challenged conventional wisdom. They determined that an MCQ with four options was notably superior to those with three or five options. The rationale for this is twofold. First, four options strike a balance, reducing the cognitive burden on students. There is no need to juggle too many choices, allowing us to focus on the content rather than the form of the question. Second, it curtails students' chances of benefiting from random guessing, ensuring that the assessment reflects genuine knowledge rather than sheer luck.

This study's results have several implications. Educators recognizing the merits of these findings have begun to re-evaluate their assessment designs. The shift towards four-option MCQs is not just a change in number, but a move towards optimizing the assessment process. This study underscores the continuous evolution of education, where established practices are revisited and refined in the pursuit of excellence.

2.6.2 Effective Learning Practices

The educational sphere has long recognized the value of Multiple-Choice Questions (MCQs), not merely as assessment tools but also as formidable instruments of learning. This dual functionality of MCQs, emphasized by [105], underscores their potential in both gauging and enhancing comprehension.

Educators can create a holistic learning environment by meticulously aligning MCQs with their core learning objectives. In this paradigm, MCQs have transitioned from mere evaluative instruments to potent vehicles that reinforce knowledge and rectify misconceptions. This dual utility of MCQs was further elucidated in a study by [105], which found that students who received elaborate feedback, especially in online quizzes, exhibited enhanced learning outcomes. Such feedback mechanisms, particularly when supplemented with detailed explanations of each option, serve as pivotal points in the learning journey. They allow students to reflect on their choices, understand the rationale behind their correct answers, and assimilate their knowledge more effectively.

A study 2018 by [106] added another dimension to this discourse, suggesting that MCQs, particularly when well-structured, can be among the most beneficial tools for student learning. This perspective is further corroborated by research such as [107], which emphasizes the significance of learning outcomes and the alignment of MCQs with a well-defined taxonomy.

Furthermore, the integration of technology has amplified the efficacy of MCQs. Online tests, when judiciously implemented and instrumental in fostering learning, as posited by [108], echo the sentiments of numerous educators and researchers.

2.6.3 Online Quizzes

The digital revolution has profoundly affected the educational domain, particularly in the realm of assessment. With the rise of online platforms, MCQ-based assessments have evolved from traditional paper-and-pencil methods to dynamic digital quizzes that can be accessed anytime and anywhere. This shift not only offers unparalleled convenience but also enhances the overall learning experience.

The study of 2020 by [105] delved deeply into this evolution. Their research, conducted in the context of online quizzes with closed questions, highlights the transformative power of feedback in digital environments. They discovered that when students received elaborate feedback, their learning outcomes improved significantly. Such detailed feedback often instantaneously offers students a unique opportunity to immediately address and rectify their misconceptions, fortifying their understanding in real time.

Another perspective emerges from the work of Reedy ([109], who emphasized the efficacy of online tests in fostering learning. Their findings resonate with the broader sentiment that online tests, when used effectively, can be instrumental in enhancing educational experience.

Zeri et. al. [110] further exemplify the growing reliance on technology in education. Their study highlighted the variability in teaching and assessment methods, suggesting that online quizzes, when blended with traditional methods, offer a holistic and comprehensive learning environment.

2.6.4 Evidence-Based Practice

In the realm of education, decisions grounded in empirical evidence are pivotal for enhancing student outcomes and optimizing teaching methodologies. The foundation of this perspective can be traced back to models like the "Iowa Model of Evidence-Based Practice" introduced by Reavy et. al., [111]. This model, which has been influential in shaping educational strategies, underscores the iterative nature of evidence-based practice. It advocates a continuous cycle of evaluation and refinement, ensuring that educational practices evolve in tandem with emerging evidence.

A study by Ashayeri et al. [112] offers a contemporary perspective on this paradigm. Their study delved into the intricacies of evidence-based practices, emphasizing their cyclical nature. By constantly refining assessment strategies based on empirical findings, educators can ensure that their methodologies remain relevant, effective, and aligned with recent pedagogical insights.

Furthermore, research by [113] highlights the significance of developing an evidence base for interdisciplinary learning. Their findings suggest that evidence-based practices are not just confined to traditional educational settings but are equally relevant in interdisciplinary domains.

The evaluation of evidence-based practices in online learning environments further broadens the scope of this discussion [114]. With the rise of digital education, grounding online teaching methodologies in evidence has become paramount. Their findings highlight the importance of continuous evaluation and adaptation in online settings to ensure that digital learning environments are both effective and engaging.

In essence, the journey towards evidence-based education is continuous and evolving. By embracing the principles of evaluation and refinement, educators can navigate the complexities of the modern educational landscape, ensuring that their practices are always grounded in evidence and optimized for student success.

2.7 Machine Learning in Online Formative Assessment: K-Means Cluster Using the Elbow Method

The combination of K-means clustering with the elbow method constitutes a machine learning analysis, leveraging the K-means algorithm to unveil patterns within the data. The primary goal is to determine the most suitable number of clusters to enhance our understanding of the inherent patterns. The elbow method adds a systematic and data-driven dimension to the analysis, facilitating the exploration of inherent structures in data across various fields.

Recent academic research on higher education has underscored the transformative impact of K-means clustering on educational analytics. Radovic et al. [115] demonstrated its effectiveness in illuminating student learning patterns, aiding educators in identifying misconceptions and areas of difficulty. This extends to the identification of student groups with similar learning needs, facilitating personalized instruction and support.

Further exploration reveals the broader implications of K-means clustering in refining educational experience. Ifenthaler et al. [116] highlight its role in dissecting student engagement with self-assessments, leading to more effective pedagogical approaches. When applied to online formative assessments, k-means clustering generates rich datasets for learning analytics, tracing trends and patterns in student performance, shaping curriculum development, and supporting evidence-based educational decision-making.

Studies employing k-means clustering and the elbow method have underscored their effectiveness in classifying student populations based on performance metrics. This classification is crucial for crafting customized educational strategies. An innovative approach to determining the optimal number of clusters introduces novelty to educational data analysis, offering varied levels of detail for comprehensive student performance analysis [117].

The role of learning analytics in understanding patterns in students' self-regulated learning was further explored in. The predictive analysis of student success using K-means clustering additionally highlights the significance of this method in segmenting students to improve their performance understanding [118].

The integration of the k-means clustering method with the elbow method, primarily in customer profiling, has analogous applications in educational contexts [119]. This combination effectively determines the optimal number of clusters, which is fundamental for categorizing student performance. Moreover, applying the K-means algorithm to analyze learning outcomes and self-regulated learning demonstrates the method's utility in grouping students based on their learning strategies and performance.

The versatility of K-means clustering in various research domains is further illustrated in a paper focusing on statistical methodologies in prosthodontics research, emphasizing its broad applicability, including educational settings.

Despite these advancements, employing K-means clustering in online formative assessments remains a challenge. Gligorea et al., [120] raise concerns about algorithmic reliance, pointing to potential oversights in the nuanced nature of individual learning experiences. The implementation of this method also necessitates careful consideration of privacy and handling of ethical data. Nevertheless, the application of K-means clustering in online formative assessments presents a nuanced avenue for enhancing higher education by offering personalized learning experiences and data-driven decision-making while addressing the complexities and ethical considerations involved.

The use of k-means clustering in online formative assessments in higher education, as detailed in recent academic research, is a transformative approach to educational analytics. Khosravi et al. [121] elucidated how this method illuminates student learning patterns, enabling educators to pinpoint and address common misconceptions and areas of difficulty. This capability extends to the identification of student groups with similar learning needs, facilitating personalized instruction and support. The integration of k-means clustering not only enhances tailored teaching strategies but also promotes self-regulated learning among students by providing insights into their strengths and weaknesses.

Further exploration of this domain reveals the broader implications of k-means clustering in refining educational experience. Gligorea et al. [120] emphasize its role in dissecting student engagement with self-assessments, paving the way for more effective pedagogical approaches and interventions. This analytical tool yields a rich dataset for learning analytics when employed in formative online assessments. Such data are instrumental in tracing trends and patterns in student performance, shaping curriculum development, and bolstering evidence-based educational decision-making.

Concurrently, a study employing K-Means Clustering and the Elbow Method accentuates the method's effectiveness in classifying student populations based on performance metrics [116]. This classification is crucial for crafting customized educational strategies. A novel approach to determining the optimal number of clusters in K-means introduces an innovative aspect to educational data analysis, offering varied levels of detail for comprehensive student performance analysis [122].

The role of learning analytics in understanding patterns in students' self-regulation has been explored further [123]. K-Means Clustering uncovers distinct behavioral patterns that are essential for developing personalized teaching methods. A predictive analysis of student success using K-Means Clustering additionally highlights the method's significance in segmenting students for improved performance understanding [124].

The integration of the k-means Clustering Method with the Elbow Method, primarily in customer profiling, has analogous applications in educational contexts [119]. This combination effectively determines the optimal number of clusters, which is fundamental for categorizing student performance. Moreover, applying the K-Means Algorithm to analyze learning outcomes and self-regulated learning demonstrates the method's utility in grouping students based on their learning strategies and performance [125].

The versatility of K-Means Clustering in various research domains is further illustrated in a paper focusing on statistical methodologies in prosthodontics research. This adaptability emphasizes the broad applicability of the method, including in educational settings [126].

Despite these advancements, employing k-means clustering in online formative assessments remains a challenge. Concerns about algorithmic reliance for understanding student learning patterns were raised by Farida and Sudibyo [125], who pointed to potential oversights in the nuanced and complex nature of individual learning experiences. The implementation of this method also necessitates careful consideration of privacy and handling of ethical data.

The application of k-means clustering to formative online assessments presents a nuanced avenue for enhancing higher education. While offering a blend of personalized learning experiences and data-driven decision-making, it also brings to light the complexities and ethical considerations involved in its implementation.

Chapter 3 - Methodology

3.1 Research Design

The purpose of this study to introduce a research methodology used to evaluate innovative scoring methods for formative assessments in online courses that can improve learning in higher education settings. This study aimed to determine how these methods can enhance learning outcomes in higher education settings, particularly in the context of the transition from face-to-face to online lectures. This study begins with an extensive literature review to establish a comprehensive theoretical framework. This review is instrumental in situating research within the existing academic landscape and identifying the critical gaps in this study. It serves two purposes: providing historical perspectives and shedding light on current trends in online formative assessments [127].

Following the literature review, this study adopts a predominantly quantitative research approach. This approach was chosen meticulously to facilitate empirical evaluation of the innovative scoring methods under study. This methodology includes several key statistical tools and techniques.

Comparative Analysis of Assessment Scores: This study involved a comparative analysis of formative assessment scores before and after the transition to online lectures, enabling an assessment of the impact of this shift.

Regression Analysis: To quantitatively determine how changes in lecture style (face-to-face vs. online) affect learning outcomes.

T-tests: These tests were employed to assess the statistical significance of the differences in the assessment scores across various sessions, particularly between 2019 and 2020.

Scatterplot Matrices and Descriptive Statistics: Utilized for detailed data exploration and visualization, aiding in understanding the nuances of the transition's impact.

K-means Clustering: This method is applied to categorize student performance based on their formative assessment scores. This study used the k-means algorithm with steps, including initialization, assignment, centroid update, and convergence checks, supplemented by the elbow method, to determine the optimal number of clusters.

This research set the stage for a comprehensive overview of the research design; data collection, analytic techniques, and ethical concerns were also the primary components of this study.

3.2 Research Questions

These research questions aim to represent the depth of study, from the effectiveness of new assessment methods to a detailed analysis of student performance using advanced techniques, and to consider the perspectives of key stakeholders in the educational process.

RQ1: How did the evaluation scores in formative assessments change between 2019 and 2020, given the shift from conventional to online instruction?

RQ2: How does the introduction of a new Four-Multiple Choice scoring system impact the efficiency of online formative assessments in higher education?

RQ3: In what ways do students and educators perceive the efficacy of the Four-Multiple Choice scoring method in terms of its application in online formative assessments within the context of higher education?

RQ4: How does connectivity and technological infrastructure influence the effectiveness of online learning?

RQ5: What is the student learning outcome performance in higher education using k-means clustering as an analytical method?

3.3 Data Collection

Data for this study were collected from formative assessments in the "Advanced Research and Development Strategies" course offered at the Graduate School of Innovation Science and Technology, Yamaguchi University, across two key academic years: 2019 and 2020. This period marks the transition from traditional to online teaching, enabling an analysis of its impact on student outcomes. The anonymized dataset safeguarding student privacy included comprehensive engagement metrics from 458 participants in 2019 and 443 participants in 2020, providing a robust basis for evaluating the effects of instructional changes on learning.

3.3.1. Assignment

The course saw a large enrollment, with approximately 500 students in 2016 and 2017, and roughly 250 students per quarter from 2018 onwards. This necessitated the adoption of an assessment method capable of efficiently grading a large number of students within a short timeframe. Given that the course content focused on R&D strategies, traditional testing formats such as calculations or direct comparisons were not suitable.

3.3.2 Test Item Analysis

Percentage of Correct Responses: This straightforward descriptive statistic is often represented as p. This was computed as the ratio of test-takers who answered an item correctly to the total number of test-takers. It provides an immediate understanding of item difficulty. A low p-value indicates a high difficulty level, whereas a high p-value indicates a lower difficulty level.

Item Variance: Mathematically represented as sigma squared, variance offers insight into the dispersion of scores on a particular item. These were calculated using a specific formula that considered the individual, mean, and total number of scores. A high variance suggests that test takers' performance on that item is spread out from the mean, indicating diverse levels of understanding or potential ambiguities in the item.

The formula:

$$\sigma^2 = \frac{\Sigma(x_i - \overline{x})^2}{N}$$

where x_i is the individual score, $\overline{x}$ is the mean score, and N is the total number of scores.

Point Biserial Correlation (r_pb): This is a special case of the Pearson product-moment correlation. It gauges the relationship between a test taker's performance on a single item and their performance on the test as a whole. The formula considers the means of the total scores for correct and incorrect answers, the standard deviation of the total test scores, and the proportions of correct and incorrect answers.

Formula:

$$r_{pb} = \frac{\overline{y}_1 - \overline{y}_0}{s_t} * \sqrt{\frac{pq}{N}}$$

Where are $\overline{y}_1$ and $\overline{y}_o$, the means of the total scores for those who answered the item correctly and incorrectly, $s_t$is the standard deviation of the total test scores, p is the proportion answering correctly, q is the proportion answering incorrectly.

Alpha Coefficient (Cronbach's alpha): Represented as alpha, this metric assesses the internal consistency of a test. It is computed using a formula that considers the number of items on the test, variance of individual items, and total test variance. A high alpha value suggests that the test items are interrelated and likely to measure the same underlying construct.

Formula:

$$\infty \frac{N\bar{C}}{\bar{u} - (N-1)\bar{C}}$$

where is $\bar{u}$ average variance of item, $\bar{C}$ average inter-item covariance between items and N number of items on the test.

3.3.3 Item Variance

Item variance is a statistical measure used to determine the spread of scores for a particular test item. In the context of four-choice questions, understanding item variance can provide insights into the discriminatory power of a question. Items with higher variance indicate a broader range of student performance, whereas items with low variance suggest that the question is either too easy or too difficult for the target group [128].

The present data and the variable code in Tables 3.1 and 3.2 are designed to systematically categorize data based on distinct parameters, such as year, quarter, individual, and module type. This organized structure facilitates efficient filtering, sorting, and querying of the dataset, ensuring streamlined data analysis and management.

Table 3. 1 The name lists of the dataset

Year	Campus	2nd Quarter	3rd Quarter
2019	Yoshida	RD2019_Q2_Yoshida	RD2019_Q3_Yoshida
	Tokiwa	RD2019_Q2_Tokiwa	RD2019_Q3_Tokiwa
2020	Yoshida	RD2020_Q2_Yoshida	RD2020_Q3_Yoshida
	Tokiwa	RD2020_Q2_Tokiwa	RD2020_Q3_Tokiwa

Table 3. 2 List the variable code for each lecture (2019 and 2020)

Year	Campus	2nd Quarter	3rd Quarter
2019	Yoshida	"B", "C", "F", "R", "K", "Q", "L"	"B", "C", "F", "R", "K", "Z", "Q"
	Tokiwa	"B", "C", "F", "R", "K", "Q", "L"	"B", "C", "F", "R", "K", "Z", "Q"
2020	Yoshida	"B", "C", "F", "R", "S", "L", "Q"	"B", "C", "F", "R", "S", "L", "Q"
	Tokiwa	"B", "C", "F", "R", "S", "L", "Q"	"B", "C", "F", "R", "S", "L", "Q"

Finally, the dataset in Table 3.3 provides a structured and organized way to view data sizes and counts for two individuals across different years, quarters, and categories. This format allows for easy comparison and analysis of data across these parameters.

Table 3. 3 The structure of Total dataset size

Campus		2019		2020	
All		2nd Quarter	3rd Quarter	2nd Quarter	3rd Quarter
Yoshida	Total	85	42	93	41
	4	28	28	24	26
	1	57	14	61	14
	2	0	0	0	1
Tokiwa	Total	194	137	174	135
	4	72	61	70	64
	1	120	76	98	66
	2	2	0	0	5

3.3.4 G-P Analysis

G-P Analysis (Goodman & Kruskal's predictive power) is a non-parametric measure of association used to determine how well a particular item predicts overall test performance. In formative assessment, it is useful for identifying items that are particularly good (or poor) indicators of overall mastery [129].

3.3.5 Factor Analysis

Factor analysis is a statistical method used to describe the variability among observed correlated variables in terms of a potentially lower number of unobserved variables called factors. For four-choice questions, factor analysis can be employed to determine the underlying dimensions measured by a set of items [130].

3.3.6 Spearman's correlation matrix

Spearman's correlation matrix is a non-parametric measure of association that assesses how well the relationship between two variables can be described using a monotonic function. Formative assessment can be used to analyze the relationship between students' performance on individual four-choice questions and other measures of their learning or ability [131, 132].

3.4 Analysis Methods

3.4.1 Regression Analysis

This method is pivotal for investigating the relationship between independent variables (such as lecture style and whether face-to-face or online) and the dependent variable (learning outcomes).

This involves the following formula:

$$y = a + bx + e$$

where y is the learning outcome, x represents the lecture style, a is the y-intercept, b is the slope, and e denotes the error term. This approach not only elucidates the relationship between these variables through regression coefficients and variance analysis, but also enables the prediction of future values of the dependent variable, thereby offering a comprehensive understanding of the dynamics between lecture styles and learning outcomes.

3.4.2 Performing a t-Test

The t-test is a statistical method used to assess whether there is a significant difference between the mean scores of the two distinct groups. This technique is particularly useful in educational research, such as in evaluating the impact of various Lecturer Formats on student performance. The t-test calculates the ratio of the difference between the group means to the pooled standard error of both groups [133]. This approach helps determine whether the observed differences in performance scores are statistically significant, indicating the effectiveness of different teaching methods.

The formula for the two-sample t-test (Student's t-test) is as follows:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

where, the data set are t, $\overline{x_1}$and $\bar{x}_2$ are the means of the two groups being compared, s^2 is the average standard error of the two groups, and n_1 and n_2 are the number of observations in each of the groups.

A higher t value indicates that the difference between the group means is greater than the pooled standard error, indicating a more significant difference between the groups.

Basic Hypotheses

The null hypothesis (H0) and alternative hypothesis (H1) of the Independent Samples t-test can be expressed in two different but equivalent ways:

- H0: μ1 = μ2 ("the sample mean from group 1 is not different from the sample mean from group 2")
- H1: μ1 ≠ μ2 ("the sample mean from group 1 is significant different from the sample mean from group 2")

In this study, to compare the using the Most of statistical software programs, including R, SPSS, Python, etc. come with an integrated t-test capability. This function calculates the t-value by processing the raw data. Subsequently, it compares the t-value with the critical value and determines the p-value.

3.4.3 Scatterplot Matrices and Descriptive Statistics

These tools are used for data visualization and summarization. Scatterplot matrices display relationships between multiple variables, whereas descriptive statistics such as mean and standard deviation provide a summary of the data [134].

3.5 Development of the New Scoring Method

The rationale behind the four multiple choice formats for the evolution of educational assessment methodologies has always been to refine the tools to better gauge a student's understanding and proficiency. Traditional Multiple-Choice Questions (MCQs), while effective in many respects, have occasionally faced criticism for potentially oversimplifying complex topics, leading to surface-level assessments [135].

The Four multiple choice format was conceived to address these concerns. By reducing the number of choices from the conventional five or six to four, each option can be made more competitive, compelling students to think critically and reducing the chances of random guessing [136]. Furthermore, this format acknowledges the nuances of the students' understanding. Instead of just recognizing the right answer, students must discern the most appropriate one from closely related options to ensure deeper cognitive engagement.

The new scoring method in this study for four multiple choices was tailored for efficiency and simplicity, particularly for online educational settings. This method employs Excel or Python for automation to streamline the scoring process. It works by directly comparing students' answers with their correct answers, ensuring a straightforward and precise assessment. This technique is highly beneficial for large-scale assessments because it allows quick and accurate grading without the need for complex computational methods. Unlike traditional MCQs, where a correct answer fetches full points and an incorrect one fetches zero or negative marks, the four-choice format demands a more nuanced scoring system [137].

The new scoring method is designed for efficiency and nuanced assessment, showing the expected Gaussian or normal distribution of scores.

The formula for the Gaussian distribution is as follows:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

Where:

f(x) is the probability density function

x is the variable

μ is the mean of the distribution

σ is the standard deviation

σ is the normalizing factor to make the total probability equal to 1

e is the base of the natural logarithm

3.6 K-means clustering Analysis

The k-means method divides a collection of N items into k clusters, each of which is represented by a centroid calculated as the mean of the objects in that cluster [138]. This algorithm is easy to use and converges rapidly to a local minimum. Calculations using the k-means algorithm primarily involve two key formulas: one for the assignment step and one for the update step.

3.6.1 Initialization of Centroids

The first step is to set k randomly selected data points as the initial centroids. These centroids represent the centers of the clusters.

The Formula:

There is a specific formula for this step: selection of random data points. If X represents the dataset, then the initial centroids are C = c1, c2…. ck are a subset of X.

3.6.2 Assignment Data Point Nearest Centroids

In this method, each data point is assigned to the nearest centroid. The nearest indicates the centroid with the smallest Euclidean distance from the data point.

The Formula:

The distance D between the data point x and centroid c is calculated using the Euclidean distance:

$$D(x,c) = \sqrt{\sum_{i=1}^{n} (x_i - c_i)^2}$$

where x_i and c_i represent the ith dimension of the data point and centroid, respectively, and n is the number of dimensions.

3.6.3 Update the Centroids

After all the data points are assigned to centroids, each centroid is updated to the mean of the points in its cluster. The new centroid c_j for the j cluster is calculated as

$$C_j = \frac{1}{|S_j|} \sum_{x \in S_j} X$$

where, S_j is the set of all data points assigned to the j the cluster, and $|S_j|$ is the number of data points in S_j.

3.7 Elbow method

The elbow searches for the best number of clusters using the k-means method. An illustration of the elbow method in conjunction with K-means clustering is represented by a graph that shows the relationship between the number of clusters (K) and the decrease in the error. As the value of K increases, the graph demonstrates a gradual decline in error, eventually reaching a point where the error reduction stabilizes, and the value of K becomes optimal.

The combined elbow and K-Means Methods can determine the value of K at the best cluster. k is determined as the typical number of clusters. This study used the elbow method to select the number of clusters k for grouping data in the K-means algorithm. The elbow method is represented through the Sum of Squared Error [119].

The formula:

$$SSE = \sum_{i=1}^{k} \sum_{x \in C_i} ||x - \mu_i||^2$$

Where:

k is the number of clusters

C_i is the set of all data points in the i cluster

x is a data point in cluster C_i

μ_i is the centroid of the i cluster

$||x-\mu_i||^2$ is the squared Euclidean distance between a data point x and the centroid μ_i of its cluster

Chapter 4 - Development of the New Scoring Method

4.1. Introduction

Amidst the global shift prompted by COVID-19, the education sector has witnessed a transformative leap towards digital technologies, marking a pivotal turn in the deployment of online formative assessments [139]. This era, characterized by the pandemic's extensive influence, catalyzed the integration of digital tools, overcoming the traditional constraints of time and location, thus enriching the educational landscape with high-quality, accessible learning resources. Within this digital revolution, the prominence of Multiple-Choice Questions (MCQs) in higher education has surged, underscoring their critical role in evolving educational paradigms.

The advent of online assessments, propelled by the necessity of adapting to remote learning environments, presents a dual-edged sword of opportunities and challenges for monitoring student advancement. Highlighted by recent scholarship, such as [140], these assessments offer immediate feedback and personalized learning paths catering to a broad spectrum of learners' needs. They foster heightened engagement and motivation, as noted by Upchurch et al. [141].

However, the imperative for timely, actionable feedback central to enhancing performance contrasts with the hurdles of ensuring equitable technological access and safeguarding academic integrity, as discussed by Beaudoin et al.[142] and Nguyen [143]. The debate on the efficacy of online versus traditional assessments continues, with

Shadnaz et al. [52] weighing in on the nuances of learning capture and advocating for the potential superiority of well-crafted online methodologies.

In essence, the discourse around online formative assessments, magnified in the wake of COVID-19's push towards digital education, reflects a complex landscape of innovation, adaptability, and persistent challenges. This underscores the need for ongoing exploration of their strategic implementation and effectiveness within diverse educational frameworks, emphasizing the enduring relevance of MCQs as a fundamental component in this digital transition.

4.2 The Characteristics of Multiple-Choice Question (MCQs) Format

The traditional Multiple-Choice Question (MCQ) format is a foundational tool in educational assessment, widely recognized for its ability to efficiently test a broad range of knowledge within constrained time frames. It presents a question with several potential answers from which students select the correct one. Brown et al., [144] note its effectiveness in offering immediate feedback, aiding both students and educators in quickly pinpointing areas of strength and knowledge gaps. This feature is particularly valuable in large-scale evaluations, where a quick analysis of student performance is crucial.

The MCQ format faces criticism for its emphasis on lower-order thinking skills such as recognition and recall, at the expense of higher-order cognitive skills such as application and critical analysis [145]. This limitation has led to calls for the inclusion of other types of questions, such as short answer and essay formats, which better assess a student’s ability to synthesize and critically evaluate information. Critics argue that an over-reliance on Multiple-Choice Question MCQs promotes a learning culture focused on memorization rather than deep engagement with the material, potentially leading to shallow learning outcomes where students prioritize rote learning over meaningful understanding [146]. The format's susceptibility to guessing further complicates the accurate assessment of comprehension, while also inadvertently prioritizing test-taking skills over actual knowledge application.

Concerns also extend to the format contributing to test anxiety and the tendency among students to focus on identifying tricks in questions rather than understanding the content deeply. Such practices detract from educational experience and challenge the validity of MCQs in measuring true understanding. In response, there is increasing support for a diversified approach to assessment, incorporating methods that engage critical thinking, analytical reasoning, and problem-solving skills to enrich learning experiences and promote deep understanding and application of knowledge [147].

Multiple Choice Questionnaires (MCQs) are pivotal in evaluating the learning outcomes of vast student demographics. In Japan, the Center Test, a nationwide standardized test featuring a mark-sensing system for high school students, stands as a testament to the widespread use of the MCQ format [97, 148]. MCQs also play a crucial role in the examinations of national medical practitioners, demonstrating their significance across diverse academic disciplines.

The A-type test, characterized by its five-choice format, requires examinees to select a single correct answer from five options [149]. This is the most fundamental structure of MCQ. Nonetheless, the effectiveness of this format in precisely gauging a respondent's skills, especially in specialized fields such as medicine, is somewhat limited. The combination of scores reflecting actual knowledge and those derived from guessing underscores the need for thorough reassessment. Consequently, Type A questions now represent only about 30% of all exam questions due to these concerns.

Type Simple 5-Choice Questions (Single Type):

(a) Option

(b) Option

(c) Option

(d) Option

(e) Option, with (e) sometimes being "None of the above."

To address the issue of guesswork owing to insufficient knowledge, multiple correct answers are required for certain questions. Additionally, to ease the workload for designing the questions and streamline the scoring process, a system employing answer codes was implemented.

K2 and K3 typologies necessitate the selection of multiple correct responses from a pre-established assortment of answer codes for each of the quintets of options presented. Specifically, the configuration that mandates a duo of selections is designated as K2 type, whereas the configuration that requires a trio of selections is denominated K3 type.

Type K2:

Select from two answer combinations (binary answer codes) of the five alternatives.

a. (1), (2)

b. (1), (5)

c. (2), (3)

and e. (4), (5).

Type K3:

Select three answers out of five choices from a combination (three-way answer code):

a. (1), (2), (3)

b. (1), (2), (5)

c. (2), (4), (5)

d. (2), (3), (4)

and e. (3), (4), (5)

To solve this specific issue, a K'-type question format was created. This format does not tell students how many answers are correct; it only provides a code for answering. According to Ohshima etal. [38] and Saito et al. [150], when students who usually get lower grades try a K'-type question (which has five choices), and they know one right and one wrong answer out of the five, they surprisingly have a 75% chance of scoring as much as 60 points. This occurs even if they understand only two of the five options.

However, the K'-type has a limitation because it uses a set number of answer codes, which in this case is five. This means that the answers were set up in such a way that some were always next to each other. Therefore, it was difficult for students to avoid guessing the correct answer if they did not understand all options well. Because of this problem, K'-type questions are not currently used in exams.

To compensate for the shortcomings of the question format, a format in which no answer code was provided was devised. This is called the Xn type, where n represents the number of answers to be selected [151]. Therefore, it is believed to offer a fairer evaluation of respondents' knowledge.

Type X2:

Select two of the following five options:

a. Option 1

b. Option 2

c. Option 3

d. Option 4

e. Option 5

Type X3:

Select three of the five options:

a. Option 1

b. Option 2

c. Option 3

d. Option 4

e. Option 5

Ikebukuro et al. [97] have contributed significantly to the ongoing research on optimizing the format of multiple-choice questions (MCQs), especially within the realm of medical licensing examinations. Their study investigated the ideal number of options per MCQ and the impact of different question types on assessment accuracy. Ikebukuro et al. pointed out a fundamental issue with traditional MCQs, which typically offer four options, with only one correct answer. This format, they argue, allows examinees to guess answers, potentially leading to what is known as "irregular scores."

To illustrate this point, Ikebukuro et al. provided an example of an MCQ designed to test examinees' understanding of the options presented to them. This example underscores two key insights: first, that the respondent needs to discern the "correct" option based on its description, and second, that there is invariably only one correct answer. However, they caution that an examinee lacking sufficient knowledge could still chance the correct answer, with a probability of 1/N (25% for four options), resulting in an irregular score.

The study further discusses strategies employed in medical licensing examinations to minimize the occurrence of irregular scores, such as complicating question structures and capping the proportion of simple MCQs to 30%, with the remainder being more complex. While these strategies are effective, they also increase the complexity, cost, and burden of question preparation. Ikebukuro et al. emphasize the necessity of designing MCQs across three cognitive levels recall, application, and analysis according to Bloom's taxonomy, which adds to the challenge, particularly for exams with a large number of participants [152]. This complexity necessitates additional measures, such as preparing reserve questions and implementing technological aids, to ensure a smooth examination process.

One notable issue identified by Ikebukuro et al. is the difficulty in distinguishing between candidates at knowledge levels 4 and 5 in MCQs that offer five options and allow for more than one correct answer. To address this, they proposed a novel questioning method that eschews the specification of the number of correct answers. This approach aims to discern between closely matched higher knowledge levels more accurately by reducing the likelihood of irregular scores and enhancing the precision of the assessments. This innovative questioning strategy, as outlined by Ikebukuro et al. (1999), seeks to refine the evaluation of examinees' knowledge and understanding, potentially offering a more nuanced and accurate measure of their capabilities.

4.3 Design Insights New Scoring MCQs Method

The literature review presented earlier highlights the notable limitations of traditional multiple-choice questions (MCQs), their focus on lower-order thinking skills, and their tendency to encourage only surface-level learning [102]. This critical oversight reveals a profound gap in current assessment methodologies, which do not adequately reflect the comprehensive understanding and complex thought processes of students.

This design focuses on Ikebukuro's questioning method. By not providing the number of correct answers, the percentage of irregular scores can be significantly reduced, even for simple multiple-choice questions. Therefore, we introduced an original scoring method that did not reveal the number of correct answers. This method can reduce the percentage of irregular scores to 4% when there are four options.

The new scoring system allows contestants to set the number of correct answers, which can range from 0 to 4. As the question text does not specify the number of correct answers, respondents (students) must rely on their judgment to select options. Scoring is determined by comparing the pattern of students' responses to the questioner's intended pattern of correct answers, thereby calculating the degree of agreement. This process of score calculation can be simplified to the task of comparing four-digit binary numbers.

For example, for the question:

Among the following options, select the ones that you think are correct: Please note that there may be more than one correct answer.

a. Option 1

b. Option 2

c. Option 3

d. Option 4

This passage discusses the challenges encountered when calculating the degree of agreement between student responses and correct answers using various distance metrics and Boolean algebra. As presented in Table 4.1, the methods of calculating "distance" based on definitions such as Euclidean, Manhattan, Chebyshev, Levenshtein, Hamming, and Mahalanobis were found to be inadequate for accurately determining the level of agreement between student responses and correct answers [33-37]. The sum-of-products calculation using Boolean algebra also failed to achieve the intended calculation. The mathematical formulas for calculating each type of distance are as follows:

Table 4. 1 The method of calculating "Distance"

Distance	**Description**	**Method of Calculation**	**Availability**	**Score**
Euclidean	the distance between two points is measured as the length of a line segment connecting them	$\sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$	x	x
Manhattan	the sum of the absolute differences of the coordinates of two points, measured along axes at right angles	(\sum_{i = 1}^{n}	x	x
Chebyshev	chessboard distance is the maximum absolute difference between coordinates of two points	(\max_{i}	x	x
Levenshtein	a string metric for measuring the difference between two sequences	Dynamic programming based on string lengths.	√	x

Hamming	between two strings of equal length	Count differing bits/characters.	√	x
Mahalanobis	the distance of the test point from the center of mass divided by the width of the ellipsoid in the direction of the test point	$\sqrt{(x-y)^T S^{-1} (x-y)}$, where S is the covariance matrix.	x	x
Boolean Algebra	the logical and function which Sums two or more Products to produce an output	Sum-of-products calculation not directly applicable.	√	x

These formulas provide a standard way to calculate the distance between points (or strings), depending on the context and application. The Levenshtein and Hamming distances are specifically used for strings (such as DNA sequences or words), whereas the others are generally used for points in a geometrical space. Based on the discussing different methods of calculating "distance" for scoring.

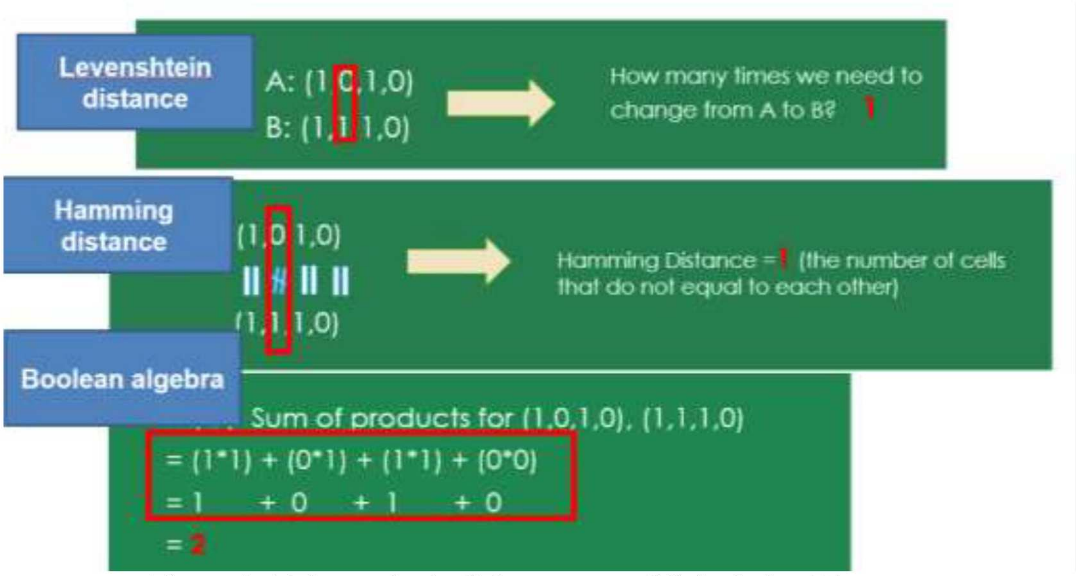


Figure 4. 1 The method of Three types of Calculating Distance

The Figure 4.1 presents three types of distances: Levenshtein distance, Hamming distance, and a calculation using Boolean algebra following each method:

Levenshtein distance:

This is a measure of the difference between two sequences (often strings).

The Levenshtein distance between two words is the minimum number of single-character edits (insertions, deletions, or substitutions) required to change one word into another.

On the slide, two sequences are shown, A and B. For A: (1, 1, 0) and B: (1, 0, 0), the Levenshtein distance is 1. This is because one edit is required (changing the second element from 1 to 0 in sequence A) to make the sequences identical.

Hamming distance:

This measures the number of positions at which the corresponding elements of two sequences of equal length are different.

In the example provided, A: (1, 0, 0) and B: (1, 1, 0) have Hamming distances of 1. This is because there is one position where the two sequences differ from the second element (A has 0 and B has 1).

Boolean algebra:

describes a "sum of products" using Boolean algebra. This is not a distance in the typical sense, but a method to evaluate a Boolean expression.

The provided expression is (1*1) + (0*1) + (1*1) + (0*0), where multiple likely represents the AND operation in Boolean algebra.

Evaluating this expression as follows:

1*1 = 1 (since both are true, the AND is true), 0*1 = 0 (since one is false, the AND is false),

1*1 = 1 (since both are true, the AND is true),

0*0 = 0 (because both are false, AND is false).

The sum of these products is 1 + 0 + 2 + 0 = 2

For those comparison algorithms, the traditional method of scoring MCQs awarding a point for a correct answer and none for an incorrect answer lacks nuance and fails to capture the degree of understanding or misunderstanding exhibited by the examinee. This binary approach does not consider the pattern of responses, which can provide deeper insights into the examinee's knowledge and reasoning process. To address this, a comparison algorithm was proposed. This algorithm compares the pattern of correct answers predetermined by the question-setter with the pattern of answers given by the student.

4.4 New Scoring System of MCQs (Four Option)

The concept of granularity in scoring refers to the level of differentiation in scoring based on the degree of agreement or disagreement between the correct answers and the student's answers. For a 4-choice question, five levels of scoring can be defined, ranging from perfect agreement (where all selected answers match the correct answers) to perfect disagreement (where none of the selected answers match the correct answers). This granularity not only allows for a more nuanced assessment of the student's understanding but also introduces a more sophisticated scoring system that goes beyond the binary correct-incorrect paradigm.

Therefore, in the case of Python language, the score calculation algorithm can be written as follows using the "where" function of the NumPy library the Python language can be used.

matches = np.where (a==x, 1, 0) (1)

ss = np.sum (matches) (2)

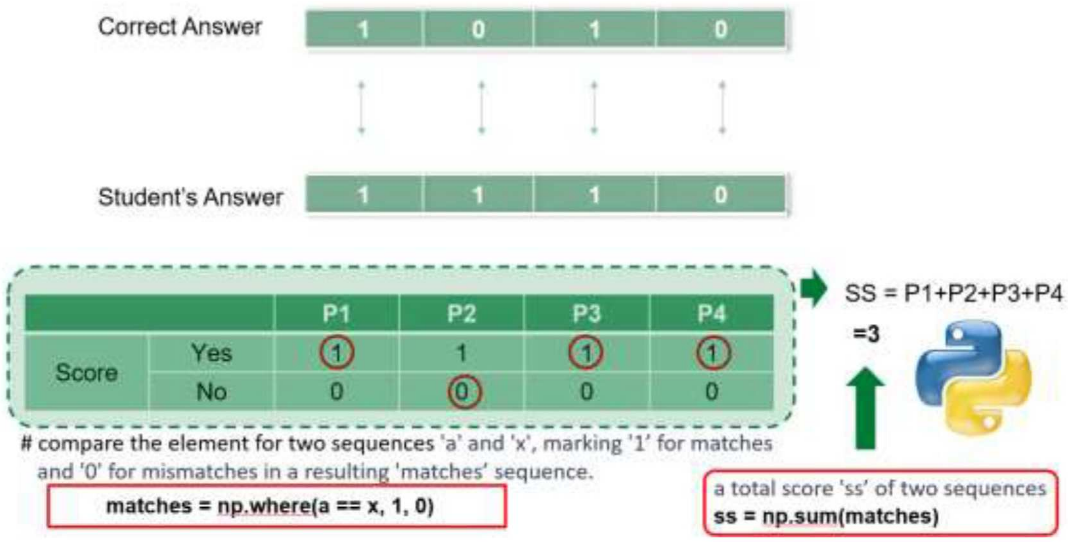


Figure 4. 2 The New System Scoring Calculation: Using Python Language

Figure 4.2 Show the demonstration of a scoring method using Python language. This method is used to compare a student's answers to the correct answers and calculate a score. Step-by-step explanation of the calculation:

Correct Answer: This array that represents the correct answers to a set of questions or items. In the image, the correct answers are represented as [1, 0, 1, 0].

Student's Answer: This another array that represents the student's answers to the same set of questions. The students' answers were [1, 1, 1, 0].

Comparison and Scoring:

A comparison was made elementwise between the two arrays. For each position, if the student's answer matched the correct answer, it was scored as 1; otherwise, it was scored as 0.

In the image, this is done using Python code np.where (a == x, 1, 0), where a is the array of correct answers and x is the array of the student's answers. np.where is a function from the NumPy library that returns elements chosen from either the second or third argument depending on the condition.

Score Calculation:

After the element-wise comparison, we obtain an array of 1s and 0s, where 1 represents a correct match, and 0 represents an incorrect match.

In the provided example, the matches would be [1, 0, 1, 1] (note that there seems to be an inconsistency here, as the last element should be 0 given the correct answer is 0 and the student's answer is also 0, but it's marked as 1 in the 'Score' row).

The total score (SS in the image) was then calculated by summing the elements of this comparison array. In Python, this is performed with np.sum (matches).

Based on the image, the score would be 3 (sum = 1+0+1+1), with the last element corrected, it should be 1+0+1+0 = 2.

The result is the score, which represents how many correct answers the student got from the total number of questions. The method of scoring MCQs using a comparison algorithm introduces a nuanced approach that captures the degree of understanding of the student more accurately than traditional methods. By defining granularity in scoring and generalizing the algorithm for any number of choices, this method offers flexibility and precision in assessment. In addition, the approximation of the scoring distribution by a Gaussian distribution for four-choice questions provides a theoretical foundation for analyzing test results and underscores the robustness of the proposed scoring method. This approach not only enhances the assessment of individual performance but also contributes to the broader field of educational measurement by offering a sophisticated tool for analyzing and interpreting test scores.

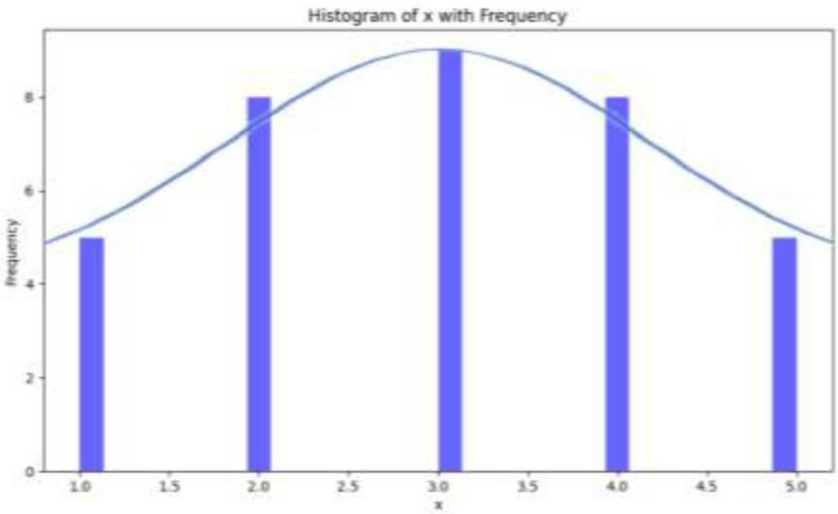


Figure 4. 3 Histogram Gaussian/normal Distribution

In Figure 4.3, to understand why the scoring distribution of the new MCQs scoring method approximates a Gaussian distribution, several factors such as First, the Law of Large Numbers suggests that as the number of MCQs increases, the average score across all examinees is likely to converge towards the mean of the population, demonstrating that the observed averages become more accurate with larger sample sizes. Second, the Central Limit Theorem posits that with a sufficiently large sample size, the distribution of scores will tend to be normal (Gaussian), irrespective of the underlying dataset's distribution. This is particularly pertinent when evaluating diverse populations of examinees with various levels of preparation, knowledge, and test-taking skills. Third, variability in examinee responses, driven by knowledge, guessing strategies, and misinterpretations, contributes to the spread of the Gaussian distribution. This variability results in some examinees performing above average because of higher knowledge levels or effective guessing strategies, and others performing below average, thus creating a score distribution with a characteristic bell shape. Finally, approximating a Gaussian distribution is profoundly significant for educational assessment, enabling the use of statistical methods to analyze test results, assess measures of central tendency and dispersion, identify outliers, compare different cohorts' performance, and evaluate the test's difficulty level.

Therefore, it can be stated that the continuous data from this new MCQ scoring method are not random but rather exhibit patterns that align with a normal distribution. The ability to test for normality within this distribution validates the precision and reliability of the scoring method, indicating a structured and predictable pattern in the data that underscores the method's robustness in accurately capturing examinee performance.

- **Granularity of Scoring**

The provided text outlines an educational scoring system where the variable "ss" represents the total score that students receive, which is derived from another variable "matches". This "matches" variable likely quantifies the extent to which each student's selected answers correspond to the correct answers predetermined by the instructor.

The scoring system was designed to assess the consistency of students' answers with the correct ones on a five-level grading scale. This scale ranges from "A," representing the highest consistency with the instructor's answers, down to "E," which indicates the lowest consistency. Such a grading system allows for a nuanced evaluation beyond the mere binary categorization of right or wrong, acknowledging varying degrees of partial understanding or correctness in student responses.

Detailed criteria for converting the "matches" into 5-point scale grades are specified in Table 4.2, Figure 4.4, 4.5 and Figure 4.6. This Table 4.1 would provide the benchmarks that define the score ranges corresponding to each of the letter grades. By employing this method, instructors can gauge student performance more accurately, offering a clear and structured grading approach.

Table 4. 2 Matrix shows the grading when the student selects all four options

				Number of Right Choice				
				0	**1**	**2**	**3**	**4**
Number of Selected answer by Student	**4**	**Number of Correct Choice**	**0**	E				
			1		D			
			2			C		
			3				B	
			4					A

The Agreement Degree Matrix for Correct Choice Number 4

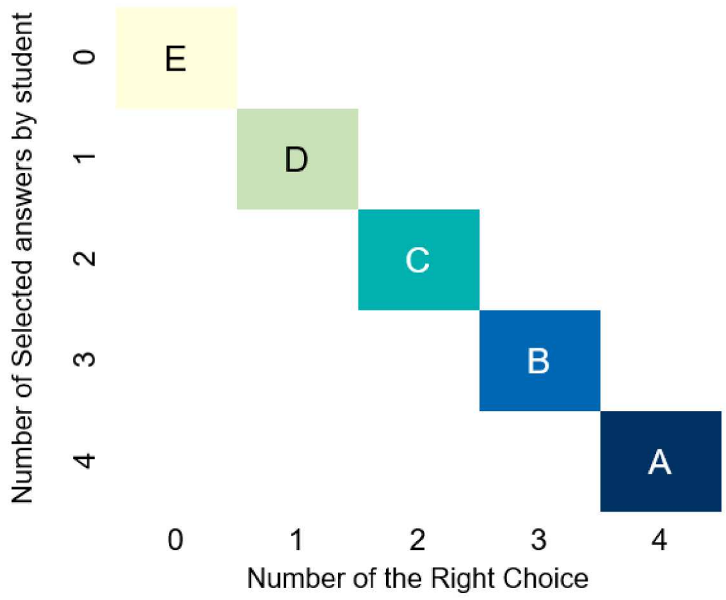


Figure 4. 4 The matrix that represents the agreement degree of the answer when the correct choice number is 4

The grade is displayed if the respondent chooses all four options, as shown in Figure 4.4. The x-axis represents the number of choices made by the contestant, and the y-axis represents the number of correct answers. The grades from 'A' to 'E' are used to denote the agreement degree. 'A' represents a perfect agreement (i.e., the contestant chose the correct number of options), while 'E' represents no agreement (i.e., the contestant did not choose any correct option).

Five possible grades were revealed if the respondent chose all four options.

(1) If the number of correct answers set by the contestant was four, 100% of the answers were correct. Grade A

(2) If the number of correct answers set by the contestant is 3, Correct answer rate 75%, Grade B

(3) If the number of correct answers set by the contestant is 2, Correct answer rate 50%, Grade C

(4) If the number of correct answers set by the contestant is 1, Correct answer rate 25%, Grade D

(5) If the number of correct answers set by the contestant is 0, the percentage of correct answers is 0%. Grade E

The Agreement Degree Matrix for Correct Choice Number 0

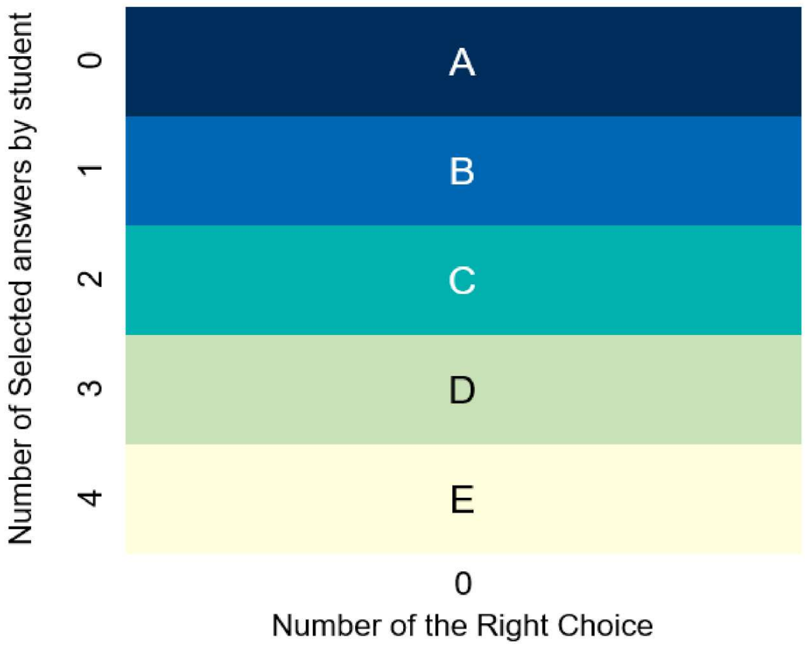


Figure 4. 5 The matrix that represents the agreement degree of the answer when the correct choice number is 0

Figure 4.5 also shows that none of the options were selected. Once again, the grade was determined by the participant's set of correct answers.

(1) If the number of correct answers set by the contestant is four, the percentage of correct answers. 0%. Grade E

(2) If the number of correct answers set by the contestant is 3, Correct answer rate 25% Grade D

(3) If the number of correct answers set by the contestant is two, the correct answer rate is 50%. Grade C

(4) If the number of correct answers set by the contestant is 1, Correct answer rate 75% Grade B

(5) If the number of correct answers set by the contestant is 0, 100% of correct answers Grade A

Agreement Degree Matrix for All Combinations of Respondent's Choice and Correct Answers.

Table 4. 3 Matrix of all combinations the number of the student selects choices (0-4) and the number of correct answers set by instructor (0-4)

Rating		Number of Right Choice				
Number of Selected Answer by Student	Number of Correct Choice	0	1	2	3	4
0	0	A	B	C	D	E
0	1					
0	2					
0	3					
0	4					
1	0	B	C	D	E	
1	1		A	B	C	D
1	2					
1	3					
1	4					
2	0	C	D	E		
2	1		B	C	D	
2	2			A	B	C
2	3					
2	4					
3	0	D	E			
3	1		C	D		
3	2			B	C	
3	3				A	B
3	4					
4	0	E				
4	1		D			
4	2			C		
4	3				B	
4	4					A

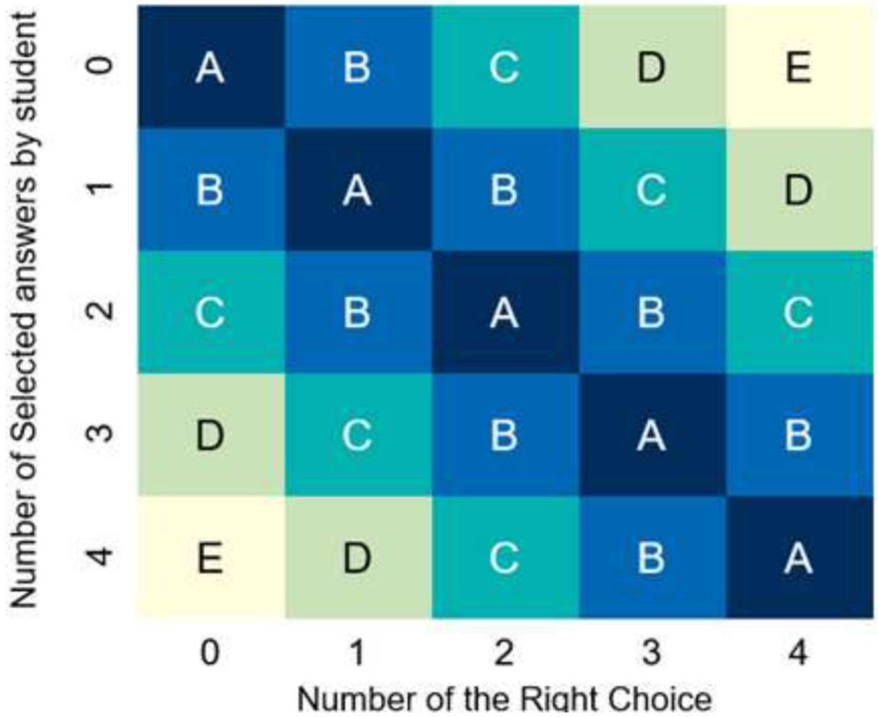


Figure 4. 6 Matrix of all combinations the number of the student selects choices (0-4) and the number of correct answers set by instructor (0-4)

Figure 4.6 shows the degree of agreement for each combination of correct answers and respondents' choices, and how well the two sets of answers match each other. In this figure, one set of answers is the choices made by a respondent (from 0 to 4), and the other set is the correct answer set by a contestant (from 0 to 4).

The scoring criteria for the four-choice tests in Table 11 are as follows:

Table 4. 4 Scoring Criteria for Four-Choice Tests

percentage of correct answers	**Note**	**Grading**
100 %	The student correctly selected the option that the instructor chose as the correct answer. This indicates a complete understanding of the material and conformity with the intended learning outcomes.	A
75 %	Three of the four options were correctly selected. This indicates a high level of substantive understanding but may have overlooked or misunderstood some important concepts.	B
50 %	Correctly selected two of the four options. I have a basic understanding of some concepts in the lectures, but also have significant gaps in my knowledge.	C
25 %	One of the four options was correctly selected. Only fragmented understanding. Most of the important concepts are not correctly understood.	D
0 %	Student choices did not match the faculty setting. Students were not able to fully extract relevant knowledge from the lecture.	E

The scoring criteria for this system are listed in Table 4.4. The four-option test featured a range of choices directly aligned with the lecturer’s material, without a specified number of correct answers. A multistep scoring system was employed to assess the degree of consistency between the students' selected answers and the correct answers intended by the instructor [11, 35, 38].

4.5 Discussion

In discussing the innovative scoring method for Multiple-Choice Questions (MCQs) introduced in this study, it is crucial to position the findings within the broader context of digital education's evolution, particularly in response to the global shift toward online learning catalyzed by the COVID-19 pandemic. This method, advancing beyond Ikebukuro's foundational work, represents a significant leap in assessing student knowledge by implementing a detailed five-level scoring mechanism for four-choice questions [97, 153]. This nuanced evaluation surpasses traditional binary scoring systems by rewarding not only correctness but also the degree of alignment with expected answers, thereby capturing a more comprehensive picture of student understanding.

The development of this scoring system is both timely and relevant. As online formative assessments become increasingly prevalent, the need for assessment tools that can accurately measure student learning and understanding has become paramount [18]. This system's ability to provide a more granular assessment of student responses offers a compelling advantage over existing methods. It aligns with contemporary educational paradigms that prioritize critical thinking and the application of knowledge over rote memorization.

Moreover, the study's approach to scoring MCQs, by not revealing the number of correct answers, significantly reduced the percentage of irregular scores. This reduction is crucial for maintaining the integrity of assessments and ensuring that scores accurately reflect students' knowledge and understanding [12]. By offering partial credit to answers that partially match the instructor's intended answers, the method acknowledges the complexity of learning and recognizes that partial understanding is a valuable step in the learning process.

The theoretical and practical implications of this scoring method extend beyond the immediate context of MCQ assessments [147]. This finding underscores the importance of aligning assessment methods with educational goals and learning outcomes. Traditional assessments often fail to capture the nuances of students' understanding, leading to a skewed representation of their knowledge [34]. In contrast, this new scoring system facilitates a more accurate and fair evaluation of student performance, thereby supporting a more effective and responsive educational process.

Furthermore, the method's emphasis on granularity in scoring reflects a deeper understanding of learning as a multifaceted process. It acknowledges that learning is not binary but exists on a spectrum. This recognition is crucial in designing assessments that are not only fair but also diagnostic, providing valuable feedback to both students and instructors about areas of strength and weakness.

In conclusion, the development of this new scoring system for MCQs marks a significant advancement in educational assessment practices [98, 154]. By addressing the limitations identified in previous approaches and providing a more nuanced evaluation of student performance, this method enhances the quality and effectiveness of online formative assessments [155]. This contributes to the advancement of educational practice and outcomes, emphasizing the need for assessment tools that are not only accurate and comprehensive but also aligned with the goals of contemporary education [155, 156]. This innovative approach represents a step forward in realizing the potential of digital education to foster deep learning and understanding among students.

Chapter 5 – A Advanced Course of R&D Strategy Analysis

5.1 Introduction

The COVID-19 pandemic has precipitated global disruption, compelling a significant transformation of the education sector. This upheaval required the rapid adaptation of teaching methodologies and learning environments worldwide. In anticipation of evolving educational demands, particularly within the fields of science and engineering, Yamaguchi University embarked on a pioneering initiative in FY2016 by establishing the Graduate School of Frontier Sciences. This strategic move aimed to integrate the Graduate School of Engineering, Graduate School of Science, and Graduate School of Agricultural Science into a cohesive educational ecosystem. A key component of this integration was the introduction of the Theory of Research and Development Strategy course. This interdisciplinary program, mandatory for all first-year graduate students at the Graduate School of Frontier Sciences, is designed to equip professionals with the skills necessary to navigate and lead in rapidly changing technological and business contexts, underscoring the university's commitment to innovation and forward-thinking education [157].

Recognizing the imminent need for adaptable learning modalities, Yamaguchi University has integrated digital technology into its educational framework. They implemented an advanced remote-learning system utilizing H.264 codecs to establish a hybrid instructional model that bridged classrooms across campuses [158]. This infrastructure facilitates the live broadcast of classroom activities and presentations and offers a comprehensive educational experience that transcends geographical barriers. The deployment of on-premises conferencing equipment such as SONY PCS-XG77 and PCS-XG100 supports the fusion of in-person and remote learning [158, 159].

The 2019 pandemic necessitated a complete transition to online education to mitigate the risk of viral transmission. Embracing cloud-based conferencing services such as ZOOM and Webex, the university transitioned the delivery of the R&D Strategy Theory course to a fully online format from FY2020. This shift from a hybrid to a purely online instructional model represented a significant pivot in the university's educational strategy during the crisis [140].

The primary aim of this study was to assess the impact of this transition to online learning on student performance outcomes by comparing formative learning assessments from the hybrid model of FY2019 with those from the fully online format of FY2020. In doing so, this study seeks to explore the effectiveness of online learning environments in preserving educational quality amidst global disruptions, emphasizing the need for flexible education strategies and efficient online learning systems to navigate pandemic-related challenges.

Moreover, this research endeavors to examine the broader implications of online learning system implementation on students. Evidence categorized into different research streams suggests varied impacts: the first underscores the negative effects linked to the digital divide and network infrastructure inadequacies, which can also adversely affect students' mental health; the second stream posits the high efficacy of online learning systems; the third suggests a moderately negative impact on students; and the fourth and fifth streams focus on the positive impacts on educators, highlighting the correlation between faculty ICT literacy and online learning effectiveness. This multifaceted analysis concludes that traditional face-to-face learning outperforms hybrid models, which are more effective than exclusive online learning. Consequently, enhancing ICT literacy among faculty has emerged as a critical factor for the success of online learning systems, pointing towards the need for targeted development efforts in this area.

5.2 History Advanced Course of Research and Development Strategy

Through its evolutionary teaching formats, ranging from traditional face-to-face sessions to hybrid and fully online modes, the Advanced Course of Research and Development Strategy charts the historical progression of educational delivery methods at Yamaguchi University. This diversification reflects a strategic response to the changing landscape of higher education and its impact on students' learning outcomes. By examining the course's adaptation over the years, we gained insight into the university's commitment to leveraging technology and pedagogical innovation to enhance its academic excellence.

Established in FY2016, Yamaguchi University's Graduate School of Frontier Sciences represents a pivotal moment in the institution's history, embodying an interdisciplinary strategy that merges Engineering, Science, and Agricultural Science. This approach is not just about broadening the academic horizon; it is a deliberate effort to cultivate a learning environment that sparks innovation and equips students with versatile R&D skills for research and development. The Advanced Course, as a cornerstone of this educational model, plays a critical role in preparing students to navigate and contribute to a rapidly evolving scientific landscape.

Annually, attracting around 400 students, the Advanced Course underscores its significance and appeal in the university's curriculum. Operating on a quarter system featuring 180-minute classes, the course's structure was meticulously designed to cover comprehensive modules in an intensive format. With admissions in both spring and fall, the course offers flexibility and accessibility, catering to students' diverse scheduling needs. This operational strategy highlights the university's dedication to providing a dynamic and impactful learning experience.

Table 5. 1 Description of the Advanced Course of Research and Development Strategy Theory course

Year	Method	Schedule
2016	Face to Face and Remote Tele meeting (Hybrid)	2^{nd} Quatre
2017	Face to Face and Remote Tele meeting (Hybrid)	2^{nd} Quatre
2018	Face to Face and Remote Tele meeting (Hybrid)	2^{nd} and 3^{rd} Quatre
2019	Face to Face and Remote Tele meeting (Hybrid)	2^{nd} and 3^{rd} Quatre
2020	Full online	2^{nd} and 3^{rd} Quatre
2021	Full online and trial for Hyflux operation	2^{nd} and 3^{rd} Quatre
2022	Full online	2^{nd} and 3^{rd} Quatre
2023	Full online	2^{nd} and 3^{rd} Quatre

As a mandatory component for students enrolled at the Graduate School of Soka Kagaku, in Table 5.1, the description of the Advanced Course of Research and Development Strategy Theory course exemplifies strategic curriculum integration across the Yamaguchi University campus. Lectures are held at the Tokiwa Campus for Engineering students and at the Yoshida Campus for those in Science and Agricultural Science, utilizing a sophisticated remote lecture system to bridge geographical gaps. This logistical arrangement not only facilitates interdisciplinary learning but also reflects a strategic approach to making advanced research and development education accessible to all students, regardless of their field of study or physical location.

5.2.1 Remote Lecture System

The remote lecture system at Yamaguchi University relays lectures using an on-premises conferencing system in the case of Yamaguchi University, SONY PCD-80, installed in a specific classroom at each campus [158]. The on-premises conferencing system is capable of simultaneously transmitting and receiving camera images in the full view of the classroom in a zoomed view of the lecturer and computer screens [160]. Each classroom was equipped with two large screens so that the camera image and computer screen were projected onto each screen.

5.2.2 Structure of the Lecturer Each subject

First, the composition and evolution of this subject are described, and Table 5.2 present the Alphabet name of the lecturer for each subject from 2018 to 2022, and sometimes the lecturer might change in some subjects.

Table 5. 2 Lecturer each subject for the Advanced Course of Research and Development Strategy

2018		**2019**		**2020**		**2021**		**2022**	
On-Site		**On-Site**		**On-Line**		**On-Line**		**On-Line**	
Q2	**Q3**	**Q2**	**Q3**	**Q2**	**Q3**	**Q2**	**Q3**	**Q2**	**Q3**
B	B	A, G	A, G	A	A	A	A	A, B	A, B
C	C	B	B	B	B	B, T	B, T	C	C
K	K	C	C	C	C	C	C	T, W	T, W
L	G	F	F	F	F	U	U	W	W
P	R	R	R	R	R	R	R	R	R
I	Q	K	K	S	S	S	S	S	S
F	F	L	Z	L	L	V	V	X	X
A	A	Q	Q	Q	Q	F	F	F	F

5.2.3 The Year 2016 and 2017

In the first and second years, the course was offered only in the second quarter. Since the course is offered in quarters, there are two sessions of 180 minutes per day and one session of 90 minutes. In the omnibus format, the course consisted of two lectures per class day, with one lecture teaching each session in Table 5.3, showing the starting arrangement and lecture outline for 2016. The course schedule for 2017 was similar to that for 2016.

Table 5. 3 Lecturer assignment and lecture outline for the Advanced Course of Research and Development Strategy in 2016

Class Schedule	Session	Lecturer	Outline
Day 1st	1st	Lecturer A	The necessity of R&D for companies and the relationship between "science and technology" and "R&D" will be explained. In addition, issues related to the organization and human resources to conduct R&D will be presented.
	2nd	Lecturer B	After an overview of the meaning of strategy from the perspective of business administration, the main issues in Advanced Course of R&D Strategy formulation will be understood. Then, using the case of P&G, the relationship between innovation and R&D will be strategically examined.
Day 2nd	1st	Lecturer C	Overseas Advanced Course of R&D Strategy(1) The current status and strategy of R&D in Indonesia, Thailand, and Malaysia will be explained.
	2nd	Lecturer C	Overseas Advanced Course of R&D Strategy(2) The current status and strategies of R&D in Vietnam and India will be explained.
Day 3rd	1st	Lecturer D	Advanced Course of R&D Strategy in IT Field Explanation of R&D trends in digital business utilizing big data, AI, and IoT, and their impact on existing industries.
	2nd	Lecturer E	Advanced Course of R&D Strategy for Bio-based Ventures, this lecture will outline the transition of the bio-based software market, barriers to entry, and capabilities required of players (algorithmic imagination and coding speed), and will discuss the significance of starting a business in an advanced technological field and the risk

			management, value creation, customer satisfaction, and social responsibility required for ongoing operations.
Day 4th	1st	Lecturer F	Advanced Course of R&D Strategy in the Chemical Field History of the Japanese chemical industry, current trends, and Advanced Course of R&D Strategy of chemical companies will be discussed.
	2nd	Lecturer G	Advanced Course of R&D Strategy in the Automotive Field Research strategies in the automotive field from the viewpoints of research strategy planning, management, industry-academia collaboration, etc.
Day 5th	1st	Lecturer H	Advanced Course of R&D Strategy in the Pharmaceutical Field This lecture will introduce the operations of pharmaceutical companies and discuss the characteristics of their R&D activities, the history of their R&D activities up to the present, and future developments.
	2nd	Lecturer I	Advanced Course of R&D Strategy in the Food Field. The lecture will provide an overview of the characteristics of product development in the food field and points to keep in mind, while reading each company's Advanced Course of R&D Strategy from the product lineups and market shares of dairy companies.
Day 6th	1st	Lecturer J	R&D in the High-Tech Field Semiconductor devices (miniaturization, three-dimensional structure, diversification of materials), semiconductor manufacturing equipment (plasma etching equipment, etc.), and semiconductor evaluation equipment (electron beam evaluation equipment, etc.) will be described. The importance of stable production of cutting-edge technologies at the mass production level and the relationship between manufacturing and evaluation equipment for this purpose will be shown.
	2nd	Lecturer K	Advanced Course of R&D Strategy in the Social Infrastructure Field Starting with the history of technology centered on air conditioning technology, the relationship between human health and comfort, productivity, manufacturing processes, and global environmental issues will be explained, including how it is viewed, future issues, and R&D strategies.
Day 7th	1st	Lecturer L	Advanced Course of R&D Strategy in the IoT Electronics and Semiconductor Industries

			The latest trends in the Internet of Things (IoT) will be examined in the context of the semiconductor industry as a whole, and the nature of research and development for both miniaturization and 3D semiconductor devices, which form the backbone of the IoT, will be discussed, as well as strategies for improving international competitiveness.
	2nd	Lecturer M	Advanced Course of R&D Strategy in the Biotechnology Field This session will outline research on the functions of the multifunctional milk protein "lactoferrin" and research strategies for the development of functional food products based on this protein.
Day 8th	1st	Lecturer N	Summarization
	2nd	Lecturer N	Final Examination

The two lecturers conducted their lectures in person in a room at the Tokiwa Campus. These lectures were then transmitted to the classrooms at Yoshida Campus using an intramural remote Lecturer System.

5.2.4 The Year, 2018

In 2018, there were significant changes in the Lecturer Schedule and overall course structure. The number of lecturers per Lecturer Day was reduced from two to one, and the time allotted to each lecturer was increased from 90 min (one session) to 180 min (two sessions). In 2016 and 2017, some lecturers ran out of time, leading the extended lectures. When the first lecturer went over time, the available Lecturer Hours for the second lecturer were reduced. If the second lecturer could not conclude by the scheduled end time, the class had to be abruptly terminated, even in the middle of the lecture. Feedback from students indicated a desire for longer lecture times and an end to abrupt termination. This feedback was a factor in the decision to reduce the number of lecturers to one per day.

Furthermore, the course was offered twice per year, once in the second quarter and once in the third quarter. As the students attending each quarter were different, the same content was delivered in both lectures. This course is mandatory for the Graduate School of Frontier Sciences at Yamaguchi University. Fourth-year undergraduate students planning to enter a master's program can also take the course in advance. With enrollment exceeding 400 students, the administrative tasks (attendance, report management, grading, etc.) for the course were handled by a single instructor. By offering the course twice, the number of students per class was halved, thereby reducing the instructor's workload. Table 5.4 details the lecturer assignment in 2018.

Table 5. 4 Details the lecturer assignments for 2018

2018 On-Site	2^{nd} (1^{st} Semester)	3^{rd} (2^{nd} Semester)
Day 1^{st}	Lecturer A(Yamaguchi Univ.)	Lecturer A(Yamaguchi Univ.)
Day 2^{nd}	Lecturer B(Yamaguchi Univ.)	Lecturer B(Yamaguchi Univ.)
Day 3^{rd}	Lecturer G	Lecturer G
Day 4^{th}	Lecturer H	Lecture O(Yamaguchi Univ.)
Day 5^{th}	Lecturer M	Lecture P
Day 6^{th}	Lecturer E	Lecturer Q
Day 7^{th}	Lecturer L (Yamaguchi Univ.)	Lecturer L (Yamaguchi Univ.)
Day 8^{th}	Lecturer N (Yamaguchi Univ.)	Lecturer N (Yamaguchi Univ.)

5.2.5 The Year 2019 to 2022

Lecturer Assignments for 2019 through 2022 are shown in Tables 5.5-5.8. Lectures in 2019 were offered in a hybrid format with face-to-face lectures and remote relay; due to the corona disaster in late 2019, the Lecturer Format was shifted entirely online, beginning in 2020.

Table 5. 5 Instructor Assignment Table for 2019

2019 On-Stie	2nd (1st Semester)	3rd (2nd Semester)
Day 1st	Lecturer N and Lecture O (Yamaguchi Univ.)	Lecturer N and Lecture O (Yamaguchi Univ.)
Day 2nd	Lecturer A(Yamaguchi Univ.)	Lecturer A(Yamaguchi Univ.)
Day 3rd	Lecturer B(Yamaguchi Univ.)	Lecturer B(Yamaguchi Univ.)
Day 4th	Lecturer L (Yamaguchi Univ.)	Lecturer L (Yamaguchi Univ.)
Day 5th	Lecture P	Lecture P
Day 6th	Lecturer G	Lecturer G
Day 7th	Lecture H	Lecture P
Day 8th	Lecturer Q	Lecturer Q

Table 5. 6 Lecturer assignment table for 2020

2020 On-line	2nd (1st Semester)	3rd (2nd Semester)
Day 1st	Lecturer N (Yamaguchi Univ.)	Lecturer N (Yamaguchi Univ.)
Day 2nd	Lecturer L (Yamaguchi Univ.)	Lecturer L (Yamaguchi Univ.)
Day 3rd	Lecturer B(Yamaguchi Univ.)	Lecturer B(Yamaguchi Univ.)
Day 4th	Lecturer L (Yamaguchi Univ.)	Lecturer L (Yamaguchi Univ.)
Day 5th	Lecture P	Lecture P
Day 6th	Lecturer S	Lecturer S
Day 7th	Lecture P	Lecture P
Day 8th	Lecturer H	Lecturer H

Table 5. 7 Lecturer Assignment Table for 2021

2021 Online and Trial for Hyflex	2nd (1st Semester)	3rd (2nd Semester)
Day 1st	Lecturer N (Yamaguchi Univ.)	Lecturer N (Yamaguchi Univ.)
Day 2nd	Lecturer A(Yamaguchi Univ.)	Lecturer A(Yamaguchi Univ.)
Day 3rd	Lecturer B(Yamaguchi Univ.)	Lecturer B(Yamaguchi Univ.)
Day 4th	Lecture T	Lecture T
Day 5th	Lecture P	Lecture P
Day 6th	Lecturer S	Lecturer S
Day 7th	Lecture U	Lecture U
Day 8th	Lecturer L (Yamaguchi Univ.)	Lecturer L (Yamaguchi Univ.)

Table 5. 8 Lecturer Assignment Table for 2022

2022 Online	2^{nd} (1^{st} Semester)	3^{rd} (2^{nd} Semester)
Day 1^{st}	Lecturer N and Lecturer A (Yamaguchi Univ.)	Lecturer N and Lecturer A (Yamaguchi Univ.)
Day 2^{nd}	Lecturer B(Yamaguchi Univ.)	Lecturer B(Yamaguchi Univ.)
Day 3^{rd}	Lecture V and Lecture W	Lecture Vand Lecture W
Day 4^{th}	Lecture W	Lecture W
Day 5^{th}	Lecture P	Lecture P
Day 6^{th}	Lecturer S	Lecturer S
Day 7^{th}	Lecturer I	Lecturer I
Day 8^{th}	Lecturer L (Yamaguchi Univ.)	Lecturer L (Yamaguchi Univ.)

The course has changed instructors from year to year, and the structure of the classes has been refined to the present. A comparison of the structure of the classes in 2019 and 2020 shows that for these two years only, the classes were conducted with almost the same structure. In addition, the teaching style in 2019 was pre-Corona Disaster, and in 2020, the teaching style was shifted to fully online. The results of the formative evaluation of these two years were compared to examine whether the shift to fully online has had an impact.

5.3 Analysis Impact of New Scoring Methods in Multiple-Choice Assignments

To explore innovative scoring methodologies in educational assessments, this study delves into a compelling case study at Yamaguchi University. By scrutinizing data from the online course titled "Research and Development Strategy Theory," collected over the academic years of 2019 and 2020, this research aims to shed light on the effects of transitioning from traditional face-to-face instruction to online formats. The data encompass scores from formative assessments, student attendance records, and self-reported achievement of learning objectives, thereby offering a multifaceted view of their impact on student learning experiences and performance metrics.

The course under examination was offered biannually, featuring eight lectures for each term, with each session extending for 180 minutes. The culmination of these sessions was an online formative assessment consisting of three multiple-choice questions. Uniquely, these questions did not specify the number of correct answers, prompting students to discern the most applicable answers from the Lecturer Content. The grading scheme ranged from "A" to "E," reflecting how closely the students' choices aligned with the lecturers' intended answers, thereby generating a detailed scorecard for each student across both study years.

A noteworthy aspect of this study is the scoring methodology employed, which allowed for a range between 0 and 4 correct options, as determined by the lecturer. This method challenged students to engage in critical thinking because the lack of specified correct answers required them to judge the relevance of each option. To accurately assess the congruence between student selections and correct answers, a specialized scoring algorithm was developed. Traditional distance measures, including Euclidean, Manhattan, Chebyshev, Levenshtein, Hamming, and Mahalanobis, were deemed unsuitable for this analysis. Similarly, a Boolean algebraic sum-of-products calculation failed to capture nuanced agreement levels effectively. Consequently, a custom scoring algorithm was crafted in Python, utilizing the "where" function from the Numpy library to precisely evaluate the degree of alignment between students' responses and expected answers.

matches = np.where (a==x, 1, 0)   (1)

ss = np.sum (matches)   (2)

The subsequent analysis will delve into the comprehensive dataset cleaning process for "The Advanced Course of Research and Development Strategy Theory" and the construction of models tailored to each data category. Table 5.9 illustrates the dataset sizes for each quarter of "The Advanced Course of Research and Development Strategy Theory," providing a foundation for further discussion on the implications of these innovative scoring methods.

Table 5. 9 The size of dataset for analysis

		2019		2020	
WRT		2nd Quarter	3rd Quarter	2nd Quarter	3rd Quarter
Yoshida	Total	43	22	62	30
	4	16	14	17	22
	1	27	8	41	7
	2	0	0	4	1
Tokiwa	Total	110	79	135	100
	4	47	34	53	45
	1	63	45	78	51
	2	0	0	4	4

MCQ		2nd Quarter	3rd Quarter	2nd Quarter	3rd Quarter
Yoshida	Total	53	22	72	30
	4	19	14	20	22
	1	34	8	48	7
	2	0	0	4	1
Tokiwa	Total	135	80	128	97
	4	52	35	53	44
	1	83	45	71	49
	2	0	0	4	4

5.3.1 Data Exploration Analysis

This section outlines the initial exploration of data from the Webex platform for the Advanced Course of Research and Development Strategy Theory, involving approximately 400 students annually. The process involves:

- Utilizing Data Visualization Techniques: To identify patterns and trends in student performance data.
- Standardization of Scores: Essential for comparing variables across the dataset to ensure uniformity and accuracy in the analysis.
- Selective Presentation of Results: Focusing on findings that directly contribute to our research objectives, particularly those that might influence model development.

Pair plots were used to visually compare variables before and after standardization, aiding in the identification of underlying structures within the data. This preliminary analysis is crucial for preparing the dataset for a more detailed examination and potential future analytical methods.

Quater2: Admitted in spring (2019)

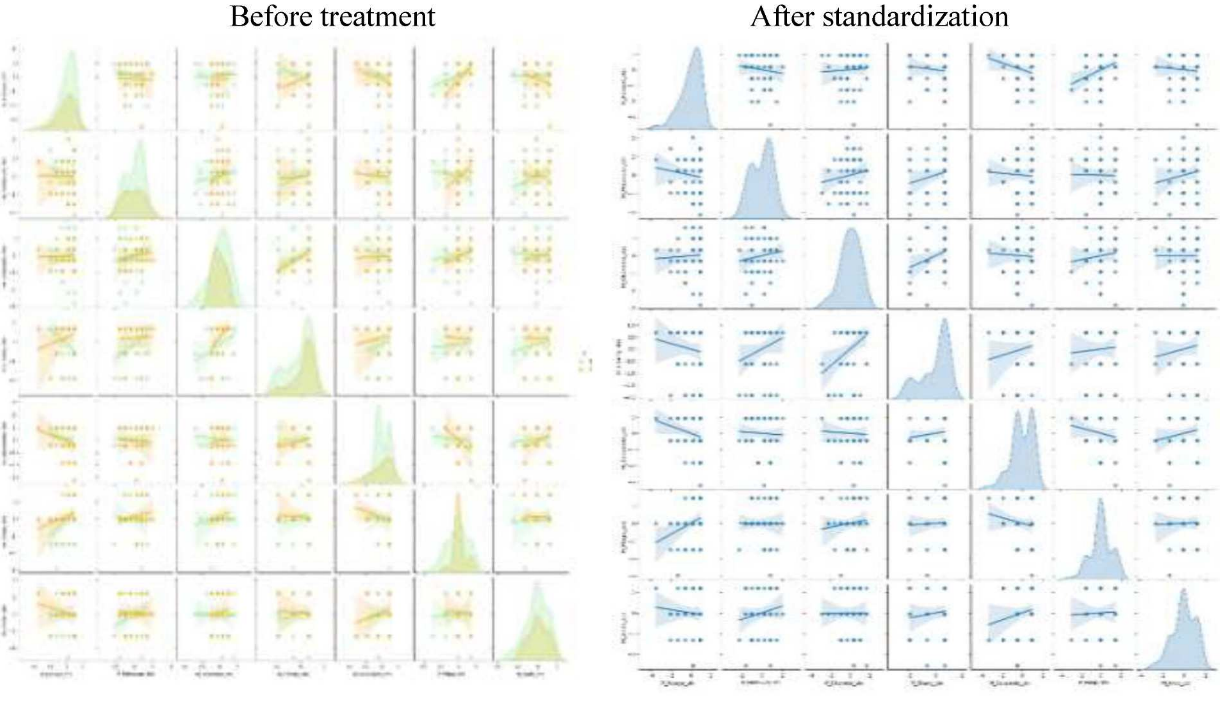


Figure 5. 1 rem0_RD2019_Q2_Yoshida_MCQ_stn

Table 5. 10 The Standardized Performance Scores Students Across Different Lectures on Yoshida_Q2 in 2019

index	SN	Y	Student ID	Lecturer B	Lecturer C	Lecturer F	Lecturer R	Lecturer K	Lecturer Q	Lecturer L
count	53	53	53	53	53	53	53	53	53	53
mean	40.4717	2.075472	1851152589	-3.79E-16	4.45E-17	9.95E-17	9.87E-16	-1.84E-16	-2.68E-16	-5.77E-16
std	25.90115	1.452439	182323828.5	1.009569596	1.009569596	1.009569596	1.009569596	1.009569596	1.009569596	1.009569596
min	1	1	1522030610	-3.513325506	-2.137315889	-2.830867879	-1.917903934	-3.219057124	-2.940625948	-2.546999805
25%	16	1	1622030701	-0.545895198	-0.951161521	-0.287884869	-0.6147128	-0.444910334	-0.027482485	-0.047166663
50%	39	1	1988010134	0.195962379	0.234992846	0.347860883	0.688478335	-0.444910334	-0.027482485	-0.047166663
75%	62	4	1988020041	0.937819956	0.8280703	0.983606636	0.688478335	0.942163061	-0.027482485	1.202749908
max	85	4	1988020408	0.937819956	2.014224398	1.619352389	0.688478335	0.942163061	1.429089246	1.202749908

The data provided in Table 5.10 and Figure 5.1 represent the performance of students in two types of assessments, which are both multiple-choice questions with four options, across various lectures. The data consisted of the performance scores of 53 students, which were standardized across all lectures, as evidenced by the mean values being close to zero and the standard deviations being close to one. Standardization of the scores allowed for a comparison of performance across different lectures. The scores for each lecture varied within a specific range. For instance, in Lecturer B's lecture, the standardized scores ranged from approximately -3.51 to 0.93, and in Lecturer C's lecture, the range was roughly between -2.14 and 2.01, with similar ranges observed in the other lectures. This table enables a comparison of student performance in different lectures using a common scoring system.

Before treatment After standardization

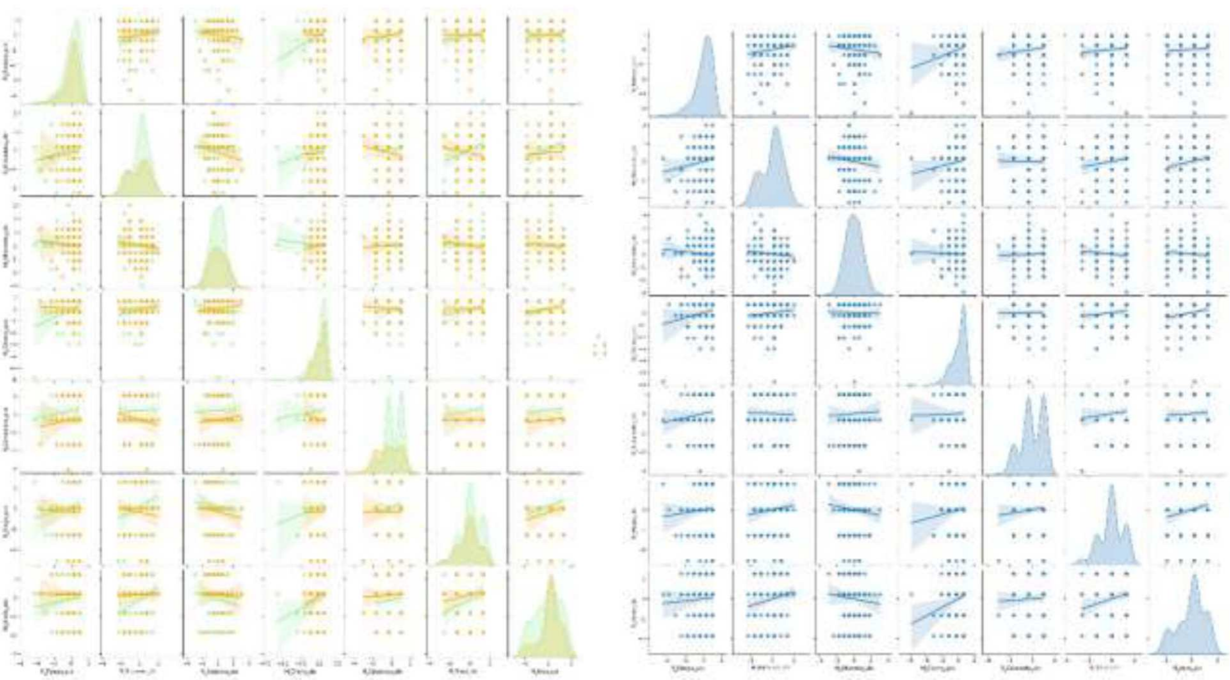


Figure 5. 2 rem0_RD2019_Q2_Tokiwa_MCQ_stn

Table 5. 11 The Standardized Performance Scores Students Across Different Lectures on Tokiwa_Q2 in 2019

index	SN	Y	Student ID	Lecturer B	Lecturer C	Lecturer F	Lecturer R	Lecturer K	Lecturer Q	Lecturer L
count	135	135	135	135	135	135	135	135	135	135
mean	95.48148148	2.155555556	1851923326	-2.57E-16	-3.22E-16	-5.58E-16	-7.30E-16	-3.95E-17	1.45E-16	-1.05E-16
std	54.78109106	1.465354456	173749813.1	1.003724408	1.003724408	1.003724408	1.003724408	1.003724408	1.003724408	1.003724408
min	2	1	1625010112	-4.322516964	-2.24280652	-2.931231671	-5.749118983	-3.012577431	-2.572543607	-1.856925269
25%	49.5	1	1625040584	-0.370780236	-1.031690999	-0.547398686	-0.244643361	-0.328102492	0.009563359	-0.816738915
50%	94	1	1988030290	0.287842552	0.179424522	0.048559561	0.672769243	-0.328102492	0.009563359	0.223447439
75%	144	4	1988060150	0.94646534	0.784982282	0.644517807	0.672769243	1.014134977	1.300616842	0.223447439
max	193	4	1988060913	0.94646534	1.996097803	3.028350793	0.672769243	1.014134977	1.300616842	1.263633793

In Table 5.11 and Figure 5.2, an analysis of the academic performance of 135 students across standardized lectures reveals notable variations in student scores attributed to different teaching methodologies. The mean scores were centralized around zero, with a standard deviation of approximately one, indicating a normalized distribution. Specifically, the scores ranged widely with Lecturer B's challenging lectures resulting in scores from -4.32 to 0.95, Lecturer C's dynamic sessions yielding scores between -2.24 and 2.00, and Lecturer F's unique approach leading to scores from -2.93 to 3.03. Additionally, Lecturer R's rigorous discussions produced scores ranging from -5.75 to 0.67, highlighting the impact of lecture style on student performance. The diverse teaching methods of Lecturers K, Q, and L also demonstrated a broad range of student performances, with scores spanning from -3.01 to 1.30. This variability underscores the significance of different teaching approaches in influencing academic outcomes, and offers valuable insights into educational strategies.

Quater3: admitted in fall (2019)

Before treatment | After standardization

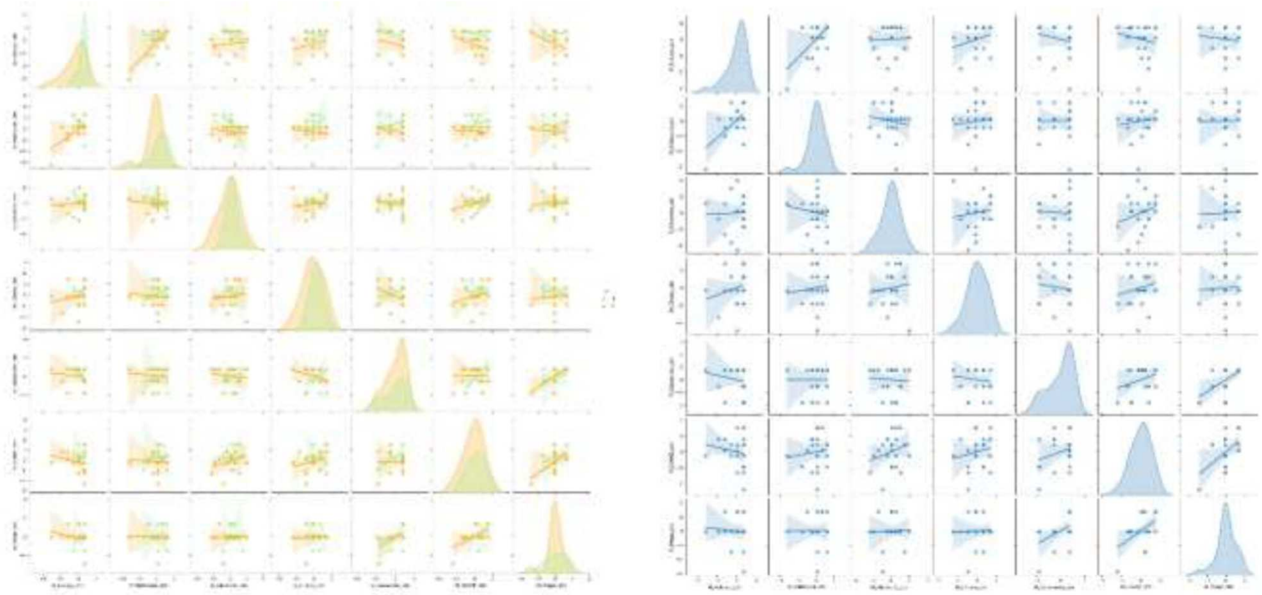


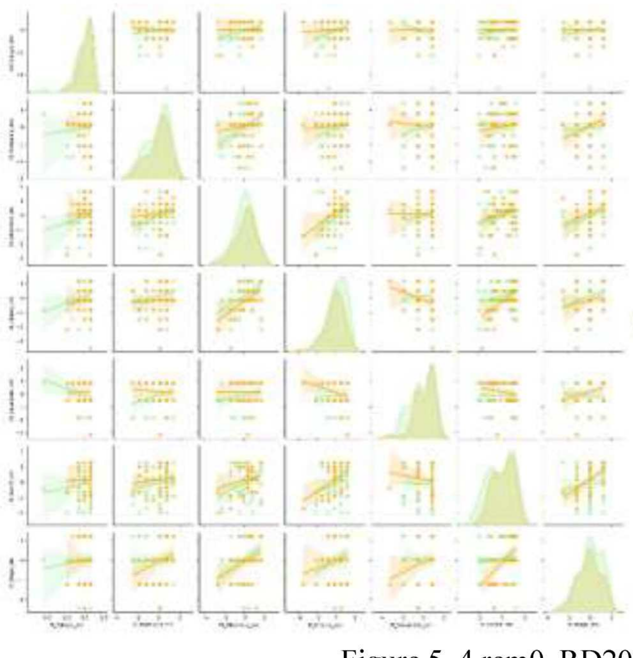
Figure 5. 3 rem0_RD2019_Q3_Yoshida_MCQ_stn

Table 5. 12 The Standardized Performance Scores Students Across Different Lectures on Yoshida_Q3 in 2019

index	SN	Y	Student ID	Lecturer B	Lecturer C	Lecturer F	Lecturer R	Lecturer K	Lecturer Q	Lecturer L
count	22	22	22	22	22	22	22	22	22	22
mean	25.09090909	2.9090909	1762764572	1.92E-16	-4.14E-16	-1.01E-16	8.07E-17	-1.31E-16	2.47E-16	-6.06E-16
std	11.057896	1.4770979	174323486	1.0235326	1.0235326	1.0235326	1.0235326	1.0235326	1.0235326	1.0235326
min	2	1	1634010050	-3.087538	-3.239416	-2.29139	-2.444506	-1.811039	-2.389585	-2.898705
25%	16.25	1	1634020125	-0.389549	-0.433623	-0.389104	-0.715891	-0.525786	-0.791146	-0.064416
50%	24.5	4	1634020377	0.4039769	0.1275361	0.0864675	-0.139686	0.7594681	0.0968751	-0.064416
75%	34.25	4	1988070173	0.7213873	0.5484052	0.562039	0.6285873	0.7594681	0.71849	-0.064416
max	42	4	1988075021	0.7213873	1.2498536	1.9887534	1.3968606	0.7594681	1.5177092	1.3527289

In Table 5.12 and Figure 5.3, the performance of 22 students was evaluated across multiple lectures using standardized multiple-choice questions (MCQs) to ensure a consistent evaluation. The data revealed a balanced distribution of scores, with average standardized scores approaching zero, indicating an equitable distribution across the cohort. Furthermore, consistent variability in scores was observed, with standard deviations of approximately 1, reflecting a uniform fluctuation in student performance. However, significant differences were observed when analyzing individual lectures. Specifically, in Lecturer B's sessions, half of the students scored above 0.40, whereas in Lecturer C's lectures, half of the students scored below 0.13. This disparity emphasizes the impact of Lecturer Content and assessment methods on student performance and highlights the importance of tailored pedagogical approaches in improving learning outcomes.

Before treatment



After standardization

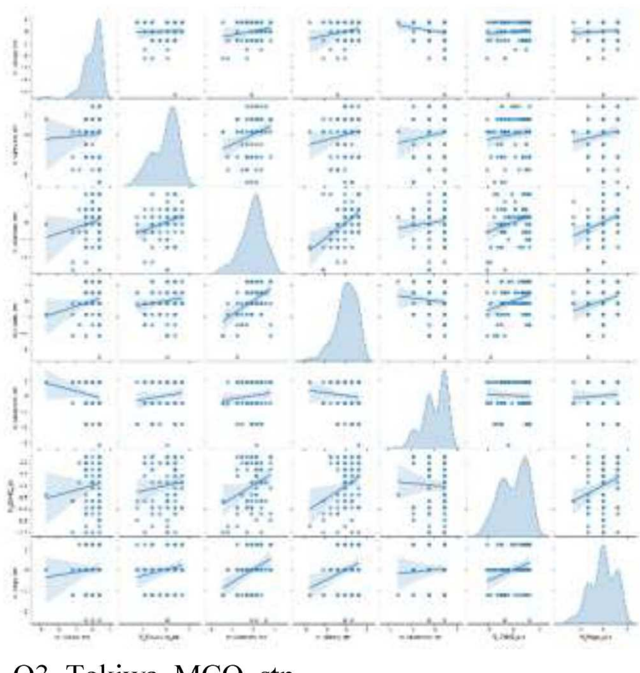


Figure 5. 4 rem0_RD2019_Q3_Tokiwa_MCQ_stn

Table 5. 13 The Standardized Performance Scores Students Across Different Lectures on Tokiwa_Q3 in 2019

index	SN	Y	Student ID	Lecturer B	Lecturer C	Lecturer F	Lecturer R	Lecturer K	Lecturer Q	Lecturer L
count	80	80	80	80	80	80	80	80	80	80
mean	66.9125	2.3125	1829227862	5.11E-16	-1.89E-16	-1.64E-16	2.22E-16	2.55E-16	2.22E-16	0
std	39.57214	1.4976247	181218359	1.0063092	1.0063092	1.0063092	1.0063092	1.0063092	1.0063092	1.0063092
min	1	1	1625020244	-5.245282	-2.352779	-2.725847	-3.50334	-3.168092	-2.009298	-2.434322
25%	32.75	1	1625030500	-0.75734	-1.106273	-0.553857	-0.318485	-0.486109	-0.93048	-1.217161
50%	66.5	1	1988040076	0.3646453	0.1402318	0.3149384	-0.150862	0.854882	0.1483375	0
75%	104.25	4	1988050169	0.7386404	0.7634844	0.7493363	0.5196342	0.854882	0.9574508	1.2171612
max	134	4	1988050695	0.7386404	1.386737	1.618132	1.1901299	0.854882	1.2271553	1.2171612

Table 5.13 and Figure 5.4 analyzes the performance of 80 students across various lectures, utilizing standardized scoring to ensure comparability. The findings indicated a balanced distribution of performance, with mean standardized scores hovering around zero and standard deviations consistently close to 1.01, reflecting uniform variation across lectures. Further analysis revealed significant differences in student outcomes between lectures; for example, 50% of students scored above 0.36 in Lecturer B's sessions, while 50% scored below 0.14 in Lecturer C's, suggesting the influence of lecture-specific factors such as difficulty levels or topics on student performance. The significance of these results lies in their potential to inform tailored teaching strategies that accommodate the diverse learning needs of students, thereby enhancing their overall educational effectiveness.

Quater2: admitted in spring (2020)

Before treatment After standardization

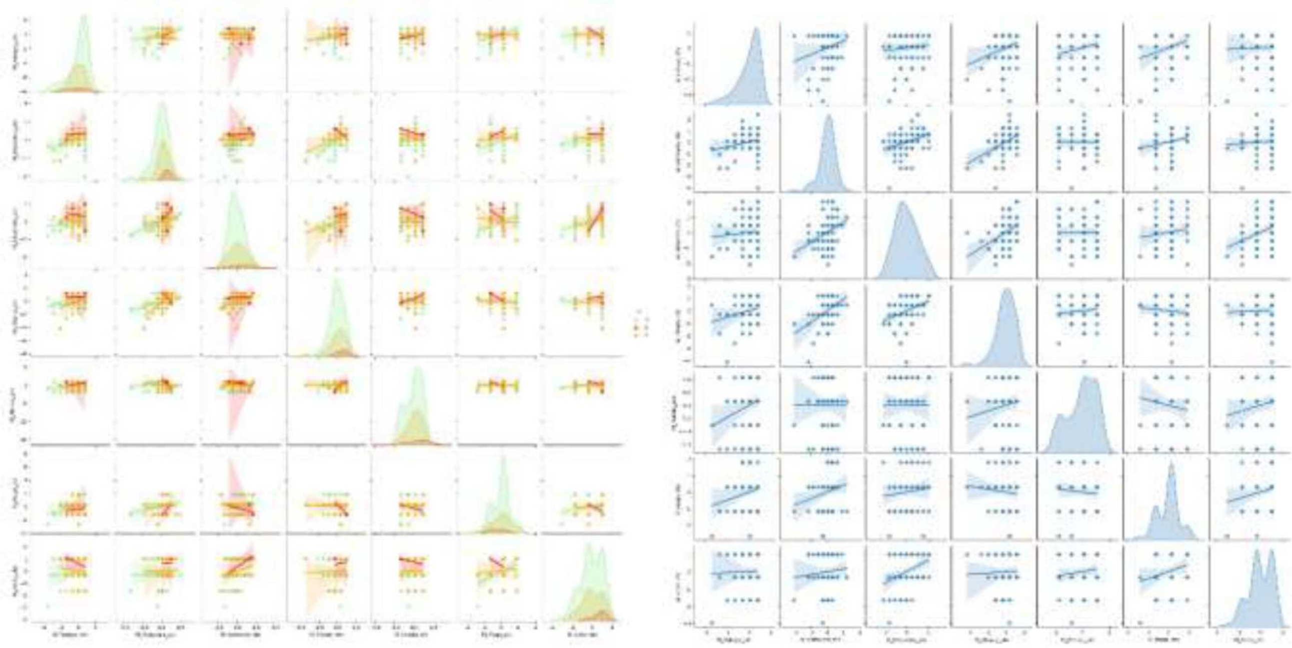


Figure 5. 5 rem0_RD2020_Q2_Yoshida_MCQ_stn

Table 5. 14 The Standardized Performance Scores Students Across Different Lectures on Yoshida_Q2 in 2020

index	SN	Y	Student ID	Lecturer B	Lecturer C	Lecturer F	Lecturer R	Lecturer K	Lecturer Q	Lecturer L
count	72	72	72	72	72	72	72	72	72	72
mean	48.375	1.888888889	1979408308	5.86E-17	-4.87E-16	4.93E-17	4.63E-16	-2.10E-16	2.34E-16	5.00E-16
std	28.0665394	1.338019932	165845179.3	1.00701763	1.00701763	1.00701763	1.00701763	1.00701763	1.00701763	1.00701763
min	1	1	1622040154	-3.401680257	-4.05812328	-2.087418997	-4.135850959	-1.69733685	-2.692764452	-2.963747982
25%	21.75	1	1722040172	-0.610557995	-0.530740469	-0.543300835	-0.318142381	-0.77151675	-1.189826153	-0.312942334
50%	49.5	1	2088010216	0.087222571	0.057156666	-0.028594781	0.445399334	0.15430335	0.313112146	-0.312942334
75%	72.25	4	2088020196	0.785003136	0.645053801	0.486111273	0.445399334	1.08012345	0.313112146	1.012460491
max	93	4	2088020503	0.785003136	2.408745207	2.030229436	1.20894105	1.08012345	1.816050444	1.012460491

In Table 5.14 and Figure 5.5, the performance of 72 students across lectures was evaluated using normalized scores for consistent comparison. The data revealed a trend in student scores, with a mean adjusted score close to zero and a uniform standard deviation of approximately 1.01. This suggests a balanced and consistent variation in performance among lectures. When examining specific lectures, there was variation in student scores. For example, 50% of the students in Lecturer B's sessions scored above 0.08, whereas 50% of those in Lecturer C's lectures scored below 0.05. These findings underscore the impact of lecture-specific factors on student performance and emphasize the need for adaptive teaching strategies to improve learning outcomes.

Before treatment After standardization

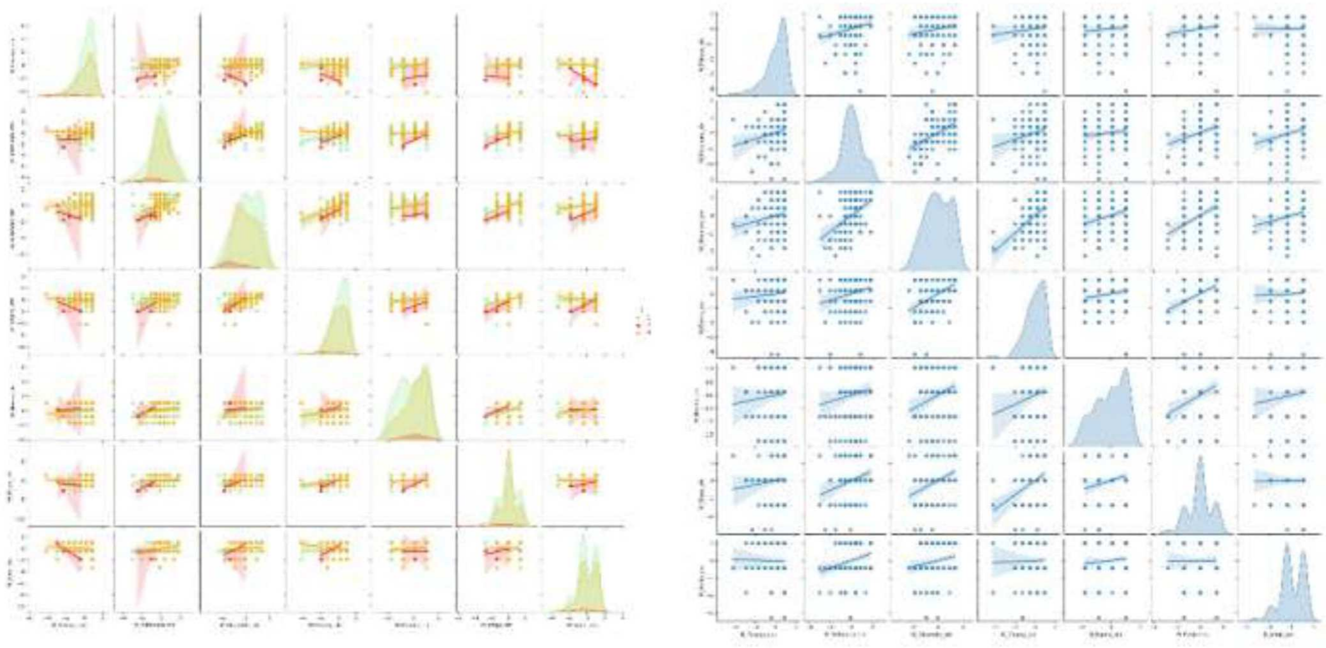


Figure 5. 6 rem0_RD2020_Q2_Tokiwa_MCQ_stn

Table 5. 15 The Standardized Performance Scores Students Across Different Lectures on Tokiwa_Q2 in 2020

index	SN	Y	Student ID	Lecturer B	Lecturer C	Lecturer F	Lecturer R	Lecturer K	Lecturer Q	Lecturer L
count	128	128	128	128	128	128	128	128	128	128
mean	86.6640625	2.2734375	1936955609	-1.39E-17	0	1.39E-17	-5.38E-17	-4.86E-17	-6.94E-17	2.08E-17
std	51.43764321	1.467306943	179553556.9	1.003929288	1.003929288	1.003929288	1.003929288	1.003929288	1.003929288	1.003929288
min	1	1	1425010421	-4.175423735	-2.96816629	-2.301173508	-4.202235182	-1.755617208	-2.764137254	-3.281282698
25%	40.75	1	1725040504	-0.433620435	-0.581700931	-0.937515133	-0.513030084	-0.81928803	0.02176486	-0.424111369
50%	85	1	2088030094	0.190013449	-0.104407859	-0.028409549	0.224810936	0.117041147	0.02176486	-0.424111369
75%	136.25	4	2088060556	0.813647332	0.372885212	0.880696034	0.962651955	1.053370325	0.02176486	1.004474295
max	173	4	2088060984	0.813647332	1.804764427	1.335248826	0.962651955	1.053370325	1.414715918	1.004474295

In Table 5.15 and Figure 5.6, the study examines the performance of 128 students across several lectures. To ensure consistency, the scores were normalized. It was observed that the adjusted scores tended to be centered around the average, as evidenced by the near-zero averages recorded. A standard deviation of approximately 1.00 was noted in the scores across the lectures, indicating a regular fluctuation. Upon closer examination of the individual lectures, a diverse range of results was evident. For instance, in Lecturer B, approximately half of the students achieved normalized scores of around 0.19, while in Lecturer C, roughly half recorded scores of around -0.10. These disparities may be attributed to the varying intricacies of the topics covered in each lecture.

Quater3: admitted in fall (2020)

Before treatment After standardization

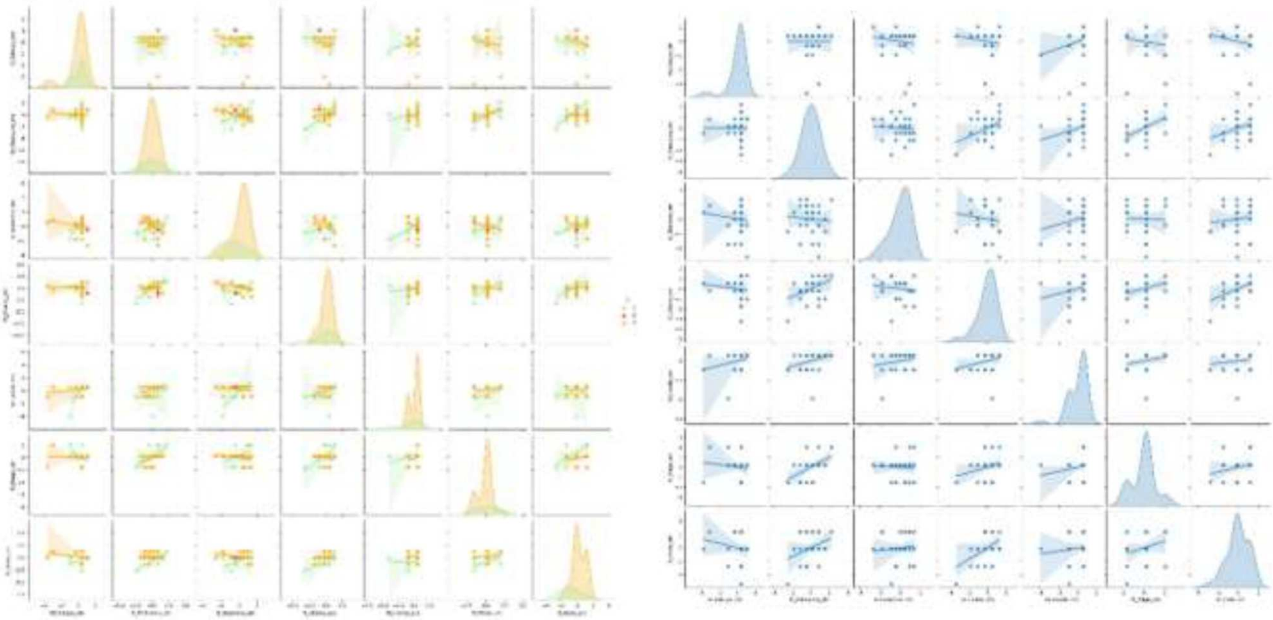


Figure 5. 7 rem0_RD2020_Q3_Yoshida_MCQ_stn

Table 5. 16 The Standardized Performance Scores Students Across Different Lectures on Yoshida_Q3 in 2020

index	SN	Y	Student ID	Lecturer B	Lecturer C	Lecturer F	Lecturer R	Lecturer K	Lecturer Q	Lecturer L
count	30	30	30	30	30	30	30	30	30	30
mean	18.633333333	3.233333333	1825097264	-1.33E-16	4.40E-16	-1.30E-16	-5.77E-16	5.11E-16	-1.04E-16	2.96E-16
std	10.72053567	1.304721752	154597883.1	1.017095255	1.017095255	1.017095255	1.017095255	1.017095255	1.017095255	1.017095255
min	1	1	1734010061	-3.68085583	-2.452178044	-2.625265661	-3.256703632	-3.91964748	-1.542816156	-2.677992119
25%	9.5	2.5	1734020132	-0.124200657	-0.463925576	-0.42532237	-0.227211881	-0.904534034	0.237356332	-0.086386843
50%	18.5	4	1734020317	0.383892939	0.198825247	0.454654947	0.530161056	0.603022689	0.237356332	-0.086386843
75%	26.75	4	1924557843	0.383892939	0.86157607	0.78464644	0.530161056	0.603022689	0.237356332	1.209415796
max	37	4	2088070201	1.061351068	2.187077715	1.334632263	1.287533994	0.603022689	2.017528819	1.209415796

Table 5.16 and Figure 5.7 in this analysis of 30 students' academic performance across various lectures, standardized scores revealed average values around zero for both

Lecturer B and Lecturer C, with a consistent standard deviation of approximately 1.01 across all lectures, indicating a uniform spread of scores. Detailed distributional insights showed median standardized scores of 0.38 for Lecturer B and 0.19 for Lecturer C, suggesting that half of the students scored above these values in their respective lectures. This uniformity in score dispersion, along with the specific median values, highlights comparative academic performance across lectures, offering a foundational understanding of the impact of different instructional strategies on student outcomes.

Before treatment After standardization

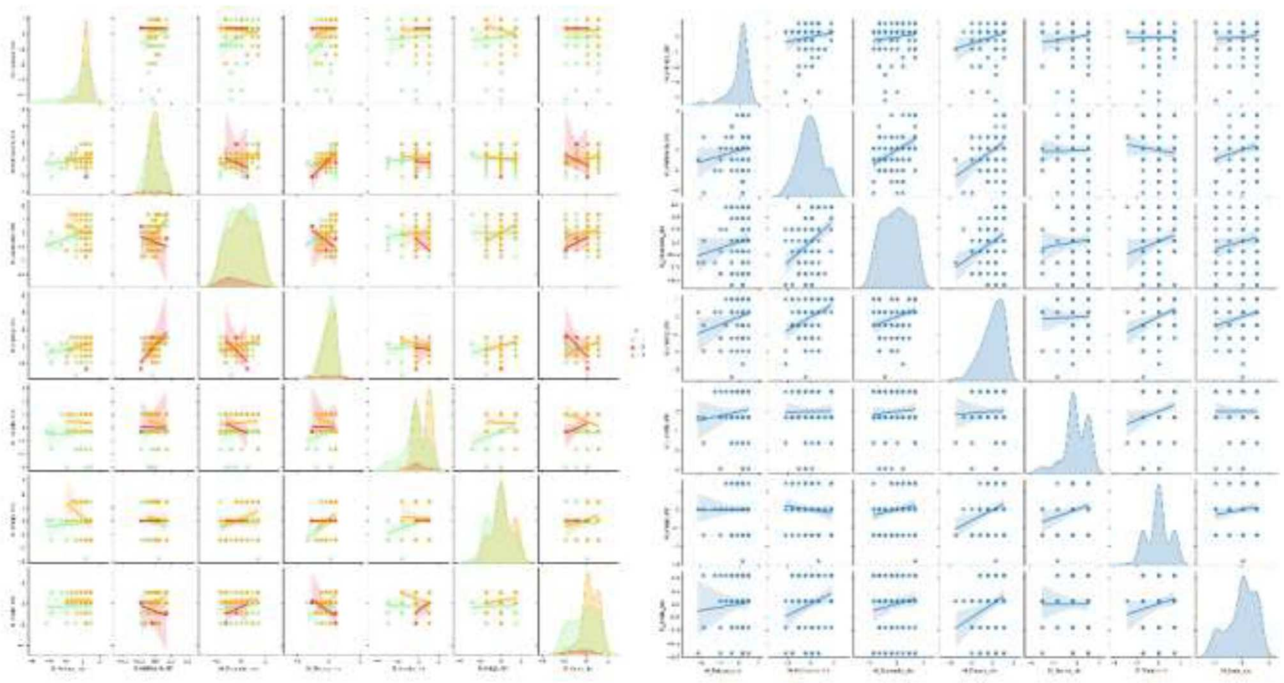


Figure 5. 8 rem0_RD2020_Q3_Tokiwa_MCQ_stn

Table 5. 17 The Standardized Performance Scores Students Across Different Lectures on Tokiwa_Q3 in 2020

index	SN	Y	Student ID	Lecturer B	Lecturer C	Lecturer F	Lecturer R	Lecturer K	Lecturer Q	Lecturer L
count	97	97	97	97	97	97	97	97	97	97
mean	68.65979381	2.4020618556	1919259609	-2.82E-16	-3.30E-16	-1.75E-16	3.11E-16	-1.28E-16	-1.46E-16	1.12E-16
std	36.84338662	1.476621946	178961089.6	1.00519484	1.00519484	1.00519484	1.00519484	1.00519484	1.00519484	1.00519484
min	4	1	1725020111	-4.258367106	-2.15942682	-1.709868299	-3.439647059	-2.958279892	-2.815019293	-1.877942136
25%	39	1	1725030575	-0.214407295	-0.461066808	-0.827649017	-0.460667017	-0.288948268	0.029323118	-0.887940032
50%	69	1	2088040014	0.36330125	0.105053197	0.054570265	0.284077994	-0.288948268	0.029323118	0.102062073
75%	99	4	2088050020	0.36330125	0.671173201	0.936789547	1.028823004	1.045717543	0.029323118	1.092064177
max	133	4	2088050745	0.941009794	1.803413209	1.377899187	1.028823004	1.045717543	1.451494323	1.092064177

In the evaluation of 97 students' performance across various lectures, as detailed in Table 5.17 and Figure 5.8, scores were standardized to enable fair comparison, resulting in means close to zero and indicating that student performances were generally average. The standard deviations remained consistent at approximately 1.00 across all lectures, suggesting uniform variability in student scores. The specific analysis revealed distinct performance patterns, such as a higher central performance for Lecturer B, with a median standardized score of approximately 0.36, whereas Lecturer C had a lower median performance of approximately 0.10. These findings highlight the influence of lecture-specific factors on student outcomes and emphasize the usefulness of standardization in assessing academic performance across different teaching contexts.

5.3.2 Analysis of Formative Assessment Trends Through Scatter Plot Matrices

The scatterplot matrix derived from the Tokiwa campus for the second quarter of fiscal year 2020 presents an insightful examination of the trends within formative assessments over seven lecture sessions after excluding the preliminary session to focus exclusively on substantive content and evaluations. This matrix serves to illustrate the comparative trends between foundational topics (Category 1) and case studies (Category 2), employing variables B, C, F, R, S, Q, and L, which denote formative assessment scores on the y-axis, with Y indicating the year.

The findings of the scatterplot analysis underscore the nuanced relationship between the assessed components of the lectures, offering a quantified view of student performance and the pedagogical impact of the sessions. The visual representation of data points, color-coded by year, enables an understanding of the longitudinal progression and potential influence of different cohorts on assessment trends. This analysis is pivotal for informing future teaching strategies, aiming to optimize learning outcomes by refining the formative assessment approach based on identified trends.

Pair Single Scatter matrix for Tokiwa Campus 2020 Compare All Lecturer

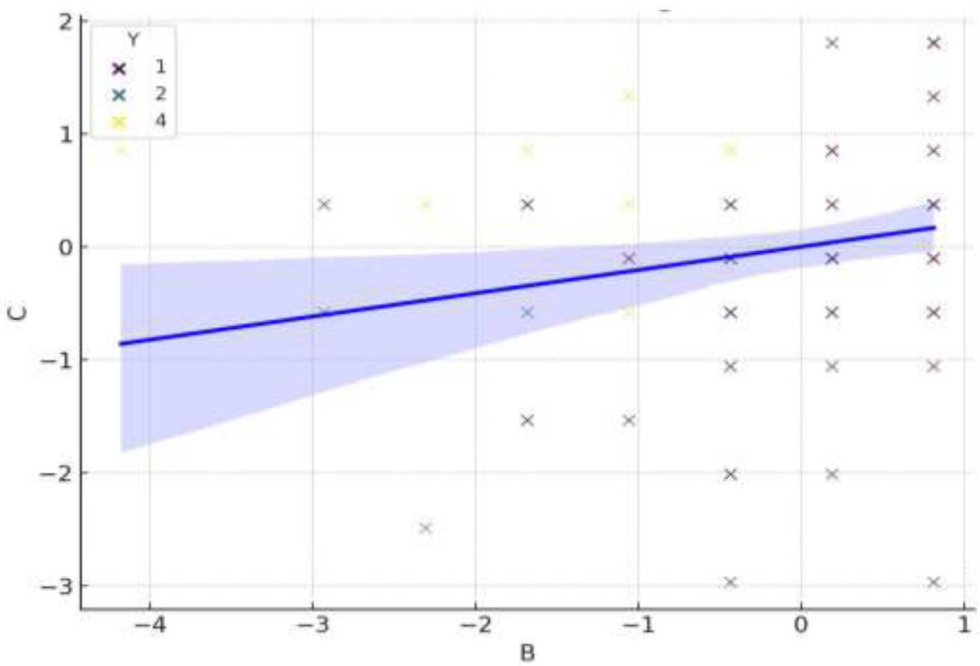


Figure 5. 9 Single Scatter matrix for Tokiwa Campus 2020, 2nd quarter 2, Compare Lecturer C and Lecturer B

In Figure 5.9, presented as a scatter plot, the pair plots methodology is utilized to scrutinize and visually contrast the student performance outcomes across sequential lecture sessions, providing an integrated view of the students' learning progression and the dynamics of their performance throughout each lecture. The plot reveals a notable positive correlation between variables B and C, which implies a potential enhancement or stability in the students' formative assessment scores longitudinally. The plotted data, differentiated by distinct symbols and hues for varying academic years, enabled a longitudinal analysis, shedding light on evolving educational patterns. A regression line, with its confidence interval represented by the shaded area, offers a quantifiable indication of the positive relationship between these variables, thus contributing essential insights for the assessment and advancement of pedagogical methodologies at the Tokiwa campus.

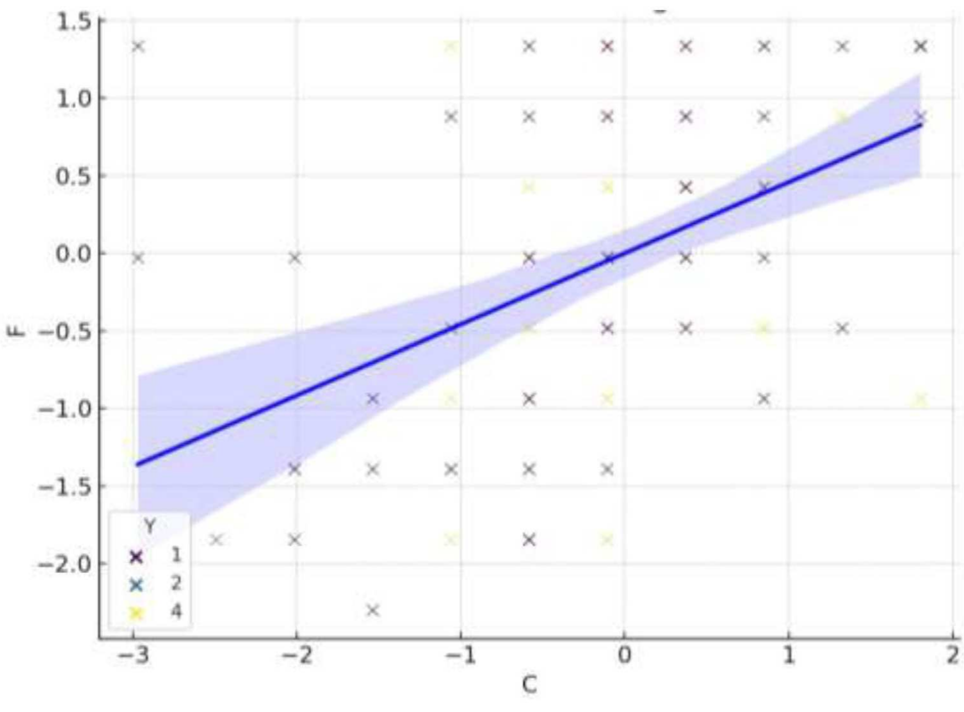


Figure 5. 10 Single Scatter matrix for Tokiwa Campus 2020, 2nd quarter 2, Compare Lecturer F and Lecturer C

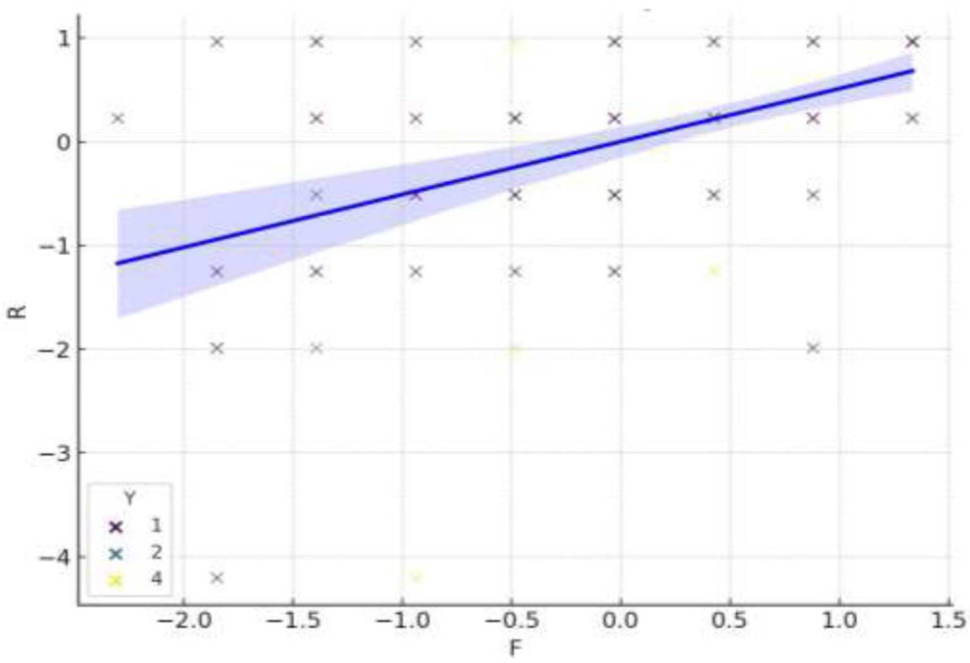


Figure 5. 11 Single Scatter matrix for Tokiwa Campus 2020, 2nd quarter 2, Compare Lecturer R and Lecturer F

The scatter plot in Figure 5.11 provides a visual representation of the positive correlation between variables F and R, suggesting that as scores in one variable increase, so do the scores in the other. This trend is consistent across different years of study, as represented by variable Y, indicating that the relationship between these formative assessment metrics is stable over time. The strength of this correlation is supported by the slope of the regression line and its accompanying confidence interval, which indicate the range within which we can be confident that the true correlation lies. This consistent positive correlation may reflect the effectiveness of the teaching methods and the interdependence of the skills assessed by variables F and R.

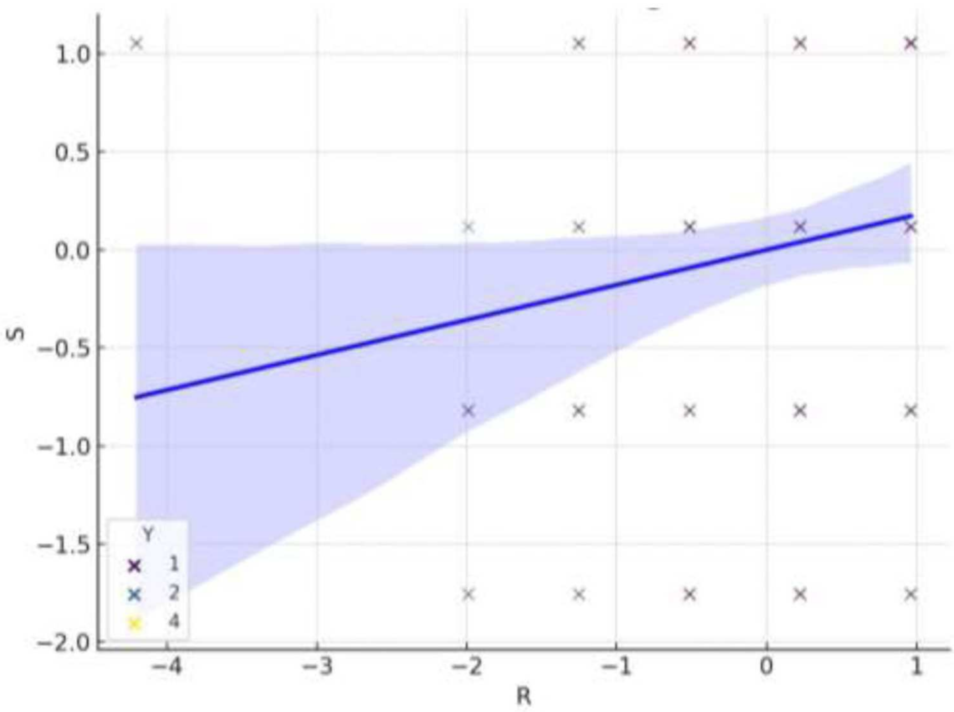


Figure 5. 12 Single Scatter matrix for Tokiwa Campus 2020, 2nd quarter 2, Compare Lecturer S and Lecturer R

The scatter plot in Figure 5.11 displays a positive correlation between variables R and S, as evidenced by the upward slope of the regression line, suggesting that increases in R are associated with increases in S. The data points, marked by different colors to denote categories within variable Y, were relatively evenly distributed around the regression line, although the wide confidence interval indicated some variability in the strength of the relationship.

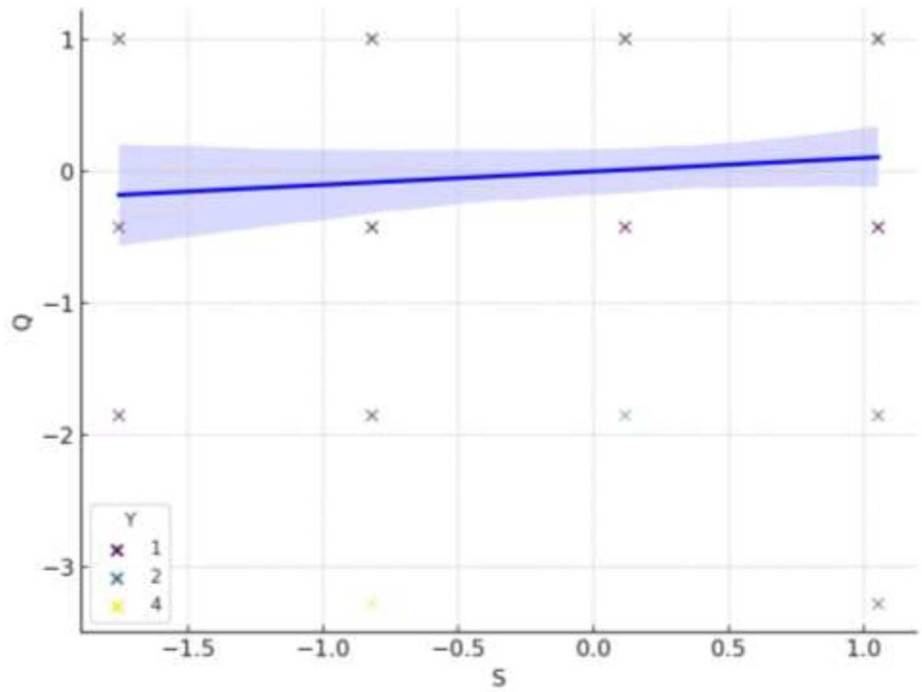


Figure 5. 13 Single Scatter matrix for Tokiwa Campus 2020, 2nd quarter 2, Compare Lecturer Q and Lecturer S

The scatter plot in Figure 5.13 elucidates a modestly positive correlation between variables Q and S, with the regression line's ascent suggesting that increases in S generally coincide with increases in Q. Notably, the expansive confidence interval surrounding the regression line underscores the presence of significant variability, suggesting that the correlation's intensity may not be consistent across all Y categories. This observed variability warrants a closer analysis to unravel the determinants of these divergences and to understand their implications for educational efficacy across different Lecturer Contexts.

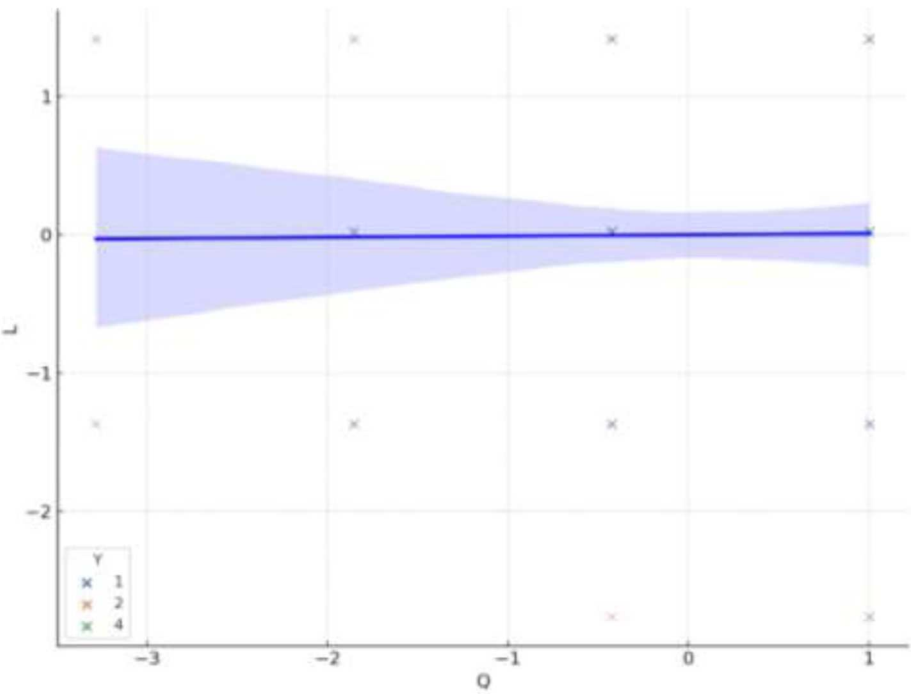


Figure 5. 14 Single Scatter matrix for Tokiwa Campus 2020, 2nd quarter 2, Compare Lecturer L and Lecturer Q

Figure 5.14 a scatter plot with a horizontal regression line, suggesting no significant relationship between variables L and Q. The data points are color-coded, likely indicating different categories within variable Y, which may represent various sessions or groups. The flat regression line indicates that changes in Q do not predict changes in L. The wide confidence interval band surrounding the regression line shows a high degree of variability in the data, indicating that other factors not shown on this graph might be influencing the relationship between L and Q. This lack of correlation is pivotal as it implies that variable Q is not a good predictor of variable L across the observed categories, suggesting the need for further investigation into other potential influencing variables

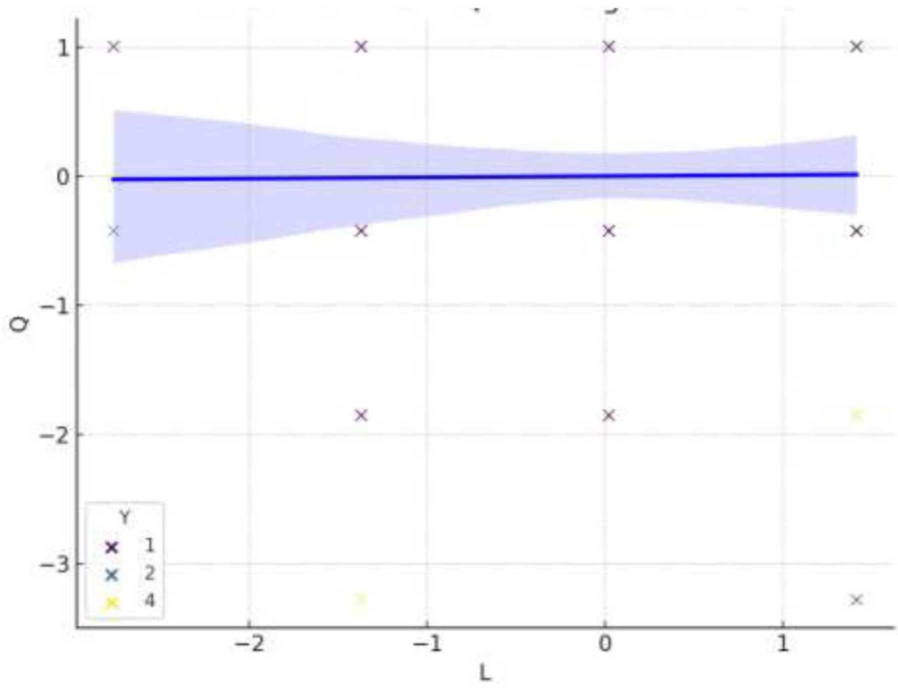


Figure 5. 15 Single Scatter matrix for Tokiwa Campus 2020, 2nd quarter 2, Compare Lecturer Q and Lecturer L

The scatter plot in Figure 5.15 shows the relationship between Q and L. The regression line indicates that there is no strong correlation between the variables representing lecturer L and lecturer Q, with color coding for a third variable Y indicating minimal influence of different categories, such as lecturers or subjects, on this relationship. This finding is significant as it suggests that the factors affecting student learning outcomes may not be directly related to the Lecturer Characteristics examined, and that other variables may need to be considered to understand and enhance student performance.

A scatterplot matrix was employed to examine trends in formative assessments within lecture sessions of a course offered biannually in the second and third quarters, attracting enrollees from both the Tokiwa and Yoshida campuses. This analytical tool is meticulously customized for each quarter and campus annually, facilitating a nuanced understanding of the dynamics between formative assessments and student performance in different educational settings. Notably, Figure 5.16 presents the analysis derived from the Tokiwa campus for the second quarter of fiscal year 2020, excluding the introductory session, to focus on the substantive content and evaluations occurring in the subsequent seven sessions. The scatterplot matrix was designed to elucidate comparative trends between foundational topics (Category 1) and case studies (Category 2), with the y-axis enumerating variables B, C, F, R, S, Q, and L. These variables represent formative assessment scores and other pertinent performance indicators, thereby shedding light on students' academic achievement and engagement levels in these specific areas. Correspondingly, the x-axis displays an identical set of variables, thereby illustrating the interplay between various formative assessments and course modules in student performance metrics. This comprehensive visual representation, as depicted in Figure 5.16, serves as an invaluable resource for educators, enabling them to discern the impact of distinct assessments and pedagogical strategies on student learning outcomes. Through detailed analysis, this study contributes to the ongoing discourse on optimizing educational practices to foster enhanced student performance and engagement.

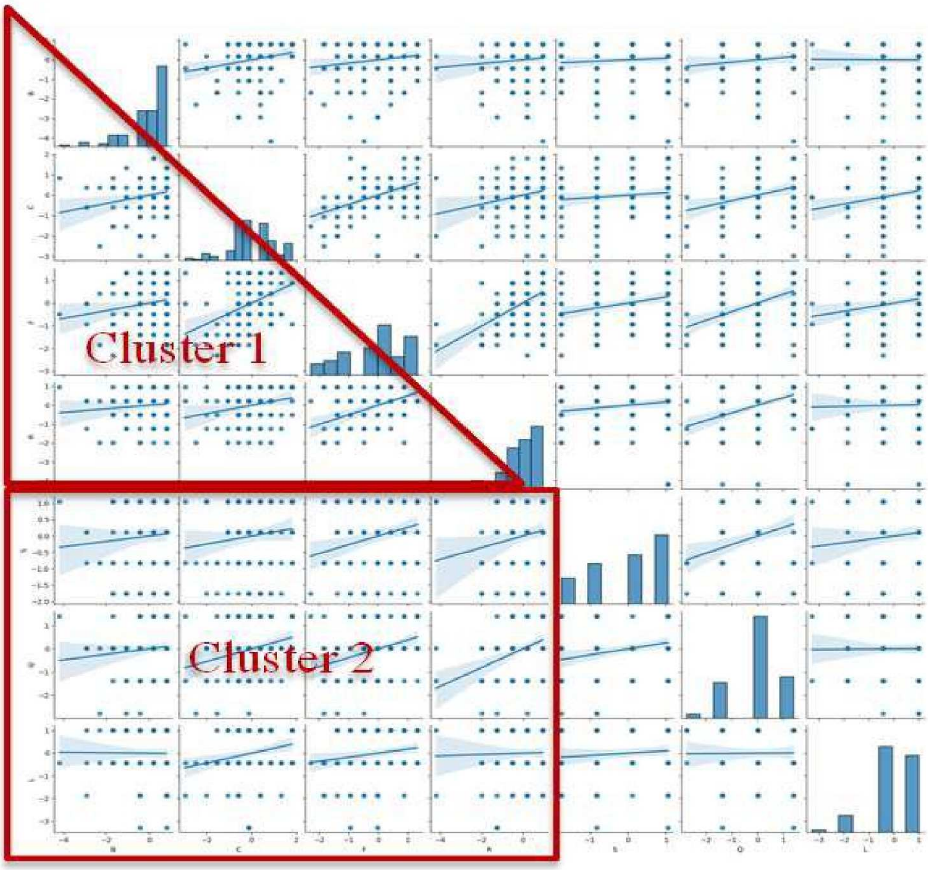


Figure 5. 16 All Lecturer Scatter matrix for Tokiwa Campus 2020, 2nd quarter 2

This section delves into an in-depth analysis of student performance data from 2019 and 2020, utilizing correlation coefficients and linear regression techniques within scatterplot matrices. The analysis is structured around Tables 5.18–5.21, each representing a different quarter, to systematically aggregate and examine the data. These tables not only highlight the temporal trends in student performance but also underscore the intricate relationships between various assessment metrics. By focusing on quantitative measures of correlation and employing scatterplot matrices for visual representation, this analysis offers a nuanced understanding of how student performance evolves over time and across different educational settings.

Table 5. 18 List of correlation coefficients for the second quarter of 2019

RD2019		Q2		
Cluster	Variable Pair	Tokiwa	Yoshida	Mean
1	B-C	0.13	-0.11	0.07
	B-F	-0.08	0.05	
	B-R	0.22	-0.12	
	C-F	-0.10	0.14	
	C-R	0.12	0.23	
	F-R	-0.03	0.35	
2	B-K	0.11	-0.22	0.05
	B-Q	0.08	0.31	
	B-L	0.05	-0.08	
	C-K	-0.02	-0.05	
	C-Q	0.11	-0.01	
	C-L	0.17	0.16	
	F-K	0.04	-0.04	
	F-Q	-0.09	0.11	
	F-L	-0.08	0.00	
	R-K	0.02	0.14	
	R-Q	0.12	0.05	
	R-L	0.22	0.12	
3	K-Q	0.09	-0.16	0.06
	K-L	0.04	0.18	
	Q-L	0.20	0.03	

Table 5.18 presents the correlation coefficients for the second quarter of 2019. This table is organized methodically into clusters, each containing pairs of variables. For instance, the variable pair B-C in cluster 1 exhibits a correlation coefficient of 0.13 in the Tokiwa

dataset and -0.11 in the Yoshida dataset, averaging 0.07. These coefficients, ranging from -1 to 1, signify the strength and direction of the relationships between the paired variables. Positive values indicate a direct relationship, whereas negative values suggest an inverse relationship.

Table 5. 19 List of Correlation Coefficients for the Third Quarter of 2019

RD2019		Q3		
Cluster	Variable Pair	Tokiwa	Yoshida	Mean
1	B-C	0.04	0.57	0.18
	B-F	0.17	0.03	
	B-R	0.18	0.21	
	C-F	0.26	-0.13	
	C-R	0.14	0.10	
	F-R	0.46	0.11	
2	B-K	-0.16	-0.18	0.07
	B-Z	0.10	-0.15	
	B-Q	0.07	-0.08	
	C-K	0.13	0.00	
	C-Z	0.12	0.11	
	C-Q	0.15	0.01	
	F-K	0.11	-0.07	
	F-Z	0.29	0.25	
	F-Q	0.32	0.04	
	R-K	-0.10	-0.12	
	R-Z	0.29	0.17	
	R-Q	0.26	0.04	
3	K-Z	-0.05	0.28	0.25
	K-Q	0.06	0.46	
	Z-Q	0.27	0.49	

Table 5.19, focusing on the third quarter of 2019, reveals significant insights into the correlation coefficients across different variable pairs, showing notable variations in student performance metrics. A key observation is the variable pair B-C, showing a minor correlation of 0.04 in the Tokiwa dataset and a significantly higher 0.57 in the Yoshida dataset, averaging 0.18. This contrast underscores the importance of using multiple analytical perspectives. In the same cluster, F-R exhibits a moderately strong positive correlation of 0.46 in the Tokiwa dataset. The second cluster presents an inverse relationship for B-K, whereas F-Z shows a consistent positive correlation across both datasets. The third cluster reveals contrasting dynamics, particularly in the K-Z pair. Overall, these results highlight the diverse and complex relationships among the variables, emphasizing the necessity of a comprehensive approach to data analysis.

Table 5. 20 List of Correlation Coefficients for the Second Quarter of 2020

RD2020		Q2		
Cluster	Variable Pair	Tokiwa	Yoshida	Mean
1	B-C	0.21	0.22	0.28
	B-F	0.17	0.09	
	B-R	0.09	0.26	
	C-F	0.46	0.33	
	C-R	0.22	0.46	
	F-R	0.51	0.38	
2	B-S	0.08	0.24	0.15
	B-Q	0.12	0.25	
	B-L	-0.01	0.03	
	C-S	0.12	-0.01	
	C-Q	0.27	0.20	
	C-L	0.22	0.08	
	F-S	0.27	0.01	

	F-Q	0.38	0.12	
	F-L	0.18	0.33	
	R-S	0.18	0.12	
	R-Q	0.40	-0.09	
	R-L	0.03	0.04	
3	S-Q	0.26	-0.11	0.10
	S-L	0.10	0.13	
	Q-L	0.01	0.21	

Table 5.20 methodically presents the correlation coefficients for the second quarter of 2020, organized into distinct clusters with various variable pairs. A notable example is the variable pair B-C in cluster 1, showing a correlation coefficient of 0.21 in the Tokiwa dataset and 0.22 in the Yoshida dataset, averaging a solid positive correlation. These coefficients, which range between -1 and 1, indicate the strength and direction of the relationships between the paired variables. In this case, the positive values for B-C suggest a direct and consistent relationship. The table's structured approach to showcasing these coefficients sheds light on the intricate dynamics of student performance, with positive values indicating direct relationships and negative values indicating inverse relationships.

Table 5. 21 List of Correlation Coefficients for the Second Quarter of 2020

RD2020		Q3		
Cluster	Variable Pair	Tokiwa	Yoshida	Mean
1	B-C	0.15	-0.00	0.13
	B-F	0.13	-0.11	
	B-R	0.23	-0.12	
	C-F	0.41	-0.07	
	C-R	0.38	0.40	

	F-R	0.29	-0.12	
2	B-S	0.11	0.25	0.15
	B-Q	-0.00	-0.13	
	B-L	0.06	-0.17	
	C-S	0.02	0.28	
	C-Q	-0.10	0.50	
	C-L	0.22	0.33	
	F-S	0.08	0.19	
	F-Q	0.17	-0.03	
	F-L	0.15	0.10	
	R-S	0.04	0.25	
	R-Q	0.31	0.28	
	R-L	0.27	0.44	
3	S-Q	0.22	0.21	0.16
	S-L	0.00	0.12	
	Q-L	0.14	0.25	

Table 5.21 focuses on the correlation coefficients for the second quarter of 2020, shedding light on the varied relationships among the different student performance metrics. In Cluster 1, the B-C pair shows a slight direct correlation of 0.15 in Tokiwa and -0.00 in Yoshida, averaging 0.13, while other pairs like C-F and C-R exhibit stronger positive correlations of 0.41 and 0.38 in Tokiwa and -0.07 and 0.40 in Yoshida. Cluster 2 reveals variable relationships; for instance, B-S varies between 0.11 in Tokiwa and 0.25 in Yoshida, and C-Q contrasts with -0.10 in Tokiwa and 0.50 in Yoshida. Finally, Cluster 3 maintains consistent positivity in pairs, such as S-Q 0.22 in Tokiwa, 0.21 in Yoshida, Q-L 0.14 in Tokiwa, and 0.25 in Yoshida, underscoring the multifaceted and complex nature of understanding student performance.

5.3.3 Analysis of Descriptive Statistical and T-Test

From the results presented in Tables 5.22 through 5.23, formative assessment scores showed a stronger correlation between basic learning sessions (Category 1) than between case study sessions (Category 2). This trend was consistent in both the 2019 and 2020 data, suggesting that students had a better understanding of the basic theoretical content, whereas case studies featuring practical industrial examples may have posed more complex learning tasks.

Therefore, for the Category 2 session group, we evaluated the differences in formative assessment scores between the 2019 (face-to-face) and 2020 (online) sessions. Twelve pairs of lecture sessions were analyzed using a t-test, with the null and alternative hypotheses set as follows:

- Null hypothesis: no difference between the two groups in 2019 and 2020
- Alternative hypothesis: there is a difference between the two groups in 2019 and 2020

Table 5.22 presents the results of a descriptive statistical analysis of the formative assessment scores for the academic years 2019 and 2020, offering a detailed comparison across different lecturers and campuses.

Table 5. 22 Descriptive Statistical Comparison of Formative Assessment Scores for 2019 and 2020

		2019			2020				Comparison INDEX
Campus	**Lecturer**	**N**	**Mean**	**Std. Dev.**	**Lecturer**	**N**	**Mean**	**Std. Dev**	
2nd Quater Yoshida	K	53	8.6	1.5	S	72	7.7	2.2	C-01
	Q	53	8.0	1.4	Q	72	7.6	1.3	C-02
	L	53	8.1	1.6	L	72	8.5	1.5	C-03
2nd Quater Tokiwa	K	135	8.5	1.5	S	128	7.8	2.1	C-04
	Q	135	8.0	1.6	Q	128	8.0	1.4	C-05
	L	135	7.6	1.9	L	128	8.6	1.4	C-06
3rd Quater Yoshida	K	22	8.8	1.6	S	30	9.2	1.3	C-07
	Q	22	8.1	1.4	Q	30	7.7	1.1	C-08
	Z	22	7.3	1.6	L	30	8.1	1.6	C-09
3rd Quater Tokiwa	K	80	8.7	1.5	S	97	8.4	1.5	C-10
	Q	80	8.0	1.7	Q	97	8.0	1.4	C-11
	Z	80	7.6	2.0	L	97	8.0	2.0	C-12

This comprehensive analysis revealed distinct patterns in student performance. At the Yoshida campus during the second quarter, the analysis of the three lecturer pairs shows varied trends. For 2019, Lecturer K's class averaged 8.6, with a standard deviation of 1.5, which contrasts with Lecturer S's 2020 class that had a lower average of 7.7, and greater variability (standard deviation of 2.2). Lecturer Q's class experienced a decrease in the average score from 8.0 in 2019 to 7.6 in 2020, though with reduced variability. However, Lecturer L's class showed an improvement, with the average increasing from 8.1 to 8.5. During the same period at the Tokiwa campus, distinct patterns emerged. Lecturer K's class saw a decrease in the average score from 8.5 to 7.8, accompanied by an increase in standard deviation. Lecturer Q's class maintained a consistent average of 8.0 across both years, while Lecturer L's class displayed a notable increase in average score from 7.6 to 8.6, along with a decrease in standard deviation. For the third quarter at the Yoshida campus, Lecturer K’s class showed a notable improvement, with the average score rising from 8.8 to 9.2. However, Lecturer Q's class saw a decline from 8.1 to 7.7, and Lecturer Z's class experienced an increase from 7.3 8.1. At the Tokiwa campus, Lecturer K's class average slightly reduced from 8.7 to 8.4, while Lecturer Q's class remained steady at an average of 8.0, and Lecturer Z's class improved from 7.6 to 8.0. These findings collectively indicate nuanced shifts in formative assessment scores over the two years, highlighting the potential influence of variations in teaching styles, course content, and learning environments.

Table 5.23 shows the results of comparing the formative assessment scores of students from 2019 (face-to-face sessions) and 2020 (online sessions) across 12 lecture pairs using t-tests.

Table 5. 23 Comparison of Category 1 scores between 2019 and 2020

C.I.	Lecturer	N	Mean	SD	SEM	t	df	P
C-01	K_2019	53	8.6	1.5	0.2	3.0	122	0.003
	S_2020	72	7.7	2.2	0.3			
C-02	Q_2019	53	8.0	1.4	0.2	1.9	123	0.067
	Q_2020	72	7.6	1.3	0.2			
C-03	L_2019	53	8.1	1.6	0.2	-1.4	123	0.163
	L_2020	72	8.5	1.5	0.2			
C-04	K_2019	135	8.5	1.5	0.1	3.2	226	0.001
	S_2020	128	7.8	2.1	0.2			
C-05	Q_2019	135	8.0	1.6	0.1	0.1	261	0.929
	Q_2020	128	8.0	1.4	0.1			
C-06	L_2019	135	7.6	1.9	0.2	-4.9	245	0.000
	L_2020	128	8.6	1.4	0.1			
C-07	K_2019	22	8.8	1.6	0.3	-0.9	50	0.355
	S_2020	30	9.2	1.4	0.3			
C-08	Q_2019	22	8.1	1.4	0.3	1.0	50	0.324
	Q_2020	30	7.7	1.1	0.2			
C-09	Z_2019	22	7.3	1.6	0.3	-2.0	43	0.056
	L_2020	30	8.1	1.6	0.3			
C_10	K_2019	80	8.7	1.5	0.2	1.3	175	0.200
	S_2020	97	8.4	1.5	0.2			
C-11	Q_2019	80	8.0	1.7	0.2	0.2	175	0.858
	Q_2020	97	8.0	1.4	0.1			
C_12	Z_2019	80	7.6	2.0	0.2	-1.0	167	0.340

	L_2020	78	7.8	2.0	0.2			

To evaluate the impact of the transition from face-to-face (2019) to online (2020) teaching on student performance in formative assessments, this study analyzed 12 pairs of lecture sessions. Utilizing t-tests to compare the mean scores between the groups for each lecture session, the null hypothesis proposed no difference in performance between the two years. The results, detailed in Table 26, revealed that for the three session pairs (C-01, C-04, and C-06), there were statistically significant differences in student performance, leading to rejection of the null hypothesis. In C-01 and C-04, the face-to-face sessions of 2019 had higher mean scores than the online sessions of 2020, while in C-06, the trend was reversed, with the 2020 online session outperforming the 2019 face-to-face session. However, no significant differences were found for the remaining nine pairs (C-02, C-03, C-05, C-07, C-08, C-09, C-10, C-11, and C-12), indicating consistent student performance across the two years.

These findings suggest that the shift to online learning did not generally impact student learning outcomes, as assessed through formative assessments. Most of the session comparisons showed no significant performance differences, implying a successful transition in maintaining educational standards. Nevertheless, the notable differences in the three pairs warrant further investigation to understand the implications of various teaching modalities on student performance. In particular, superior performance in one online session suggests potential areas where online teaching might be more effective. Overall, while the transition to online learning did not significantly hinder student performance, it did not present clear enhancements, indicating the need for strategies to optimize online teaching methods for improved learning outcomes.

5.3.4 Analysis of Course Satisfaction Survey Results

Following the transition to online lectures in 2020, a course satisfaction survey was administered after completion of the first class. This survey focused on five key aspects related to the students' online learning experience via Webex: Yoshida (a-1) and Tokiwa (a-2) the ease of connecting to Webex , Yoshida (b-1) and Tokiwa (b-2) the physical location from which students joined the session, Yoshida (c-1) and Tokiwa (c-2) the quality of the Webex connection received, Yoshida (d-1) and Tokiwa (d-2) a cross-tabulation analysis comparing reception quality with session stability, and Yoshida (e-1) and Tokiwa (e-2) the type of device utilized for the online connection. These items were chosen to gauge the connectivity and overall quality of the online class experience.

Yoshida campus

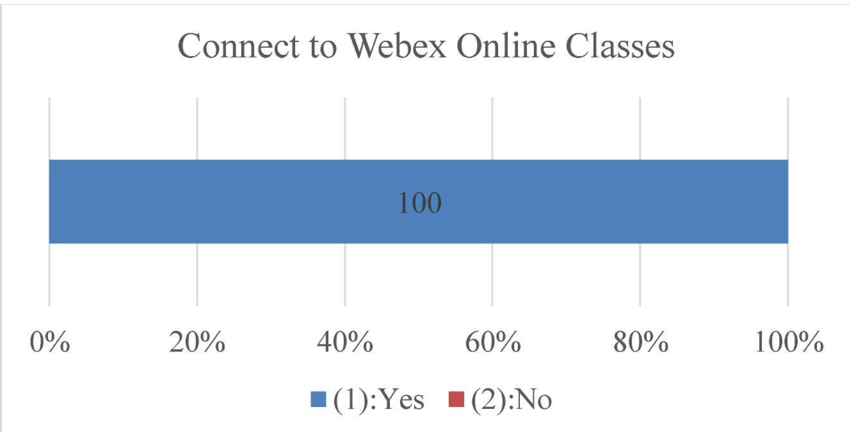


Figure 5. 17 Connect to Webex Online Classes (a-1 Yoshida campus)

The graph results in Figure 5.17 demonstrate that students uniformly managed to connect to Webex for online classes, with the initial bar chart clearly indicating that every surveyed participant (100%) successfully established a connection. This implies that Webex is universally accessible to the study population at a basic level.

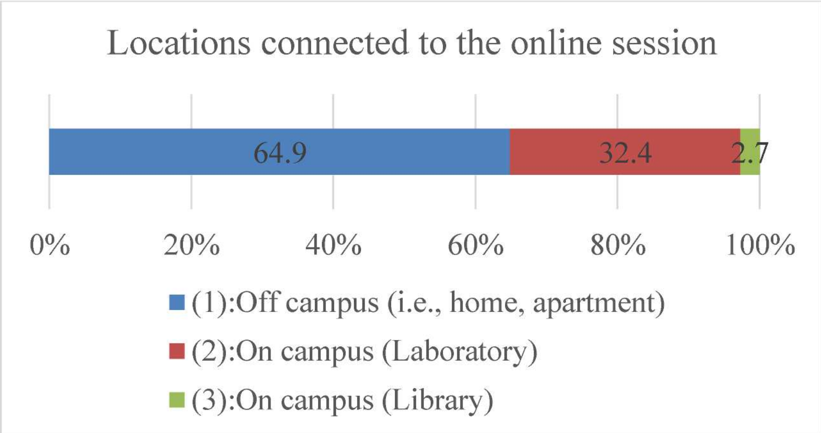


Figure 5. 18 Location connected to the online session (b-1 Yoshida campus)

The Figure 5.18 show the result analysis of student connection locations, which indicates a significant trend towards off-campus connectivity, with the majority (64.9%) attending online classes from home or similar environments. Additionally, a substantial portion (32.4%) accessed Webex from on-campus laboratories, and a small fraction (2.7%) utilized on-campus libraries for their online classes. This distribution suggests that the choice of location is influenced by factors such as convenience, comfort, and available resources.

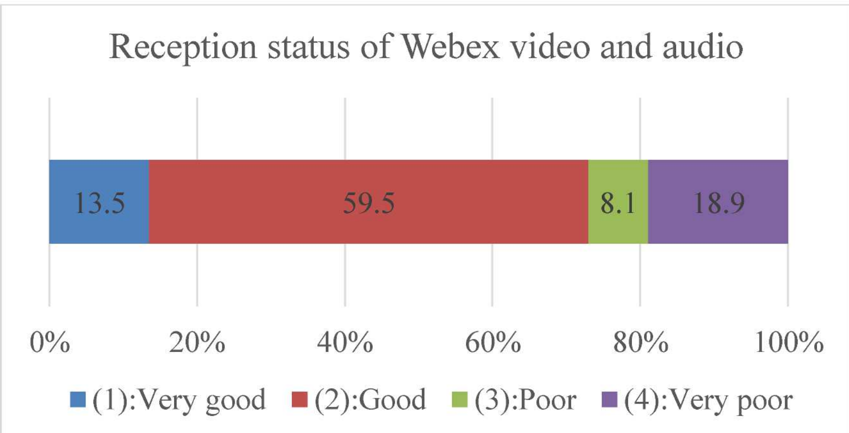


Figure 5. 19 Reception status of Webex video and audio (c-1 Yoshida campus)

The Figure 5.19 presented the results of survey responses regarding the quality of audio and video reception, a key aspect of online learning effectiveness, indicating that most students found it satisfactory, with 59.5% rating their reception as good and 13.5% as very good. Nevertheless, a significant minority reported poor (8.1%) or very poor (18.9%) reception quality. This suggests that while the platform is broadly effective, there exists a portion of users facing challenges with audiovisual quality, potentially due to factors such as Internet bandwidth, technical equipment, or geographic location.

Table 5. 24 Summarize of Student Connectivity Issues During Webex Online Classes

Null	Sometimes, audio and video reception was interrupted	I was able to connect to Webex online classes but could not get stable reception due to poor communication conditions.	Could not connect to Webex online classes at all
9	1	0	0
37	7	0	0
1	3	2	0
5	7	2	0

The Table 5.24 described appears to catalog different types of connectivity problems encountered by students during online classes hosted on the Webex platform. Each row of the table represents a count of students who have experienced a specific type of issue, ranging from intermittent audio and video interruptions to complete inability to connect to classes. The columns represent the frequency of each issue, with each column possibly corresponding to different severity levels and types of connectivity problems.

The subtitle student connectivity issues during Webex Online Classes succinctly communicates that the data in Table 5.24 relate to the technical difficulties students have faced when attempting to engage with coursework through Webex, a common platform for virtual meetings and classes. This subtitle helps to understand the technological challenges rather than other aspects of the online learning experience.

The investigation into audio and video disruptions showed that most users did not experience any interruptions (Null), and a considerable number reported occasional disturbances (sometimes). This indicates sporadic instability in Webex services, which may be influenced by varying conditions.

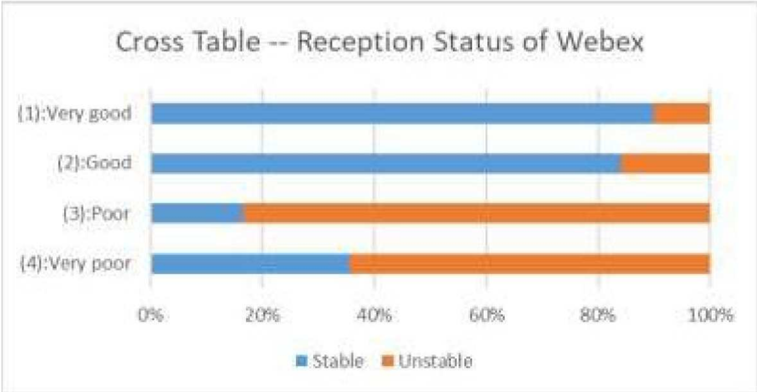


Figure 5. 20 Cross Table -Reception Status of Webex (d-1 Yoshida campus)

Figure 5.20 the result of cross-tabulation of reception quality with stability reveals a clear trend: good reception is closely linked with stability (90%), while poor reception tends to coincide with instability (10%). While anticipated, this correlation underscores the importance of addressing technical issues to enhance the overall online learning experience.

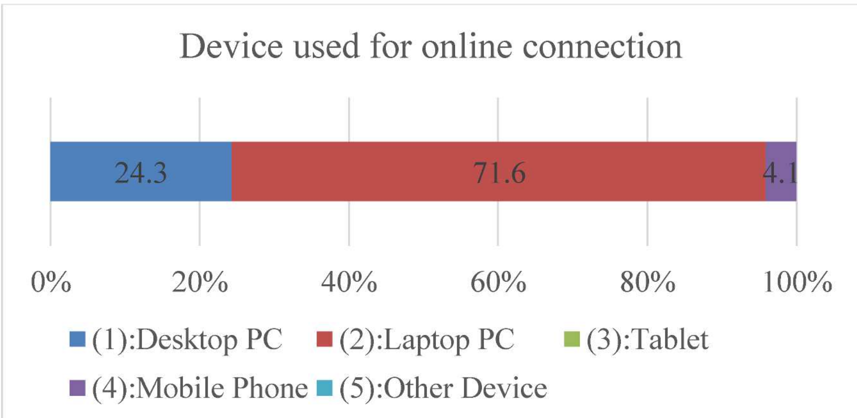


Figure 5. 21 Device used for online connection (e-1 Yoshida campus)

The Figure 5.21 the results of survey on device usage for online connectivity showed a preference for laptops (71.6%), with mobile phones being the second-most common choice (24.3%). Desktop PCs, tablets, and other devices were used less frequently. This indicates that portability and convenience are significant factors in device selection for online learning, highlighting potential considerations for the design of educational content and interfaces.

In conclusion, the data presented a largely positive picture of connectivity to Webex online classes, with good reception quality for most users and a preference for portable devices. However, the experience is not uniform, with a subset of users facing challenges in both connectivity and reception quality. Addressing these issues could involve technical support, infrastructural upgrades, or even instructional design adaptations to ensure a consistent and equitable educational experience across the diverse conditions under which participants access online learning platforms, such as Webex.

Tokiwa campus

The bar charts reflect the evaluation of the connectivity and user experience of participants in Webex online classes.

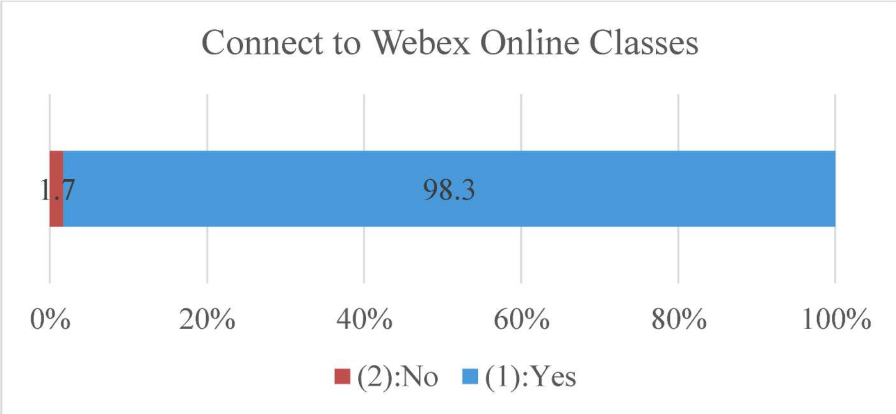


Figure 5. 22 Connect to Webex Online Classes (a-2 Tokiwa campus)

Figure 5.22 present the analysis of connection locations, which reveals a strong inclination with approximately 98.3% of attempts resulting in a successful connection to Webex classes. This high percentage underscores the platform's reliability. However, the remaining 1.7% represent a subset of users who encounter connectivity issues, suggesting the need for technical enhancements or support.

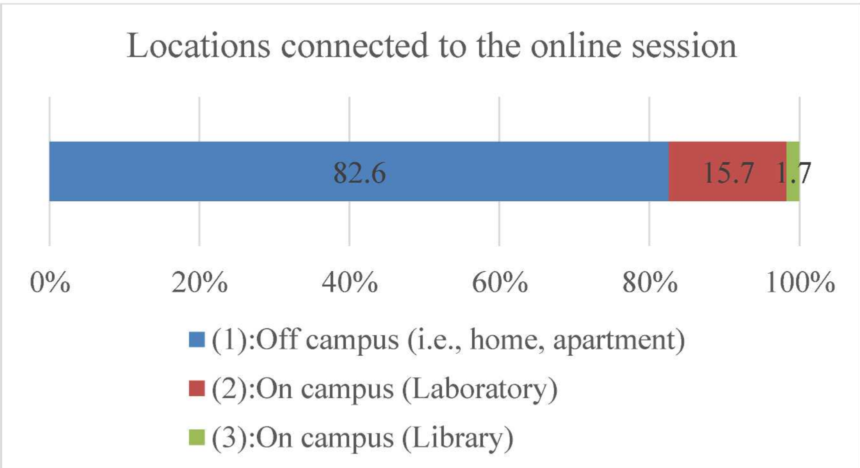


Figure 5. 23 Location connected to the online session (b-2 Tokiwa campus)

The Figure 5.23 presents quality of the reception status, with 20.9% of users experiencing 'very good' reception, indicating a seamless audio-visual experience. Conversely, 11.3% of users report 'very poor' reception, which is critically detrimental to the learning experience. The intermediary categories of 'good, ' ‘poor,’ and 'fair' reception, together accounting for the remaining 67.8%, point to a spectrum of user experiences that require attention to optimize the platform's performance.

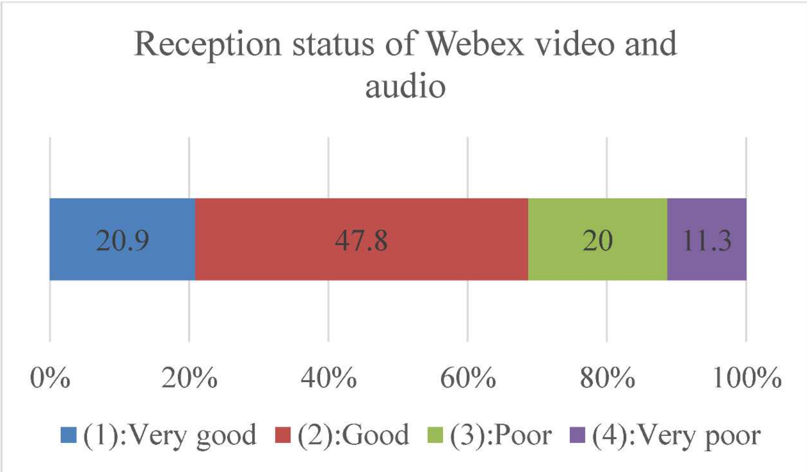


Figure 5. 24 Reception status of Webex video and audio (c-2 Tokiwa campus)

In Figure 5.24 results of user locations, it is observed that 82.6% of the connections originate from off-campus locations. This majority suggests that the platform is predominantly accessed from diverse network environments, which could affect the stability and quality of the connections. On-campus (laboratory) connections (15.7%) and on-campus (library) connections (1.7%). This distribution might reflect the convenience, comfort, and resource availability that different locations provide to the students.

The frequency of audio and video disruptions points to occasional instability, as a notable percentage of users reported experiencing interruptions 'sometimes.’ Such disruptions could potentially disrupt the learning process and suggest that there may be intermittent reliability issues with Webex services that warrant further investigation.

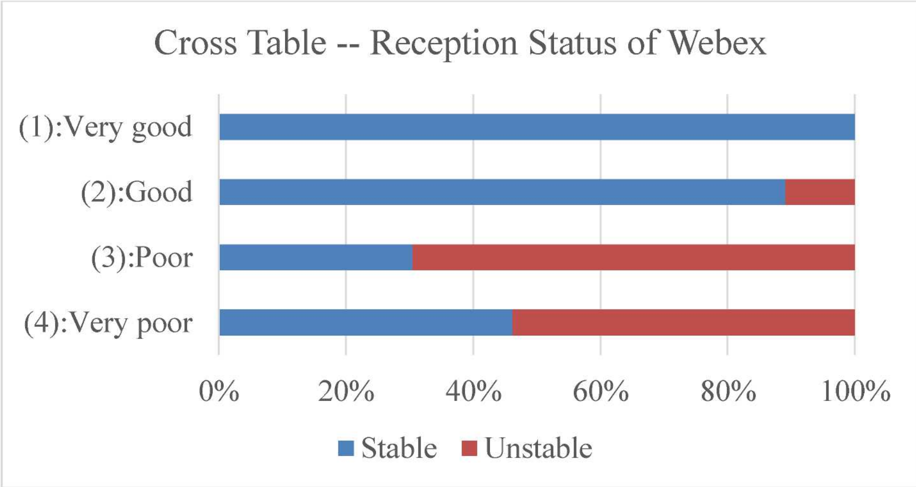


Figure 5. 25 Cross Table -Reception Status of Webex (d-2 Tokiwa campus)

A cross-analysis, as shown in Figure 5.25, of reception quality against stability draws a clear correlation: stable connections tend to yield better reception quality (100%), whereas unstable connections often result in poorer quality (0%). This link underpins the importance of a stable Internet connection for an optimal online learning experience and underscores the need for technical enhancements where necessary.

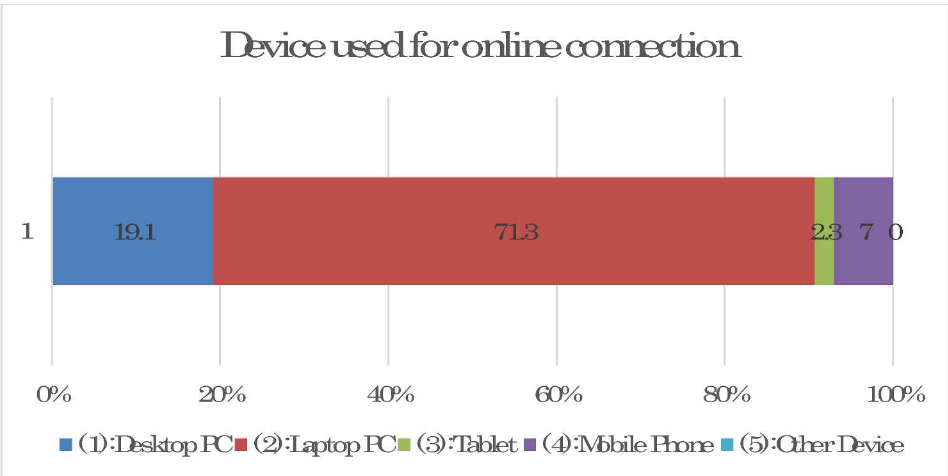


Figure 5. 26 Device used for online connection (e-2 Tokiwa campus)

In terms of devices used for online connections, as shown in Figure 5.26, laptops dominate with 71.3% usage, followed by desktop PC at 19.1%. This preference for laptops may be influenced by their portability and the convenience they offer for online learning. This trend has implications for the design and delivery of educational content, highlighting the necessity for it to be tailored to these commonly used devices.

In this comparative analysis, the findings from two studies conducted by Yoshida and Tokiwa focused on the formative learning evaluation of science and engineering graduate students using Webex for online lectures. The aim was to critically assess the insights and implications drawn from these studies, particularly concerning connectivity, user experience, and device preferences.

Connectivity and User Experience: Both Yoshida's and Tokiwa's studies indicate a high level of connectivity to Webex, suggesting that the platform is accessible to most students. However, it is crucial to note that while high connectivity rates (100% in Yoshida's study and 98.3% in Tokiwa's) are observed, they do not necessarily equate to a uniformly positive user experience.

Reception quality, as reported in both studies, revealed significant disparities. In Yoshida's study, while the majority reported good to very good reception, a considerable minority experienced poor reception. Similarly, Tokiwa's study showed a mix of reception qualities, with some students encountering very poor reception. These findings highlight a crucial aspect of online learning platforms: the variability in user experience based on factors such as Internet connectivity, location, and personal technical equipment.

Analysis of Disruptions and Location Preferences: The occurrence of disruptions in audio and video reception, as evidenced in both studies, raises concerns about the stability and reliability of the online learning experience. These disruptions, even sporadic, can significantly hinder the learning process, suggesting a need for more robust technological infrastructure and support.

The preference for off-campus connectivity, predominantly from home environments, underscores the shift in the landscape of online learning. While offering flexibility and convenience, this shift also brings forth challenges related to diverse network environments and their impact on the stability and quality of connections.

Device Usage and Educational Content Design: The predominance of laptops as the primary device for online learning, as seen in both studies, is a critical insight for educational technology design. This preference necessitates that online learning platforms and educational content be optimized for laptop interfaces, considering factors such as screen size, portability, and usability.

Critical Insights and Future Directions: The combined analysis of Yoshida and Tokiwa's studies offers a nuanced understanding of online learning experiences. While high accessibility to platforms such as Webex is a positive indicator, the variability in reception quality and the occurrence of disruptions paint a more complex picture.

Need for Enhanced Stability: There evident need for enhanced stability and reliability in online platforms to accommodate diverse user environments and technical setups.

Addressing Disparities in User Experience: The disparities in reception quality among students suggest that equal access to technology does not automatically translate into an equitable learning experience. This calls for targeted efforts to address disparities.

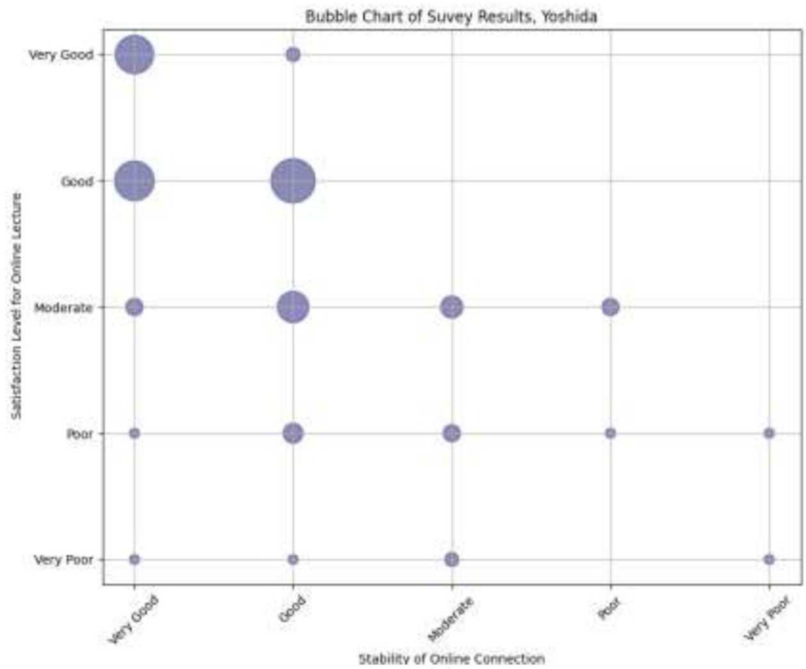
Implications for Online Learning Design: The findings emphasize the importance of designing online learning content that is adaptable to varying network conditions and optimized for the most used devices, such as laptops.

Therefore, this comparative analysis underscores the importance of not only ensuring access to online learning platforms but also focusing on the quality and consistency of the experience they provide. Future studies should delve deeper into the reasons behind the disparities in user experiences and explore strategies to make online learning more equitable and effective for all students.

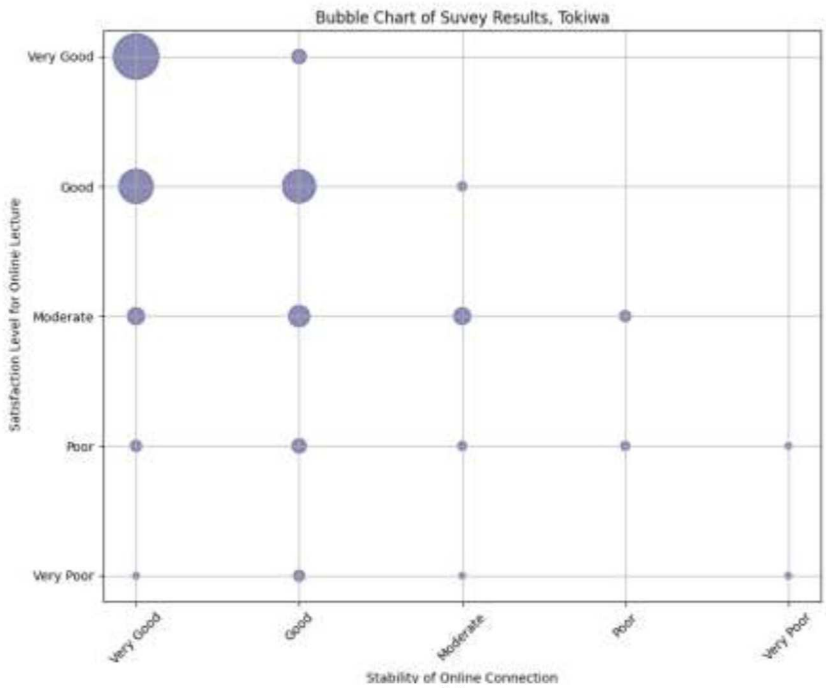
5.3.5 End-of-course satisfaction survey

After completion of the course, a satisfaction survey was conducted regarding online lectures. The survey included questions on the usability of the Webex online meeting service, stability of the online connection, and overall satisfaction with the online lecture. Responses to the questions were rated on a 5-point Likert scale. The results for the usability of Webex were generally positive; however, some students expressed a preference for Zoom over online lectures in their free feedback. The cross-tabulation of the responses to Items 2 and 3 is represented in a bubble chart in Figure 5.26.

Figures 5.27 (a) and (b) show the aggregate results for Yoshida and Tokiwa campuses, respectively. The figures indicate that there is a clear divide between the two groups, one with high levels of satisfaction (Very Good and Good) and the other with lower levels of satisfaction (Moderate, Poor, and Very Poor).



(a)



(b)

Figure 5. 27 Cross-tabulation of responses to Satisfaction and Stability

5.4 Discussion

This study embarked on a comprehensive examination of the transition to online learning at Yamaguchi University during the COVID-19 pandemic with the primary aim of assessing its impact on student performance outcomes. By comparing formative learning assessments from the hybrid model of FY2019 to the fully online format of FY2020, this study sought to understand the effectiveness of online learning environments during significant global educational disruptions.

Student performance was assessed using the new scoring methodology for multiple-choice questions (MCQs), which represents a methodological innovation aimed at enhancing the assessment of student understanding. By not specifying the number of correct answers, this approach necessitated a higher level of critical thinking from students, as they were required to discern the most applicable answers based on Lecturer Content. This scoring method, developed to capture nuanced levels of agreement between student responses and expected answers, signifies an important step towards more sophisticated and reflective online assessments[97, 98, 153].

The key finding of this study was consistent student performance across the two academic years examined. Despite the drastic shift in teaching methodologies and learning environments, there has been no significant decline in formative assessment scores from face-to-face to online formats. Student performance remained consistent despite the transition from face-to-face to online format. This indicates that the shift in teaching methodologies and learning environments did not lead to a significant decline in formative assessment scores [161].

The results suggest that students were able to adapt more effectively to the online learning environment, maintaining their performance levels compared to the face-to-face format. This finding highlights the resilience of students and the effectiveness of online learning methods in maintaining educational standards, even during challenging circumstances, such as the COVID-19 pandemic [69].

This study also explored technological adaptations and student connectivity. By reviewing the connection status of the students surveyed, we acknowledge the crucial role of technology in facilitating online learning [162]. Understanding student connections aids in assessing the technological infrastructure and adaptations necessary to support effective online education. The focus on connection status reflects the study's consideration of technological adaptations to support student learning in an online environment [9]. This emphasis on student connectivity underscores its importance in online learning. This indicates that student connectivity is a critical factor in the success of online learning experiences [53]. The review of connection status reflects the study's commitment to ensuring that students have the necessary connectivity to participate effectively in online lectures and engage with course materials. This emphasis on student connectivity aligns with the broader theme of enhancing student engagement and interaction in an online learning environment [155].

The observed consistency in student performance between face-to-face and online learning environments, coupled with the successful implementation of innovative assessment methods, offers valuable insights for educational researchers and practitioners alike [163]. This highlights the comparison of formative assessment scores between the face-to-face format in 2019 and the online format in 2020. While the study focused on the Advanced Course of Research and Development Strategy, the results indicated that well-designed online courses could offer a learning environment as effective as traditional face-to-face classes. Given proper instructional design and technological support, online learning can help maintain educational standards and ensure consistent student performance. The mean scores per Lecturer Remained steady across both academic years, indicating that students' levels of understanding and learning, as measured by formative assessments, remained consistent across the two formats [164]. This suggests that students were effectively able to adapt to the online learning environment and maintain their performance levels relative to traditional face-to-face instruction [156].

Overall, the results indicate that with appropriate instructional design, technological support, and student adaptability, online learning can be as effective as traditional face-to-face instruction in maintaining educational standards and ensuring positive student outcomes.

This study contributes to the understanding of the impact of online learning on student performance and assessment methodologies in the context of a global pandemic. Yamaguchi University's findings offer a foundation for further exploration of the optimization of online higher education, advocating for a balanced integration of technology, pedagogy, and student support services to effectively navigate future educational challenges.

Chapter 6 - Machine Learning in Online Formative Assessment Analysis

6.1 Introduction

The exploration of k-means clustering in the context of student performance analysis has been a transformative advancement in educational research. This technique, rooted in the domains of vector quantization and data mining, offers a powerful means of partitioning student data into distinct clusters [165]. Each cluster represents a group of students with similar performance characteristics, thus providing invaluable insights into the various dimensions of educational outcomes. Central to the effective application of k-means clustering is the elbow method, a heuristic used to ascertain the optimal number of clusters. By analyzing the variation within the data and identifying the point of inflection, or elbow, educators and researchers can determine the most appropriate number of clusters to use, ensuring that data segmentation is both meaningful and manageable.

The k-means clustering methodology involves grouping students based on a range of performance indicators [165]. This segmentation sheds light on patterns and trends that may otherwise remain obscured in traditional analyses. For example, by categorizing students into clusters based on their academic achievements and learning behaviors, educators can identify unique groups such as high achievers, average performers, and those who might require additional support. This nuanced understanding is crucial for tailoring educational strategies to the needs of each student group. The Elbow method complements this process by guiding the selection of an appropriate number of clusters, thereby enhancing the accuracy and relevance of the analysis [119].

Numerous practical applications of this clustering technique exist in the educational setting. In a study conducted by Bowen et al. [166] at a large public university, k-means clustering revealed distinct groups of students, categorized by their engagement levels and study habits. This information empowered the university to develop specialized support programs targeted at each student group. Similarly, a high school study by Da Silva et al. [167] utilized k-means clustering to uncover the correlations between academic performance and extracurricular participation. Such insights are invaluable for shaping educational policies and practices that are more responsive to the diverse needs of the student population.

However, the application of k-means clustering in educational research is not without its challenges. The algorithm assumes that clusters are spherical and of similar size, which may not always align with the complex nature of educational data. Moreover, effectively determining the number of clusters using the elbow method can be subjective and highly dependent on the specific characteristics of the dataset. These considerations highlight the need for careful analysis and interpretation of the results obtained from k-means clustering.

Meanwhile, the utilization of k-means clustering, augmented by the elbow method, represents a significant step forward in the field of educational data analysis. This approach allows for a more granular and nuanced understanding of student performance, and facilitates the development of tailored educational interventions. As the field of educational research continues to evolve, techniques such as k-means clustering will undoubtedly play a pivotal role in enhancing our understanding of student learning patterns, thereby contributing to more effective and personalized educational experiences.

6.2 k-Means Analysis: Case Studies in Science and Engineering Education

Clustering techniques, which serve as the cornerstone of data mining, have been instrumental in unearthing patterns within datasets across various domains. Among these methods, the k-means algorithm has emerged as a particularly notable approach owing to its simplicity, efficiency, and adaptability to large datasets [168, 169]. Originating in the 1950s, k-means has undergone significant evolution, paralleling advancements in machine learning and data analysis to find applications in diverse fields ranging from finance and medicine to urban planning and education [170].

The k-means algorithm is a partitioning method that segregates data into clusters based on their proximity, thereby grouping the data points with similar characteristics. Its ease of implementation and straightforward approach make it an appealing choice for large-scale data analysis tasks [171]. However, the necessity to predefine the number of clusters and the sensitivity to initial centroid placements are recognized limitations that often require iterative experimentation to ascertain the optimal cluster count [138].

In contrast with k-means, other clustering methodologies such as hierarchical clustering, spectral clustering, and Gaussian mixture models offer greater flexibility in handling complex data structures. Despite their versatility, these methods tend to be computationally intensive, making them less feasible for large-dataset applications [172].

A pivotal advancement in refining k-means clustering involves the elbow method, which aids in determining the optimal number of clusters by identifying the point where the reduction in the intracluster sum of squares diminishes, signaling a balance between the compactness and separation of clusters [119]. This approach has proven effective in various analytical scenarios, including customer behavior analysis and academic performance evaluations, by enabling a more nuanced understanding of data distributions.

This research delves into the application of the k-means algorithm augmented by the elbow method within the context of science and engineering education. By analyzing data from courses offered to graduate students at the Graduate School of Frontier Sciences at Yamaguchi University, this study aimed to cluster students based on multiple variables, such as grade, affiliation, online test registration timings, and scores from formative assessments. The objective was to explore the potential of k-means clustering in categorizing students' academic performance, thereby offering insights that could tailor educational strategies to diverse student needs [165].

6.2.1 Data Collection and Preprocessing

The results of formative learning evaluations conducted in the course "Research and Development Strategies" offered at the Graduate School of Frontier Sciences, Yamaguchi University, will be used. Data collection was conducted in the "Research and Development Strategies" course offered in the first semester of 2023. In total, 272 students were enrolled in the course. The "Research and Development Strategies" course is an omnibus lecture series with eight lectures. After the second through eighth lectures, an online formative evaluation was conducted. For each class session, the necessary variables (grade, affiliation, time taken to complete the formative assessment test, and formative assessment score) were extracted. A zero-suppression process was performed as a pre-processing step for the collected data. This process eliminated data from students who were absent. The Index and effective data size for each session are shown in Table 6.1.

Table 6. 1 The Index and effective data size

Session Index	Dataset Name	Data Size
F	dataset_AF_WT_RD2023_Q2_2_F	248
M	dataset_AF_WT_RD2023_Q2_3_M	240
C	dataset_AF_WT_RD2023_Q2_4_C	246
S	dataset_AF_WT_RD2023_Q2_5_S	242
O	dataset_AF_WT_RD2023_Q2_6_O	239
H	dataset_AF_WT_RD2023_Q2_7_H	242
K	dataset_AF_WT_RD2023_Q2_8_K	233

6.2.2 Optimizing Cluster Analysis with the Elbow Method

The primary data source for this study was the formative evaluation scores of graduate students enrolled in "Advanced Research and Development Strategies" at the Yamaguchi University Graduate School of Frontier Sciences. Data collection was conducted in the "Advanced Research and Development Strategies" course offered in the academic year 2023. The variables collected were the student ID number, name, affiliation, grade, online formative test login and logout times, and online formative test scores. Student ID numbers and names were excluded after completing student identification. The log-in and log-out times were used to calculate the time taken to complete the online formative test in minutes. The results of the elbow analysis for the second (Session Index F) through eighth (Session Index K) lectures are shown below:

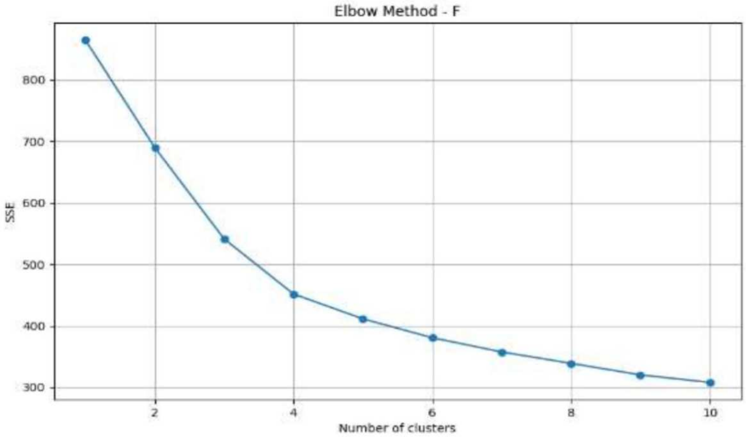


Figure 6. 1 (a) Elbow curve for Session F

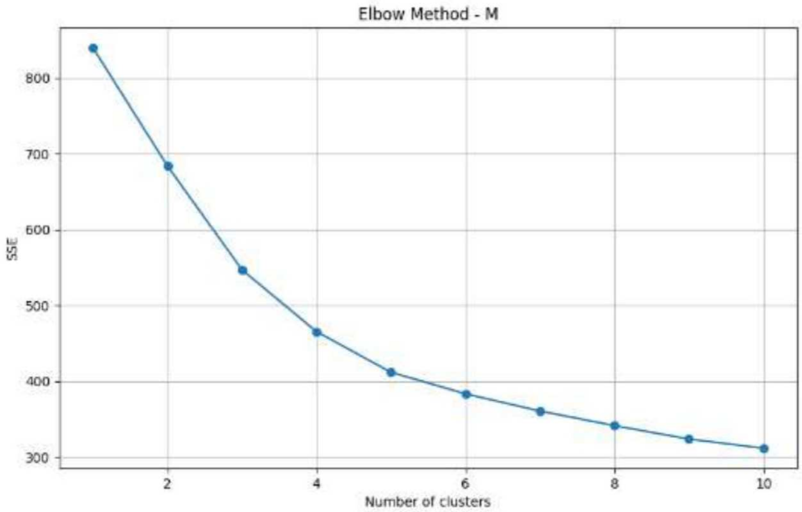


Figure 6. 2 (b) Elbow curve for Session M

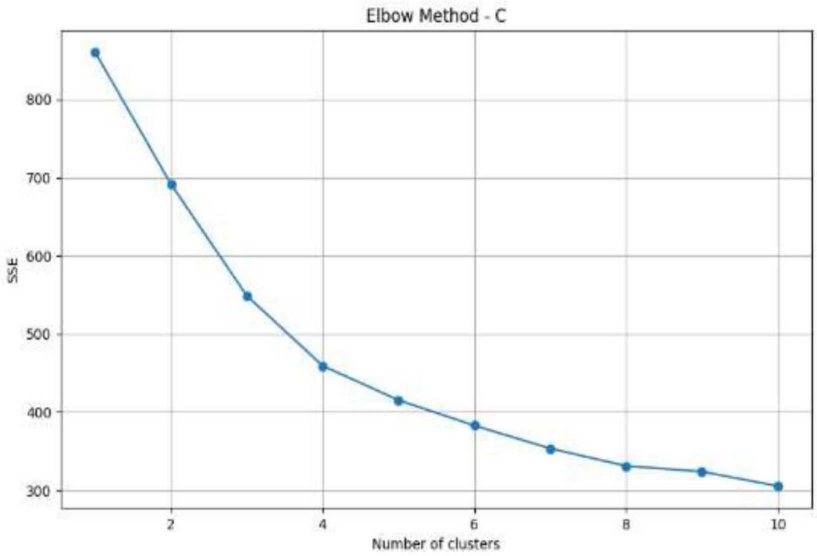


Figure 6. 3 (c) Elbow curve for Session C

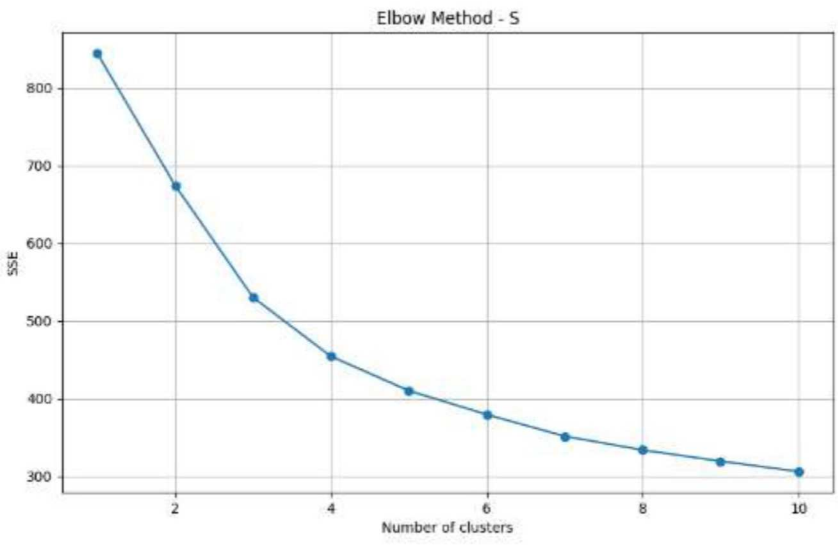


Figure 6. 4 (d) Elbow curve for Session S

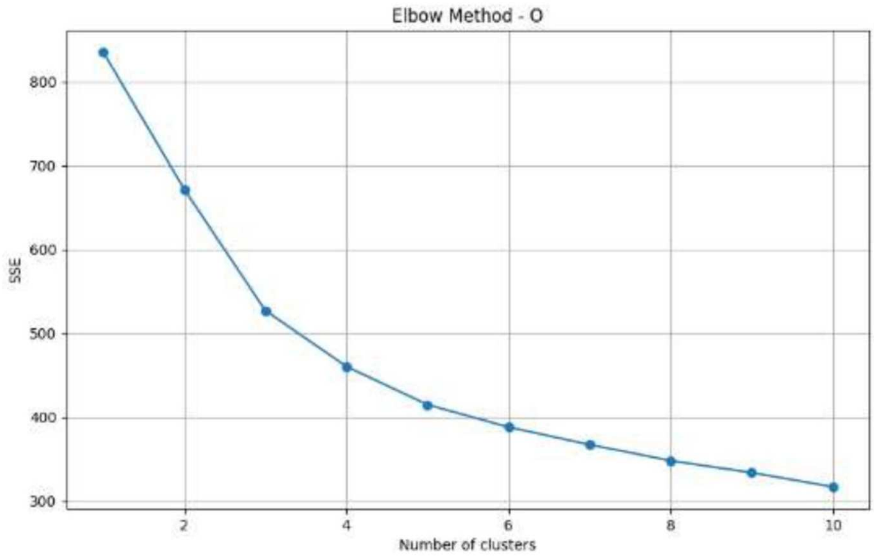


Figure 6. 5 (e) Elbow curve for Session O

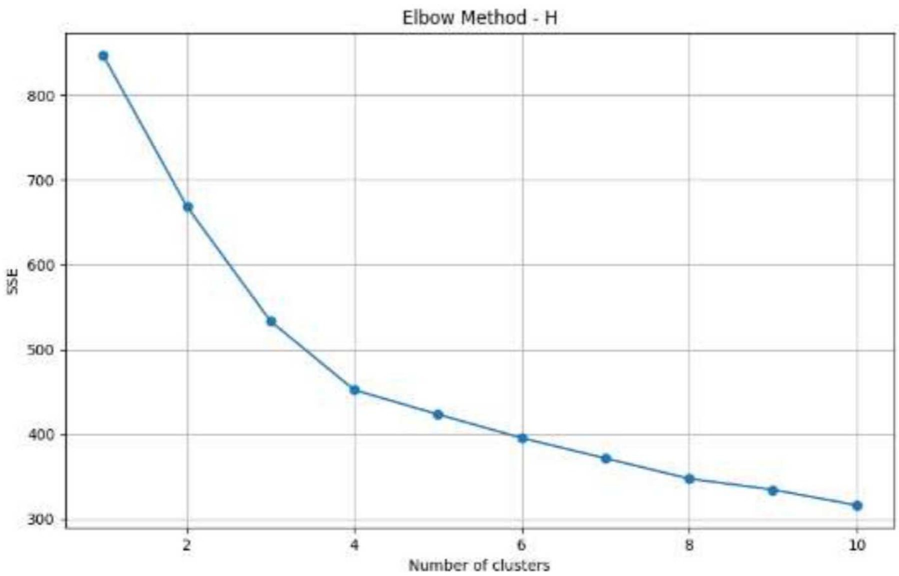


Figure 6. 6 (f) Elbow curve for Session H

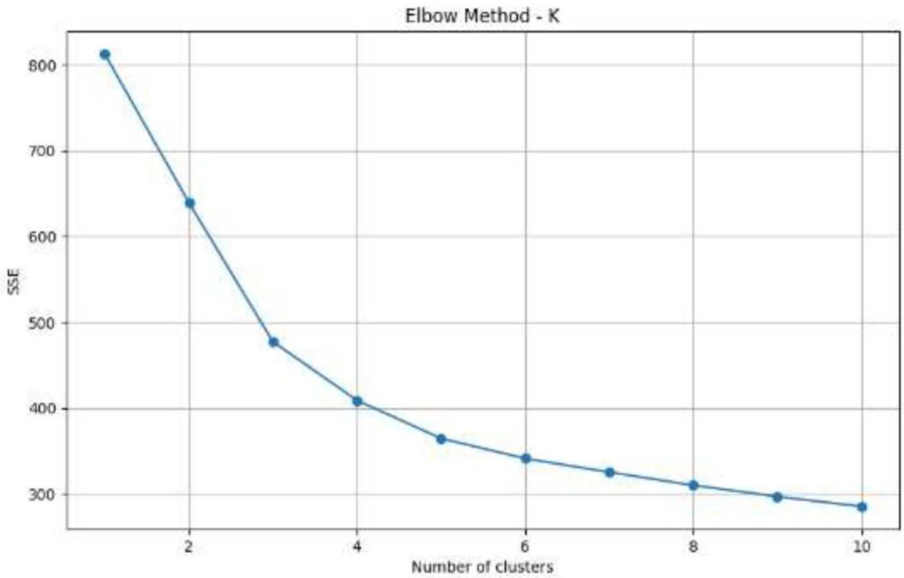


Figure 6. 7 (g) Elbow curve for Session K

In Figure 6.1 to 6.7, the calculated elbow curves are all smooth and do not necessarily have a distinct "elbow" shape. Therefore, the point with the largest curvature was recognized as the elbow number. Then, the appropriate number of clusters for all times is "4.” The elbow curvature also varies depending on the explanatory variables. In this study, three combinations of explanatory variables were investigated: (A) [time to answer formative assessment test, formative assessment score], (B) [grade, affiliation, time to answer formative assessment test, formative assessment score], and (C) [grade, affiliation, time to answer formative assessment test, formative assessment score, self-evaluation of learning goals] were investigated for the three combinations. The results showed that the optimal number of clusters for combination (A) was "3," for combination (B) "4," and for combination (C) "5. In the case of combination (A), the range of response times tended to be smaller. This result indicates that when the number of clusters was "3,” the range of formative evaluation scores tended to be wider and the range of response times narrower. This result means that the groupings were based on the response time. In the case of combination (C), the boundary between the groups tended to be unclear. In combination (B), both the formative assessment scores and response time ranges were appropriate and well aligned with the grouping based on the formative assessment test scores, which was the goal of this study. Therefore, combinations (A) and (C) were rejected, and combination (B) was adopted.

6.2.3 K-Means Clustering in Student Performance Analysis

The horizontal axis in Figure 16 shows the time taken for the formative assessment test, and the vertical axis shows the formative assessment test score. The formative assessment test was administered online using the Yamaguchi University Learning Support System. Therefore, the time taken to complete the test was calculated from the log-in and log-out times recorded by the Yamaguchi University Learning Support System. The formative assessment test consisted of three four-choice questions, each with a score of 10 points (30 points for three questions). From these scatter plots, two characteristics can be observed: examination time and evaluation test score. First, the shorter the examination time, the wider the range of the assessment test scores. The second characteristic is that the longer the test-taking time, the higher the score. These two features are manifested in the results, where most of the scatter plots are located to the left of the diagonal line from the origin to the upper right.

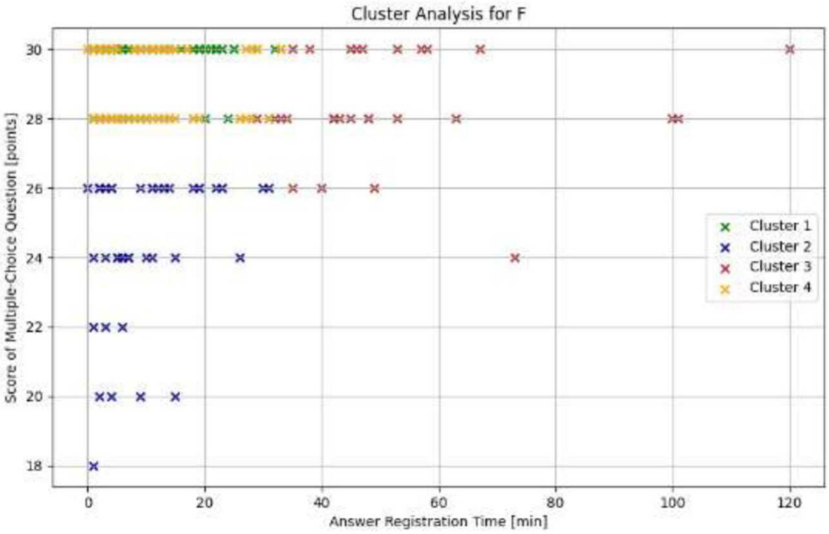


Figure 6. 8 (a) Clustered scatter plot for Session F

In Figure 6.8, the analysis of student performance using K-Means clustering, the scatter plot for session F provides a visual representation of how students' scores on a multiple-choice assessment relate to the time they took to register their answers. The plot, situated on a coordinate plane, employs the x-axis to denote the answer registration time, which spans from 0 to 120 min, and the y-axis to display the obtained scores, which range from 18 to 30 points. The data points coalesced into four distinct clusters, each marked by a unique color and symbol, encapsulating the performance and temporal patterns of the test-takers.

Cluster 1 is characterized by green 'X' marks, aggregating students who largely scored around 26 points, with answer registration times scattered from the commencement of the test to slightly over the 100-minute mark. Cluster 2, denoted by red 'X' marks, groups students with scores around 24 points, and like Cluster 1, showcases a wide temporal distribution of answer submission. Cluster 3, represented by blue 'X' marks, comprises students who primarily scored between 22 and 23 points, again with a broad range of answer registration times akin to the first two clusters. The final group, Cluster 4, with orange 'X' marks, stands out as it includes the highest-scoring students, those who achieved between 28 and 30 points, registering their answers in times ranging from approximately 20 minutes to 100 minutes.

The scatter plot reveals several key insights. First, the score distribution highlights that the highest scores are predominantly found within Cluster 4, suggesting that these participants fared the best in the assessment. Second, the time distribution across clusters does not present a clear or consistent pattern that correlates the time taken to register answers with the scores attained, as students with varied scores submitted their answers throughout the available time spectrum. Third, the density of the clusters indicates a closer grouping of students in Clusters 1, 2, and 3, as opposed to the more dispersed arrangement in Cluster 4, implying a variation in the performance of these top-scoring students concerning the time they utilized to respond.

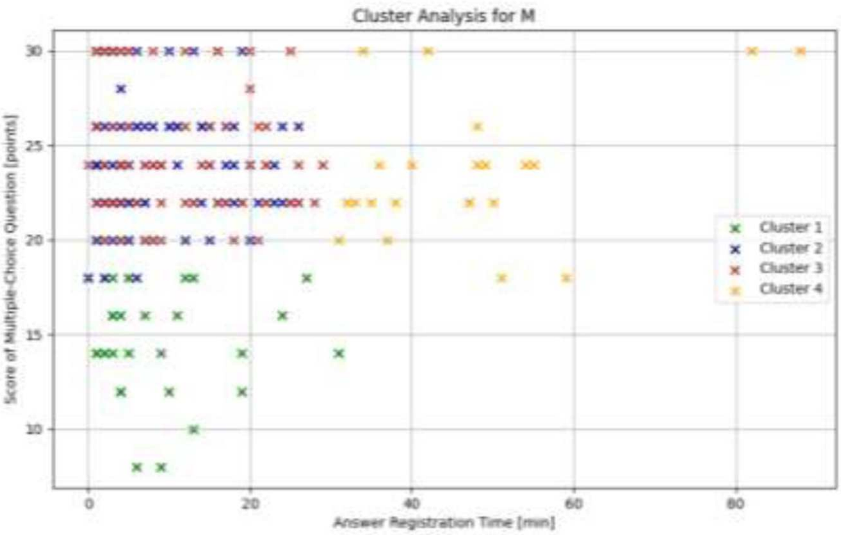


Figure 6. 9 (b) Clustered scatter plot for Session M

Cluster Analysis for session M in the Figure 6.9 serves as a graphical tool for discerning patterns in student performance as a function of response times during a formative assessment. The horizontal axis delineates the answer registration time, capped at 80 min, while the vertical axis quantifies the scores achieved on multiple-choice questions, stretching from below 10 to a full score of 30 points. The analysis unfolded across four distinct clusters, each color-coded for clarity.

Cluster 1, identified by green 'X' symbols, captures a subset of students scoring below 15 points with a commonality of prompt answer submissions within the initial 20 minutes. This cluster was notably sparse, indicating a smaller contingent of students who both underperformed and completed the test expeditiously. In contrast, Cluster 2, marked by red 'X' symbols, encompasses a broader spectrum of scores ranging from 15 to approximately 25 points, with a denser aggregation of data points reflecting a broad variability in response times, yet with a discernible concentration of participants finishing before the 40-minute threshold. Cluster 3, with blue 'X' markers, depicts an even wider score dispersion, from just over 10 to nearly 30 points, indicative of a diverse student performance with no apparent preference for answer registration times.

Standing out from the array is Cluster 4, denoted by orange 'X' symbols, which constitutes students who not only attained the highest scores, ranging from 25 to 30 points, but also predominantly registered their answers swiftly, within the first 40 minutes. Although this cluster is less dense, its positioning suggests a trend in which higher achievement is potentially associated with quicker responses, a conjecture that aligns with certain educational hypotheses that equate rapid information recall and better performance.

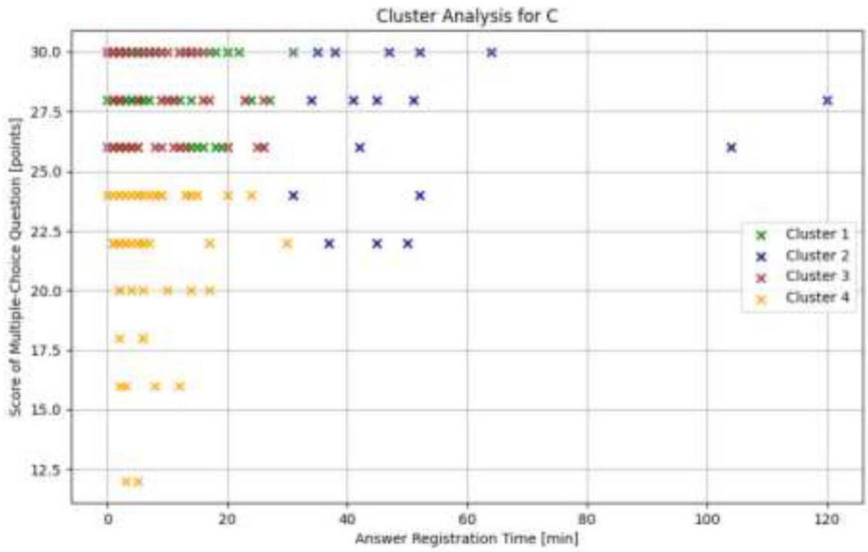


Figure 6. 10 (c) Clustered scatter plot for Session C

The scatter plot in Figure 6.10 presents the cluster analysis for Session C; the plot extends the horizontal axis up to 120 min to represent answer registration times, mirroring the breadth of the first plot examined. The vertical axis quantifies performance, displaying a score spectrum from approximately 12.5 to 30 points.

Cluster 1, depicted with green 'X' marks, aggregates top-performing students, scoring between 27.5 and 30 points. Their answer registration times varied, with modest clustering occurring within the initial 40 min. Cluster 2, marked with red 'X' symbols, consists of students scoring slightly lower, between roughly 25 and 27.5 points, and displays a wide dispersion of answer registration times, lacking a discernible pattern. Cluster 3, denoted by blue 'X' markers, comprises students with scores in the range of 22.5 to 25 points, and like Cluster 2, exhibits a broad range of answer registration times. Finally, Cluster 4, represented by orange 'X' signs, encompasses students with the broadest score range, from 15 to 22.5 points, most of whom registered their answers within the first 60 minutes. The plot provides a visual distribution of scores, with the highest achievers grouped in Cluster 1 and the lowest in Cluster 4.

The analysis revealed that while there was a slight trend of high-scoring students submitting answers quickly in Cluster 1, there was no overarching evidence to suggest a strong correlation between answer registration time and scores across all clusters. Understanding these factors could be pivotal for enhancing educational strategies and supporting student success. The scatter plot cluster analysis for Session C extends the horizontal axis up to 120 min to represent answer registration times, mirroring the breadth of the first plot examined. The vertical axis quantifies performance, displaying a score spectrum from approximately 12.5 to 30 points.

Cluster 1, depicted with green 'X' marks, aggregates top-performing students, scoring between 27.5 and 30 points. Their answer registration times varied, with modest clustering occurring within the initial 40 min. Cluster 2, marked with red 'X' symbols, consists of students scoring slightly lower, between roughly 25 and 27.5 points, and displays a wide dispersion of answer registration times, lacking a discernible pattern. Cluster 3, denoted by blue 'X' markers, comprises students with scores in the range of 22.5 to 25 points, and like Cluster 2, exhibits a broad range of answer registration times. Finally, Cluster 4, represented by orange 'X' signs, encompasses students with the broadest score range, from 15 to 22.5 points, most of whom registered their answers within the first 60 minutes. The plot provides a visual distribution of scores, with the highest achievers grouped in Cluster 1 and the lowest in Cluster 4.

The analysis revealed that while there was a slight trend of high-scoring students submitting answers quickly in Cluster 1, there was no overarching evidence to suggest a strong correlation between answer registration time and scores across all clusters. Understanding these could be pivotal in enhancing educational strategies and supporting student success

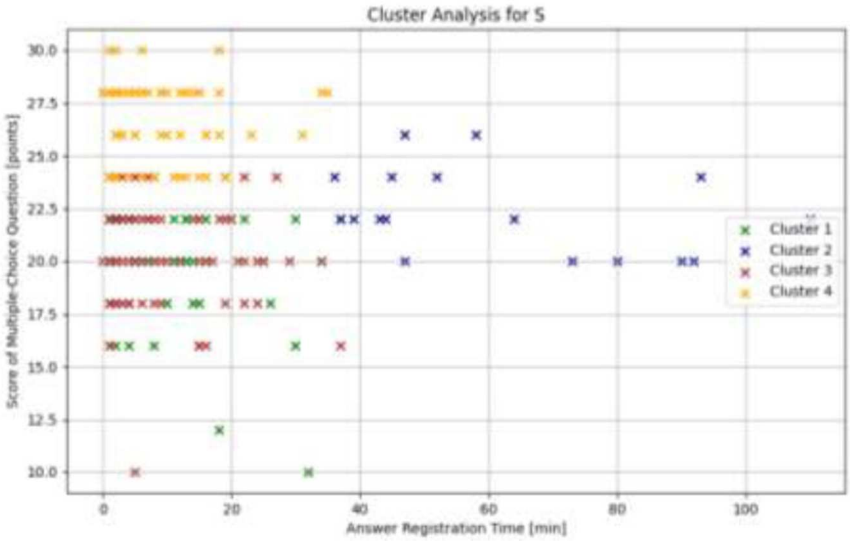


Figure 6. 11 (d) Clustered scatter plot for Session S

The Figure 6.11 scatter plot cluster analysis for Session S the plot extends the x-axis denotes the span of time participants utilized, up to 100 minutes, to register the responses.

Cluster 1, marked with green 'X' symbols, encapsulates those who scored in the lower bracket, specifically between 10 to 15 points, displaying a trend where the majority registered their answers early, within the first 40 minutes of the assessment period. Cluster 2, represented by red 'X' marks, includes a broader scoring range of participants, from 15 to 22.5 points, and is characterized by a wide distribution of answer registration times, although a gap is observed between the 40 and 60-minute marks. Moving up the performance scale, Cluster 3, denoted by blue 'X' symbols, captures those with scores from 22.5 to 27.5 points, registering their answers at various intervals across the time spectrum. The highest achievers are grouped into Cluster 4, with orange 'X' signs, predominantly consolidating their answers within the first 40 minutes, suggesting a correlation between prompt response submission and higher scoring, despite a few deviations from this pattern.

The observations found that a potential trend in which expedited answer registration may be associated with higher scores is particularly evident in Cluster 4. However, the data also indicate a divergence in outcomes; some high scorers deviated by taking longer, while some lower scorers demonstrated rapid response times. The most densely populated Cluster 2 indicated that a significant segment of the cohort achieved mid-range scores, albeit with varying time efficiencies. These insights hint at a complex relationship between the speed of answering and score outcomes, potentially influenced by diverse test-taking strategies or differential familiarity with content.

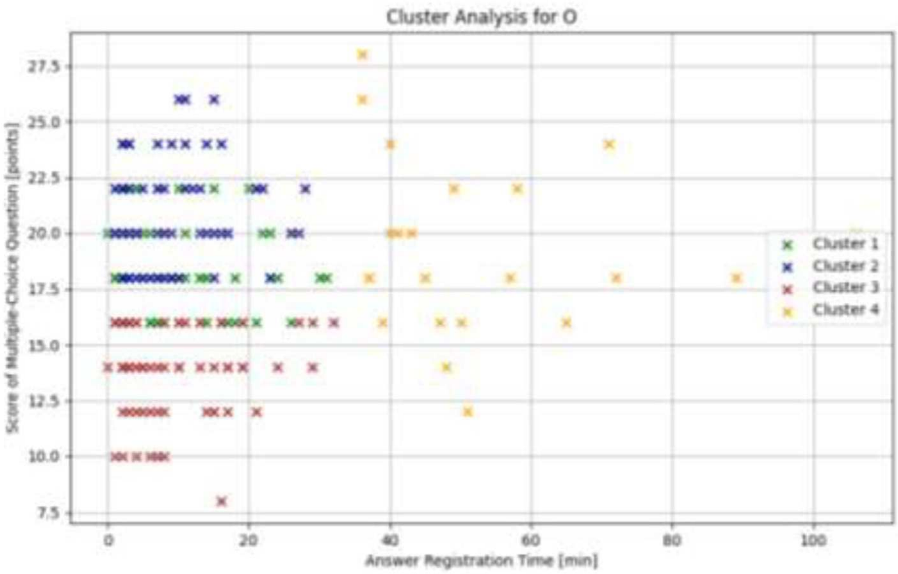


Figure 6. 12 (e) Clustered scatter plot for Session O

The scatter plot in Figure 6.12 cluster analysis for Session O delineates the time taken for answer registration on the x-axis, ranging from 0 to 100 minutes, and student scores on the y-axis, with a spectrum from 7.5 to just over 27.5 points.

Cluster 1, identified by green 'X' marks, consists of the higher-scoring participants, with scores between approximately 22.5 and 27.5 points. The answer registration spans the entire time range, yet a substantial number of these points were clustered before the 60-minute mark. Red 'X' symbols mark Cluster 2, capturing a mid-range scoring group with scores from 17.5 to 22.5 points and a wide distribution of registration times. Cluster 3, denoted by blue 'X' symbols, embodies participants scoring between roughly 12.5 and 17.5 points, with a notable majority submitting their answers in the initial 40 minutes. Conversely, Cluster 4, represented by orange 'X' marks, includes the lowest scoring participants, with scores ranging from 7.5 to 12.5 points, and a pronounced density of responses within the first 20 minutes.

In terms of score distribution, there was a clear descending trend from Cluster 1 to Cluster 4. Notably, this plot reveals a more pronounced pattern in which many lower-scoring participants registered their answers promptly, indicating that quicker answer submission is not consistently associated with higher performance. Cluster density showed a demarcation based on scores rather than registration times, with a significant early response rate among participants in the lower score ranges.

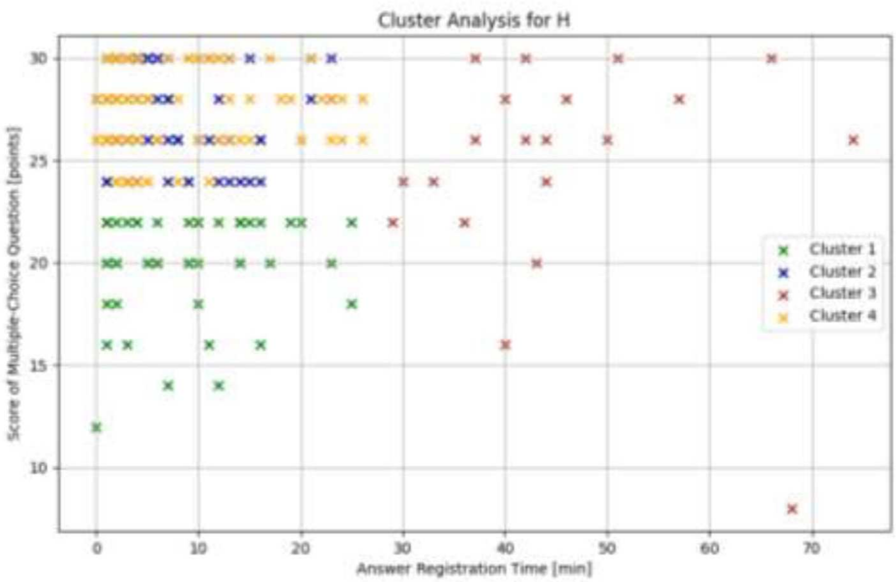


Figure 6. 13 (f) Clustered scatter plot for Session H

The scatter plot in Figure 6.13 cluster analysis for Session H is constructed with the x-axis representing the time taken by students to register their answers, which is capped at 70 min, and the y-axis illustrating the range of scores achieved on the questions, spanning from 10 to 30 points.

Cluster 1, symbolized by green 'X' marks, encapsulates the high-achieving participants who scored between 25 and 30 points, predominantly registering their answers within the first half-hour of the allotted time, suggesting a link between rapid response and high scores. Cluster 2, denoted by red 'X' marks, includes participants with scores ranging from 20 to 25 points and displays a broader temporal distribution, albeit with a mild predilection for registering answers before the 30-minute mark. Cluster 3, marked by blue 'X' symbols, represents students with scores between 15 and 20 points and a varied answer registration timeline. Finally, Cluster 4, indicated by orange 'X' marks, is composed of participants scoring the lowest, between 10 and 15 points, with a notable clustering of quick answer registrations, primarily within the initial 20 minutes.

This distribution suggests a possible correlation between the quickness of answer registration and higher achievement, as seen in Cluster 1 and a portion of Cluster 2. The score distribution presented a descending trend from Cluster 1 to Cluster 4, clearly delineating the clusters along the score axis.

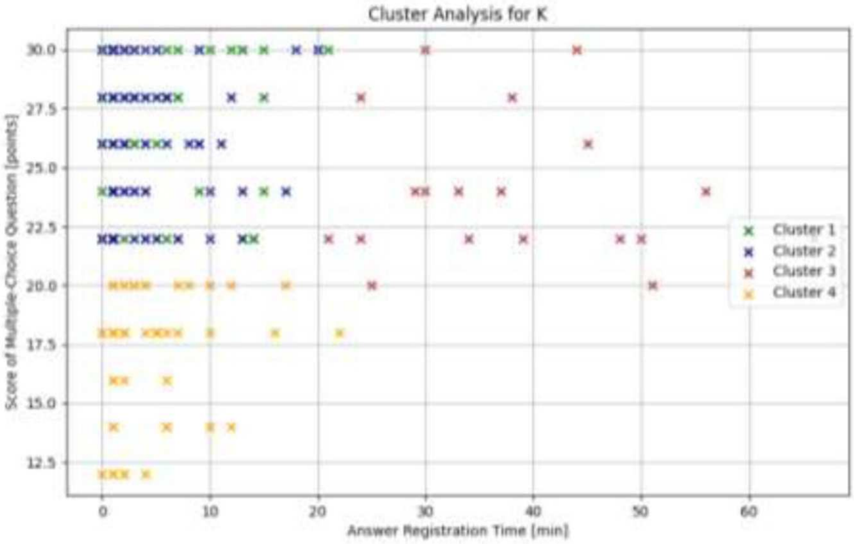


Figure 6. 14 (g) Clustered scatter plot for Session K

The Figure 6.14 scatter plot cluster analysis for Session K, the x-axis of the plot delineates the duration taken by participants to register their answers, extending up to 60 minutes, while the y-axis represents the range of scores achieved, fluctuating between approximately 12.5 to 30 points.

Cluster 1, marked by green 'X' symbols, aggregates the top scorers, those achieving between 27.5 and 30 points. A significant characteristic of this cluster is the concentration of these high scores registered within the first 10 min, suggesting a trend where rapid answer submission may align with higher scores. Cluster 2, denoted by red 'X' marks, includes participants scoring between 22.5 and 27.5 points, with a broader spread of registration times, yet predominantly within the first 30 minutes. Cluster 3, indicated by blue 'X' symbols, encapsulates a mid-range scoring group with scores from 17.5 to 22.5 points, exhibiting a wide distribution of answer registration times. Contrastingly, Cluster 4, represented by orange 'X' signs, comprises students scoring between 12.5 and 17.5 points, with a notable number of these students registering the answers rather quickly, within the first 20 minutes.

These observations found that there is a discernible correlation in Cluster 1 between swiftness of response and attainment of high scores, implying that faster answer registration could be associated with higher academic performance. The score distribution across the clusters was markedly stratified, indicating clear distinctions in performance levels.

6.2.4 Interpreting Student Performance: A Cluster Analysis of Formative Assessment in Online Learning

Interpreting the cluster analyses conducted on the formative assessment tests administered through the Yamaguchi University learning support system, several intriguing patterns and correlations emerged, offering valuable insights for educational strategies and course improvement. The horizontal axis of each scatter plot represents the time taken to complete the test, calculated from the login and logout times recorded by the system, while the vertical axis displays the scores achieved on the test, which comprised three four-choice questions, totaling 30 points.

Two primary characteristics were consistently observed across the scatter plots analyzed for sessions F, M, C, S, O, H, and K. First, there was a notable range in the assessment test scores among students who completed the test in shorter durations. This variability suggests that a quicker completion time does not necessarily equate to a higher score. This observation is crucial, as it challenges the conventional assumption that speed and efficiency in test-taking correlate directly with a better understanding of the material. Second, an opposite trend is observed where longer test-taking times are associated with higher scores. This pattern indicates that students who spend more time on the test may be more meticulous or thoughtful about their responses, potentially leading to better performance.

The cluster analyses further revealed that in each scatter plot, there were distinct groups of students who completed the test in 20 min or less and scored 20 (or 25) points or less. Despite the variations in color coding and category numbers across the scatter plots, this grouping is consistent, suggesting a specific cohort of students. However, it is essential to note that being in this category does not necessarily imply a high level of understanding of the course material. This is a critical observation, as it implies that rapid completion of the test is not an infallible indicator of a student's grasp of the subject matter.

These results have significant implications for class improvement and teaching design. While cluster analysis does not provide specific profiles of students within this category, it lays the groundwork for future research to identify common characteristics among these students. Understanding the learning and test-taking behaviors of this group could be instrumental in refining teaching methodologies and assessment designs. If future studies can identify and understand the profiles of these students, particularly those who respond quickly but score lower, this could lead to more targeted and effective teaching strategies, potentially enhancing overall student performance and course success.

Moreover, the cluster analysis of the formative assessment tests revealed complex and nuanced relationships between test-taking time, scores, and student understanding. These findings highlight the need for educators to consider multiple factors when evaluating student performance and underscore the potential benefits of tailoring teaching methods to accommodate diverse learning and test-taking behaviors.

6.3 Discussion

The application of k-means clustering and the Elbow Method in analyzing student performance through formative assessments presents a novel approach in educational analytics. MacQueen et al. [169] studied the versatility and effectiveness of k-means clustering in various data analysis contexts. Their foundational work underpins the methodological choices in this study, emphasizing the algorithm's capacity to reveal natural groupings within educational data. The decision to employ the elbow method for determining the optimal number of clusters further aligns with the recommendations of Ketchen et al. [173], who advocate its use in ensuring analytical clarity and interpretability. The k-means algorithm and Elbow Method are essential components of machine learning, particularly in the field of unsupervised learning and clustering analysis.

The k-means algorithm is a popular clustering method in machine learning that partitions a dataset into k distinct clusters based on similarity [170]. It falls under the category of unsupervised learning, where the algorithm groups data points into clusters without the need for labeled training data. The k-means algorithm is widely used for clustering tasks owing to its simplicity, efficiency, and scalability. By iteratively assigning data points to the nearest cluster centroid and updating the centroids based on the mean of the data points in each cluster, k-means clustering can effectively identify patterns and groupings within the data [124].

The Elbow Method is a technique used to determine the optimal number of clusters (k) in a dataset for clustering algorithms such as k-means [174]. It is a common approach in machine learning for evaluating clustering performance and identifying the point where adding more clusters does not significantly improve the model's accuracy. The Elbow Method involves plotting the sum of squared distances between data points and their assigned cluster centroids (inertia) against the number of clusters and looking for the "elbow point" where the rate of decrease in inertia slows down. This point indicates the optimal number of clusters for the dataset, balancing model complexity and clustering effectiveness [174].

The methodology utilized in this study, encompassing data collection and preprocessing, adheres to the stringent standards of analytical rigor as prescribed by Romero et al. [148] in their critical review of educational data mining. Their seminal work underscores the pivotal role of meticulously curated and well-prepared datasets in facilitating incisive educational insights, a tenet that informs our methodological approach.

This study, situated within the Course Research and Development Strategies at the Graduate School of Frontier Sciences, Yamaguchi University, leverages unsupervised machine learning algorithms to elucidate distinct patterns of student engagement and achievement. In doing so, it contributes to a growing body of literature exploring the intersection of data science and education to foster enhanced learning environments.

The identification of four primary clusters of students highlights the diverse range of learning behaviors and performance outcomes within the cohort studied [137]. In the study analyzing student performance based on formative assessment scores during student login and logout times using the k-means method, each cluster represents a group of students with specific performance characteristics. The k-means algorithm assigns students to different clusters based on similarities in their formative assessment scores, thereby creating distinct groups that exhibit unique traits. By analyzing the characteristics of each cluster, educators can gain valuable insights into student performance and tailor instructional strategies to meet individual and group needs.

Cluster 1, referred to as High Achievers, comprises students who exhibit consistent performance excellence in formative assessments. These students displayed thorough comprehension of the course material and attained exceptional academic accomplishments. The students in Cluster 2 demonstrated average performance on formative assessments, indicating a general understanding of the content with potential areas for improvement. These learners displayed a good grasp of the material; however, further refinement was necessary for complete mastery. Cluster 3 Low achievers included students who struggled with formative assessments. Indicates the challenges in understanding the material or effectively applying concepts. Cluster 4 includes students who exhibit a rapid improvement in formative assessment scores as well as a consistent level of performance over time. These students displayed a strong ability to quickly comprehend and adapt to new concepts while also demonstrating reliability and consistency in their academic achievement. The numbers in the text have remained unchanged. By examining the distinguishing features of each of the four clusters, educators can acquire valuable insights into the diverse performance profiles of their students and devise effective teaching strategies to cater to the specific needs of each group. This segmentation methodology is supported by the research of Case et al. [149], who emphasized the potential of clustering techniques to reveal intricate patterns in complex datasets and demonstrated the practical applications of data clustering in educational settings.

The findings of our analysis provide valuable insights into the development of tailored educational strategies and support systems that cater to students' diverse performance characteristics. These insights offer practical guidance for educators in designing instructional approaches that effectively address the unique needs of each student. Contrary to traditional pedagogical assumptions, our study found no uniform correlation between assessment response times and scores, challenging the notion that faster responses are indicative of higher understanding or achievement. This observation is supported by Martin et al. [175], who argued that time-on-task is not a straightforward predictor of learning outcomes in online environments. The implications for educators are far-reaching, suggesting the necessity to move beyond the conventional metrics of student engagement and towards more refined measures of learning effectiveness.

In summary, this study provides new insights into the factors affecting student performance and demonstrates the potential of machine learning techniques such as k-means clustering and the elbow method to enhance educational practices and contribute to the development of more effective teaching strategies [107, 108]. Building on the foundational work of pioneers in this field, this study contributes to the evolving discourse on the application of data science in education, offering a compelling argument for the adoption of data-driven methodologies to understand and improve student learning outcomes.

Chapter 7 - Conclusion and Future Research

7.1 Summary of Findings

This dissertation represents a pivotal exploration into the domain of online formative learning assessments, leveraging the intersection of innovative scoring methods and machine learning techniques, with a particular focus on k-means clustering and the Elbow Method. This study, centered on the "Research and Development Strategies" course at Yamaguchi University, delves into the efficacy and insights provided by these advanced approaches.

Transition to Innovative Assessment Techniques: Chapter 4's shift towards a novel scoring system for MCQs is underscored by the literature on assessment methodologies in digital learning environments. As posited by Bennett et al.[46], the evolution of assessment tools is crucial for capturing a nuanced understanding of student knowledge on online platforms. This novel scoring method introduced mirror advancements highlighted by Moncaleano et al. [80], emphasizing the significance of adapting assessment strategies to meet the challenges of digital education.

Data Collection and Preprocessing: The foundational work in Chapter 5 on data collection and preprocessing echoes the sentiments of Mahesh et al. [176], who stressed the importance of meticulous data preparation in educational data mining. This chapter's methodological rigor aligns with Romero et al. [177] advocacy for accurate and relevant data handling practices, reinforcing the study's commitment to analytical precision.

Machine Learning's Role in Education: The core analysis presented in Chapter 6, employing k-Means clustering and the Elbow Method, draws from the pioneering work of MacQueen et al., [169] on k-Means and Syakur et al., [119] on the Elbow Method. This study's application of these techniques to segmenting student performance data contributes to the dialogue initiated on the transformative potential of machine learning in education. The identification of distinct learning behaviors through clustering supports Baker et al. [178] discussion on the power of data analytics to personalize learning experiences.

Broad Implications for Educational Practice: The implications of this research on educational practice are deeply rooted in the principles of personalized learning, as discussed by Hattie et al. [26]. The ability to tailor educational strategies to individual student needs, as facilitated by the insights from this study, echoes the call by Rau et al. [93] for a more nuanced approach to digital learning.

Contributions to Educational Analytics: This dissertation contributes to educational analytics discourse, particularly the work of Gligorea et al. [120], by demonstrating the application of machine learning to improve educational assessment and analysis. The innovative use of k-means clustering and the Elbow Method for formative assessment data analysis exemplifies the potential for such techniques to inform educational practices, resonating with the findings of Romero et al.[177] on the impact of educational data mining.

This research articulates a significant advancement in the realm of online formative learning assessment. By integrating a new scoring method for MCQs and the strategic application of machine learning, this study paves the way for more effective and personalized educational practices [38]. Through a detailed literature review, these findings underscore the value of incorporating data-driven approaches into educational assessment and analysis, heralding a new era of innovation in the field.

7.1.1 Efficiency in Grading Systems

The integration of online learning platforms in educational settings has necessitated a re-evaluation of grading systems. Traditional grading methods, although effective in conventional settings, have shown limitations when applied to a vast and diverse digital student base. The Four MCQ format has emerged as a solution in this context. The design of this format allows for easy digital capture of respondents' answers, streamlining the data collection process. Additionally, technological advancements have provided tools such as Excel, spreadsheets, and Python programming, which can significantly reduce the time and effort involved in the scoring process. Notably, the efficiency of MCQs is evident from their widespread adoption in large-scale examinations [11, 99]. For instance, in Japan, the Center Test, a nationwide standardized examination for high school students, employs this format. Furthermore, the use of multiple-choice questions in critical assessments such as the National Medical Practitioners Examination reinforces their effectiveness and adaptability in diverse educational settings [38, 40].

7.1.2 Role of Formative Assessment

Historically, formative assessments have been pivotal in bridging the gap between instruction and understanding, allowing educators to tweak their methods in real time based on student feedback [155, 179]. The importance of online education has skyrocketed. Without the tangible presence of a traditional classroom, continuous feedback mechanisms become a lifeline for students, providing them with clarity and direction in their learning journey.

In light of this, Yamaguchi University's approach to formative assessment for its Theory R&D course stands out as a remarkable case study. Adopting a four-choice questionnaire (MCQ) format, the university optimized the assessment for online delivery. The Four MCQ format, as opposed to traditional 5-choice or true/false questions, struck a balance between complexity and manageability, ensuring comprehensive coverage of the course material while maintaining student engagement. Digital tools and platforms have further enriched this approach, enabling real-time analytics of student performance. Such analytics have provided insights into areas where students struggle, allowing for immediate instructional adjustments [180]. The success of this method, as evidenced by improved student outcomes and feedback, underscores the potential of tailored formative assessments in online education.

7.2 Contributions

The integration of the Four MCQ formats in this research reflects the progressive trend in educational evaluations. This demonstrates the fusion of diverse assessment methodologies. Although MCQs have been a foundational component of assessments for decades, their integration with modern analytical tools paints a picture of the future of education. In particular, the Four MCQ format simplifies data collection and analysis, making it an ideal candidate for integration with contemporary tools. By merging this streamlined question format with sophisticated data analysis techniques, this study offers an unprecedented depth of insight into student performance and understanding. This synthesis ensures that educators and institutions can make informed decisions and tailor their approaches to better serve their students.

7.2.1 The Technique of Formative Assessment at Yamaguchi University

The conventional approach to assessments often involves providing feedback at the end of the learning period, which emphasizes a summative perspective. However, Yamaguchi University's adoption of the Four MCQ method demonstrates a forward-thinking approach to formative assessment. This innovative technique is an integral component of the university's teaching strategy, emphasizing continuous feedback and iterative evaluation throughout the learning process. The Four MCQ's unique design allows educators to gauge the depth and breadth of student understanding in real time, providing immediate insights that enable both educators and students to identify areas of strength and address gaps in understanding as they arise. This proactive approach ensures that learning is a dynamic and responsive process, with assessments serving as tools for ongoing improvement rather than mere endpoint evaluations. The success of this method at Yamaguchi University highlights its potential as a transformative tool in the broader landscape of education, fostering an environment in which assessments actively contribute to the learning journey rather than merely punctuating it.

7.2.2 The New Four MCQ Method

The introduction of the Four-Multiple Choice (MCQ) method was among the most significant outcomes of this study. This innovative approach was designed to enhance the accuracy and effectiveness of online assessments. The key aspects of this method include the following.

Improved Discrimination: The Four MCQ formats were found to be more effective in discriminating between different levels of student understanding compared to traditional formats. This was primarily due to the refined structure of the questions, which required a deeper level of comprehension and critical thinking

Enhanced Engagement: The format encouraged students to engage more thoroughly with the learning material. Unlike traditional MCQs, which often lead to surface-level learning, the Four MCQ format prompts students to analyze and evaluate the content more critically.

Positive Reception: Both students and educators responded positively to this new format. Educators appreciated the nuanced assessment of student knowledge, while students found the format fairer and more reflective of their true understanding.

7.2.3 Utilizing K-means for Student Performance Analysis

Another significant aspect of this research is the application of the k-means clustering algorithm to analyze student performance. This innovative approach yielded insightful results:

Identification of Learning Patterns: By clustering student responses, this study was able to identify distinct patterns in student learning and understanding. This provided a more nuanced view of student performance beyond what traditional grading methods offer.

Targeted Educational Interventions: The insights gained from the k-means analysis enabled the identification of specific areas in which students struggled. This allowed for more targeted educational interventions tailored to the needs of different student groups.

.

These key findings from the novel Four MCQ method and the use of k-means for student performance analysis significantly contribute to the field of online assessment [181]. They not only demonstrate the efficacy of innovative assessment techniques but also highlight the potential of data analytics in education. These findings provide a strong foundation for future research and practical applications in digital learning environments.

7.3 Limitations of the Study

One of the primary limitations of this research is its narrow focus on Higher Education settings. While the findings provide valuable insights for such institutions, they may not translate seamlessly to primary or secondary educational contexts, where pedagogical strategies and student learning behaviors could differ significantly.

Specificity to Yamaguchi University, the methodologies and techniques employed in this study, particularly the application of machine learning, are tailored to the courses and educational environment at Yamaguchi University. As such, generalizing these findings to other universities or courses would necessitate further research and validation. The unique culture, curriculum, and technological infrastructure in Yamaguchi may not mirror other institutions that potentially influence the outcomes.

7.4 Recommendations for Future Research

In this thesis, I focus on enhancing online formative learning assessments in higher education, particularly through the implementation of innovative scoring methods, such as the four-multiple choice format. This approach, as examined at Yamaguchi University, has shown promising results in engaging students more effectively in digital learning environments. The analysis of student performance data through machine learning techniques, especially k-means clustering, is another significant aspect of this study. This highlights the potential for tailored educational strategies based on data-driven insights.

In comparison, the National University of Laos faces unique challenges in adopting these modern educational methodologies. These challenges stem primarily from differences in technological infrastructure, cultural contexts, and possibly limited resources for such digital transformations. Despite these challenges, NUOL holds the potential for significant advancements in online education, provided that these factors are judiciously addressed.

However, my next future goals for NUOL involve adapting successful strategies from Yamaguchi University to its context. This includes not only the direct application of innovative assessment methods but also a focus on developing ICT infrastructure and providing professional development for educators in online teaching methodologies. Moreover, continuous evaluation and research on culturally contextualized educational strategies are crucial. These efforts aim to leverage technology and innovation to enhance NUOL's educational experience and outcomes.

In comparison, the National University of Laos faces unique challenges in adopting these modern educational methodologies. These challenges stem primarily from differences in technological infrastructure, cultural contexts, and possibly limited resources for such digital transformations. Despite these challenges, NUOL holds the potential for significant advancements in online education, provided that these factors are judiciously addressed.

However, my next future goals for NUOL involve adapting successful strategies from Yamaguchi University to its context. This includes not only the direct application

of innovative assessment methods but also a focus on developing ICT infrastructure and providing professional development for educators in online teaching methodologies. Moreover, continuous evaluation and research on culturally contextualized educational strategies are crucial. These efforts aim to leverage technology and innovation to enhance NUOL's educational experience and outcomes.

Acknowledgements

I started my PhD, the onset of the Covid-19 pandemic, a period that presented numerous challenges and uncertainties. Nonetheless, I have revised this to complete the line. I would like to express my deepest gratitude to the exceptional individuals who supported and guided me throughout this transformative journey, enabling me to successfully obtain my doctorate despite the many unforeseen obstacles that arose.

I would like to express my deepest gratitude to my supervisor, Professor Dr. Naoki OHSHIMA, for his guidance, constant support, guidance, and encouragement, which have been invaluable throughout the process. From the initial stages of refining my research proposal to the final submission of my thesis, my unwavering presence and wealth of wisdom have been instrumental in shaping my academic growth. I highly valued the biweekly meetings we held, which not only served as crucial checkpoints to keep me on track academically, but also provided me with plenty of encouragement. I am profoundly grateful for your immeasurable contribution to the development of my research.

I would like to thank all professors and staff at the Management of Technology (MOT) office. Their kind help and support have made my studies and life in Japan wonderful.

I dedicate this work to my parents, with special dedication to my father, Phan, my mother, Choung, my family, and my lovely son. Without your tremendous understanding and encouragement over the past three years, it would be impossible for me to complete my study.

Finally, I would like to thank all my friends, colleagues, and everyone who supported me in various ways during this academic journey.

I have taken full responsibility for all errors that may have been present in this study.

References

1. Hart, G., Peer Learning and Support Via Audio-Teleconferencing in Continuing Education for Nurses. Distance Education, 1990. **11**(2): p. 308-319. DOI: 10.1080/0158791900110209.
2. Vivien, T., Digital Learning for the Digital Environment. 2023.
3. An, Y., A History of Instructional Media, Instructional Design, and Theories. International Journal of Technology in Education, 2021. **4**(1): p. 1-21. DOI: 10.46328/ijte.35.
4. Beldarrain, Y., Distance Education Trends: Integrating New Technologies to Foster Student Interaction and Collaboration. Distance education, 2006. **27**(2): p. 139-153. DOI: 10.1080/01587910600789498.
5. Dobre I. Learning Management Systems for Higher Education: An Overview of Available Options for Higher Education Organizations. Procedia-social and behavioral sciences, 2015. **180**: p. 313-320.
6. Bezovski, Z. and S. Poorani. The evolution of e-learning and new trends. in *Information and Knowledge Management*. 2016. liste.
7. Afzal, A., et al., Addressing the Digital Divide: Access and Use of Technology in Education. Journal of Social Sciences Review, 2023. **3**(2): p. 883-895.
8. Gunawardena, C.N. and M.S. McIsaac, Distance education, in *Handbook of research on educational communications and technology*. 2013, Citeseer. p. 361-401.
9. Bashir, A., et al. Post-COVID-19 adaptations; the shifts towards online learning, hybrid course delivery and the implications for biosciences courses in the higher education setting. in *Frontiers in Education*. 2021. Frontiers.
10. DeCoito, I. and M. Estaiteyeh, Transitioning to online teaching during the COVID-19 pandemic: An exploration of STEM teachers' views, successes, and challenges. Journal of Science Education and Technology, 2022. **31**(3): p. 340-356.
11. Brown, G.T. and H.H. Abdulnabi. Evaluating the quality of higher education instructor-constructed multiple-choice tests: Impact on student grades. in *Frontiers in Education*. 2017. Frontiers Media SA.
12. Hayes, M. and L. Cejnar, Online work-integrated learning: Developing post-pandemic work-ready graduates. Ensino Superior em Transição: Estudantes Online Higher Education in Transition: Students, 2021: p. 79.
13. Limperos, A.M., et al., Online Teaching and Technological Affordances: An Experimental Investigation into the Impact of Modality and Clarity on Perceived and Actual Learning. Comput. Educ., 2015. **83**: p. 1-9. DOI: 10.1016/j.compedu.2014.12.015.
14. Means, B., et al., Evaluation of Evidence-Based Practices in Online Learning: A Meta-Analysis and Review of Online Learning Studies 2009.
15. Thiele, J.E., Learning Patterns of Online Students. J. Nurs. Educ. , 2003. **42**(8): p. 364-366. DOI: 10.3928/0148-4834-20030801-08.
16. Detyna, M., et al., Hybrid Flexible (HyFlex) Teaching and Learning: Climbing the Mountain of Implementation Challenges for Synchronous Online and Face-to-Face Seminars During a Pandemic. Learning environments research, 2023. **26**(1): p. 145-159. DOI: 10.1007/s10984-022-09408-y.
17. Yamamoto, K., et al., Innovations in online classes introduced during the COVID-19 pandemic and their educational outcomes in Japan. BMC Medical Education, 2023. **23**(1). DOI: 10.1186/s12909-023-04874-1.
18. Dunn, L., et al., *The student assessment handbook: New directions in traditional and online assessment*. 2003: Routledge.
19. Kulasegaram, K. and P.K. Rangachari, Beyond "formative": assessments to enrich student learning. Advances in physiology education, 2018. **42**(1): p. 5-14.
20. Redecker, C. and Y. Punie, Digital Competence of Educators. Edited by Yves Punie, 2017.
21. Sato, S.N., et al., Navigating the New Normal: Adapting Online and Distance Learning in the Post-Pandemic Era. Education Sciences, 2023. **14**(1): p. 19.

22. Mattingly, K.D., M.C. Rice, and Z.L. Berge, Learning analytics as a tool for closing the assessment loop in higher education. UMBC College of Engineering and Information Technology Dean's Office, 2012.
23. Imonje, R.K., Undergraduate Student Perceptions on Virtual Online Versus On-campus Teaching–Learning Modes of Delivery and Assessment in Public Universities. Journal of Education and Development, 2022. **6**(5): p. 25.
24. Hwang, G.-J. and H.-F. Chang, A formative assessment-based mobile learning approach to improving the learning attitudes and achievements of students. Computers & Education, 2011. **56**(4): p. 1023-1031.
25. Beebe, R., S. Vonderwell, and M. Boboc, Emerging patterns in transferring assessment practices from f2f to online environments. Electronic Journal of e-learning, 2010. **8**(1): p. pp1-12-pp1-12.
26. Hattie, J. and H. Timperley, The power of feedback. Review of educational research, 2007. **77**(1): p. 81-112.
27. TAN, A.Y.T., *Technology Enhanced Assessment and Feedback among Educators across Disciplines*. 2019, Monash University.
28. Chanpet, P., K. Chomsuwan, and E. Murphy, Online Project-Based Learning and Formative Assessment. Technology, Knowledge and Learning, 2020. **25**: p. 685-705.
29. Spector, J.M., et al., Technology enhanced formative assessment for 21st century learning. Journal of educational technology & society, 2016. **19**(3): p. 58-71.
30. Haarala-Muhonen, A., et al., The Impact of Pedagogical and ICT Training in Teachers' Approaches to Online Teaching and Use of Digital Tools. Front. Educ., 2023. **8**(8): p. 1223665. DOI: 10.3389/feduc.2023.1223665.
31. Mustapha, R.B., Future Assessment in Higher Education: Reframing Conventional Practices Ramlee B. Mustapha. Horizon, 2020. **2**(1): p. 19-34.
32. Regmi, K. and L. Jones, A systematic review of the factors–enablers and barriers–affecting e-learning in health sciences education. BMC medical education, 2020. **20**(1): p. 1-18.
33. Unicef, Formative assessment for quality, inclusive digital and distance learning during and beyond the COVID-19 pandemic. United Nations Children's Fund Regional Office for Europe and Central Asia: Switzerland, 2021.
34. Magno, C. and G.S. Lizada, Features of classroom formative assessment. Educational measurement and evaluation review, 2015. **6**.
35. Klein, S.P., et al., An approach to measuring cognitive outcomes across higher education institutions. Research in Higher Education, 2005. **46**: p. 251-276.
36. Gikandi, J.W., D. Morrow, and N.E. Davis, Online Formative Assessment in Higher Education: A Review of the Literature. Computers & education, 2011. **57**(4): p. 2333-2351. DOI: 10.1016/j.compedu.2011.06.004.
37. Johnson, C.I. and R.E. Mayer, A testing effect with multimedia learning. Journal of Educational Psychology, 2009. **101**(3): p. 621.
38. Ohshima, N.O., K.; Takahashi, M. , Study of Summative Evaluation by New Multiple-Choice Question. Innov. Manag., 2016.
39. Hatziapostolou, T. and I. Paraskakis, Enhancing the impact of formative feedback on student learning through an online feedback system. Electronic Journal of E-learning, 2010. **8**(2): p. 111-122.
40. Tiemeier, A.M., Z.A. Stacy, and J.M. Burke, Using Multiple Choice Questions Written at Various Bloom's Taxonomy Levels to Evaluate Student Performance Across a Therapeutics Sequence. Innov. Pharm., 2011. **2**(2). DOI: 10.24926/iip.v2i2.224.
41. Collignon, S.E., J. Chacko, and M. Wydick Martin, An Alternative Multiple-Choice Question Format to Guide Feedback Using Student Self-Assessment of Knowledge. Decision Sciences Journal of Innovative Education, 2020. **18**(3): p. 456-480. DOI: 10.1111/dsji.12213.
42. Ozkan, S. and R. Koseler, Multi-dimensional students' evaluation of e-learning systems in the higher education context: An empirical investigation. Computers & Education, 2009. **53**(4): p. 1285-1296. DOI: 10.1016/j.compedu.2009.06.011.
43. Montgomery, D.C., E.A. Peck, and G.G. Vining, *Introduction to linear regression analysis*. 2021: John Wiley & Sons.

44. Black, P. and D. Wiliam, Developing the theory of formative assessment. Educational Assessment, Evaluation and Accountability (formerly: Journal of personnel evaluation in education), 2009. **21**: p. 5-31.
45. Cowie, B. and B. Bell, A model of formative assessment in science education. Assessment in Education: Principles, Policy & Practice, 1999. **6**(1): p. 101-116.
46. Bennett, R.E., Formative assessment: A critical review. Assessment in education: principles, policy & practice, 2011. **18**(1): p. 5-25. DOI: 10.1080/0969594X.2010.513678.
47. Wafubwa, R.N., Role of Formative Assessment in Improving Students' Motivation, Engagement, and Achievement: A Systematic Review of Literature. International Journal of Assessment and Evaluation, 2020. **28**(1): p. 17-31. DOI: 10.18848/2327-7920/CGP.
48. Tran, H., et al., Data Mining of Formative and Summative Assessments for Improving Teaching Materials towards Adaptive Learning: A Case Study of Programming Courses at the University Level. Electronics, 2023. **12**(14): p. 3135.
49. Zheng, G., et al., Using Instruction-Embedded Formative Assessment to Predict State Summative Test Scores and Achievement Levels in Mathematics. J. Learn. Anal., 2019. **6**(2): p. 153–174-153–174. DOI: 10.18608/jla.2019.62.11.
50. Kannan, P. and D. Zapata-Rivera. Facilitating the Use of Data From Multiple Sources for Formative Learning in the Context of Digital Assessments: Informing the Design and Development of Learning Analytic Dashboards. in *Frontiers in Education*. 2022. Frontiers.
51. Sharp, L.A. and J.H. Sharp, Enhancing student success in online learning experiences through the use of self-regulation strategies. Journal on Excellence in College Teaching, 2016. **27**(2): p. 57-75.
52. Shadnaz Asgari, et al., An Observational Study of Engineering Online Education During the COVID-19 Pandemic. PLoS ONE, 2021. **16**(4): p. e0250041. DOI: 10.1371/journal.pone.0250041.
53. Rapanta Chrysi, et al., Balancing Technology, Pedagogy and the New Normal: Post-Pandemic Challenges for Higher Education. Postdigital Sci. Educ., 2021. **3**(3): p. 715-742. DOI: doi.org/10.1007/s42438-021-00249-1.
54. Osama Yaseen M. Al-Rawi, W.S.A.-D., Ibrahim Reda,, COVID-19 Impact on Education and Work in the Kingdom of Bahrain: Survey Study. Inf. Sci. Lett. , 2021. **10**(3): p. 427-433. DOI: 10.18576/isl/100305.
55. Fatima Lahcen Yachou Ait Yassine, Tamara Adel Maaitah, and J.A.A.-G. Dirar Abdelaziz Maaitah, Impact of COVID-19 on the University Education System in Jordan. J. Southwest Jiaotong Univ., 2022. **57**(1). DOI: doi.org/10.35741/issn.0258-2724.57.1.58.
56. Irma Wani Othman, Saifulazry Mokhtar, and M.S. Esa3, The Stages of National Education System Operation: Issues, Rationale, and Challenges for the Ministry of Education Malaysia (MOE) in Facing Post Pandemic Norms of Covid-19. Int. J. Educ. Psychol. Couns., 2022. **7**(47): p. 616-638. DOI: 10.35631/IJEPC.747048.
57. Siti Aisyah Mohamad Zin, et al., COVID-19: The Impact of Pandemic on Emotional and Educational Conflicts in Malaysia: A Literature Review. Journal of Tourism, Hospitality and Environment Management, 2021. **6**(25): p. 01-14. DOI: 10.35631/JTHEM.625001.
58. HeleDna Kovacs, Caroline Pulfrey, and E.-C. Monnier, Surviving but not Thriving: Comparing Primary, Vocational and Higher Education Teachers' Experiences During the COVID-19 Lockdown. Educ. Inf. Technol., 2021. **26**(6): p. 7543-7567. DOI: 10.1007/s10639-021-10616-x.
59. Fazri Hermanto and R.S. Mu'tamar, The Effect of Online Learning on Compass and Steering System Learning at Politeknik Pelayaran Malahayati in the Conditions of The Covid-19 Pandemic. J. Soc. Med., 2022. **1**(3): p. 73-78. DOI: 10.47353/jsocmed.v1i3.11.
60. Kunwar, R., A.K. Shrestha, and S.P. Phuyal, The Impact of Force Paradigm Shift in Teaching and Learning Higher Education in Nepal: A Study on Behavior Perspective. Eur. J. Educ. Pedagogy, 2022. **3**(2): p. 12-17. DOI: 10.24018/ejedu.2022.3.2.270.
61. Northey, G., T. Bucic, and M.B. Chylinski, Increasing Student Engagement Using Asynchronous Learning. J. Mark. Educ., 2015. **37**(3): p. 171-180. DOI: 10.1177/0273475315589814.
62. Obeidat, S.M. and J.A. Hajjat. Face-to-Face and E-learning Styles for Undergraduate Engineering Technology Students During COVID-19 Pandemic. in *In Proceedings of the 2021 ASEE Virtual Annual Conference*. July, 2021.

63. Paulsen, J. and A.C. McCormick, Reassessing Disparities in Online Learner Student Engagement in Higher Education. Educ. Res., 2020. **49**(1): p. 20-29. DOI: 10.3102/0013189X19898690.
64. Leon, C.T.-D., ESL Teachers And Students' Perceptions Toward Blended-Learning During Covid-19 Pandemic. J. Educ. Train. Stud., 2022. **13**(2): p. 45-53. DOI: 10.47750/jett.2022.13.02.005.
65. Hanane, L. and B. Djilali, ICT and the Development of Techno-Pedagogical Skills Among the Algerian University Teachers. J. Educ. Soc. Res., 2015. **5**(1): p. 129. DOI: 10.5901/jesr.2015.v5n1p129.
66. Dooly, M., New Competencies in a New Era? Examining the Impact of a Teacher Training Project. ReCALL, 2009. **21**(3): p. 352-369. DOI: 10.1017/S0958344009990085.
67. Pongsakdi, N., A. Kortelainen, and M. Veermans, The Impact of Digital Pedagogy Training on In-Service Teachers' Attitudes Towards Digital Technologies. Educ. Inf. Technol., 2021(11): p. 1-14. DOI: 10.1007/s10639-021-10439-w.
68. Nagar, N.M.-., H. Shachar, and O. Argaman, Changing the Learning Environment: Teachers and Students' Collaboration in Creating Digital Games. J. Inf. Technol. Educ. Innov. Pract., 2019. **18**: p. 61. DOI: 10.28945/4405.
69. Daumiller, M., et al., Shifting from Face-to-Face to Online Teaching During COVID-19: The Role of University Faculty Achievement Goals for Attitudes Towards This Sudden Change, and Their Relevance for Burnout/Engagement and Student Evaluations of Teaching Quality. Comput. Hum. Behav., 2021. **118**: p. 106677. DOI: 10.1016/j.chb.2020.106677.
70. Liesa-Orús, M., et al., The Technological Challenge Facing Higher Education Professors: Perceptions of ICT Tools for Developing 21st Century Skills. Sustainability, 2020. **12**(13): p. 5339. DOI: 10.3390/su12135339.
71. Rosenbusch, K., Technology Intervention: Rethinking the Role of Education and Faculty in the Transformative Digital Environment. Adv. Dev. Hum. Resour., 2020. **22**(1): p. 87-101. DOI: 10.1177/1523422319886297.
72. Joshi, S., R.K. Rambola, and P. Churi. Evaluating Artificial Intelligence in Education for Next Generation. in *J. Phys.: Conf. Ser.* 2021. IOP Publishing. DOI: 10.1088/1742-6596/1714/1/012039.
73. Muñiz, J., Test Theories: Classical Theory and Item Response Theory. Papeles del Psicólogo, 2010. **31**(1): p. 57-66.
74. An, X. and Y.-F. Yung, Item response theory: What it is and how you can use the IRT procedure to apply it. SAS Institute Inc. SAS364-2014, 2014. **10**(4): p. 1-14.
75. Kean, J. and J. Reilly, Item response theory. Handbook for clinical research: Design, statistics and implementation, 2014: p. 195-198.
76. Cai, L., et al., Item response theory. Annual Review of Statistics and Its Application, 2016. **3**: p. 297-321.
77. Ranger, J. and J.-T. Kuhn, Testing fit of latent trait models for responses and response times in tests. Psychological Test and Assessment Modeling, 2014. **56**(4): p. 382.
78. Reeve, B.B. and P. Fayers, Applying item response theory modeling for evaluating questionnaire item and scale properties. Assessing quality of life in clinical trials: Methods of practice, 2005. **2**: p. 55-73.
79. Mellenbergh, G.J., Item bias and item response theory. International journal of educational research, 1989. **13**(2): p. 127-143.
80. Moncaleano, S. and M. Russell, A Historical Analysis of Technological Advances to Educational Testing: A Drive for Efficiency and the Interplay with Validity. Journal of Applied Testing Technology, 2018: p. 1-19.
81. Osteen, P., An introduction to using multidimensional item response theory to assess latent factor structures. Journal of the Society for Social Work and Research, 2010. **1**(2): p. 66-82.
82. Buchanan, R.A., et al., Philosophy of education in a new key: exploring new ways of teaching and doing ethics in education in the 21st century. Educational Philosophy and Theory, 2022. **54**(8): p. 1178-1197.
83. Kane, M.T., Validating the interpretations and uses of test scores. Journal of Educational Measurement, 2013. **50**(1): p. 1-73.

84. Butler, S.M., W. McColskey, and R. O'Sullivan, How to assess student performance in science: going beyond multiple-choice tests. SERVE Center for Continuous Improvement at UNCG, 2005.
85. DiBattista, D. and L. Kurzawa, Examination of the quality of multiple-choice items on classroom tests. Canadian Journal for the Scholarship of Teaching and Learning, 2011. **2**(2): p. 4.
86. Kelderman, H., Loglinear multidimensional item response models for polytomously scored items, in *Handbook of modern item response theory*. 1997, Springer. p. 287-304.
87. Mahabeer, P. and F.F. Akoo, Connecting assessment and feedback: A customised and personalised experience for knowledge-building. Journal of Education (University of KwaZulu-Natal), 2021(83): p. 87-110.
88. Van der Linden, W.J. and C.A. Glas, *Computerized adaptive testing: Theory and practice*. 2000: Springer.
89. Leary, L.F. and N.J. Dorans, Implications for altering the context in which test items appear: A historical perspective on an immediate concern. Review of Educational research, 1985. **55**(3): p. 387-413.
90. Markus, K.A. and D. Borsboom, *Frontiers of test validity theory: Measurement, causation, and meaning*. 2013: Routledge.
91. Gierl, M.J., et al., Developing, analyzing, and using distractors for multiple-choice tests in education: A comprehensive review. Review of Educational Research, 2017. **87**(6): p. 1082-1116.
92. Althaus, C., et al., *The Australian policy handbook: A practical guide to the policymaking process*. 2022: Taylor & Francis.
93. Rau, M.A., A framework for educational technologies that support representational competencies. IEEE Transactions on Learning Technologies, 2016. **10**(3): p. 290-305.
94. Frey, B.B., V.L. Schmitt, and J.P. Allen, Defining authentic classroom assessment. Practical Assessment, Research, and Evaluation, 2012. **17**(1): p. 2.
95. Mao, S.S. and P. Crosthwaite, Investigating written corrective feedback:(Mis) alignment of teachers' beliefs and practice. Journal of Second Language Writing, 2019. **45**: p. 46-60.
96. Mattsson, T. and M. Pastorek Gripson. Dancing With Digital Tools: Discourses on Teaching and Learning in School-Age Educare in Sweden. in *The 8th IAFOR International Conference on Education Honolulu, USA, 5-8/1 2023*. 2023.
97. IKEBUKURO, K., A New Multiple-Choice Question Format More Parallel to the Knowledge Quantity. Relationship between Expected Correct Answer Ratio and Knowledge Quantity. Med. Educ., 1999: p. 15-20.
98. Haladyna, T.M., S.M. Downing, and M.C. Rodriguez, A Review of Multiple-Choice Item-Writing Guidelines for Classroom Assessment. Appl. Meas. Educ., 2002. **15**(3): p. 309-333. DOI: 10.1207/S15324818AME1503_5.
99. Vyas, R. and A. Supe, Multiple choice questions: a literature review on the optimal number of options. Natl Med J India, 2008. **21**(3): p. 130-3.
100. Surry, L.T., D. Torre, and S.J. Durning, Exploring examinee behaviours as validity evidence for multiple-choice question examinations. Medical education, 2017. **51**(10): p. 1075-1085.
101. Javaeed, A., Assessment of higher ordered thinking in medical education: multiple choice questions and modified essay questions. MedEdPublish, 2018. **7**(128): p. 128.
102. Glass, A.L. and N. Sinha, Multiple-Choice Questioning Is an Efficient Instructional Methodology That May Be Widely Implemented in Academic Courses to Improve Exam Performance. Current Directions in Psychological Science, 2013. **22**(6): p. 471-477. DOI: 10.1177/0963721413495870.
103. Ibrahim, A.F., Development of multiple choice questions' instructional plan for the nursing educators. Journal of Nursing Education and Practice, 2019. **9**(9): p. 12-24.
104. Manalu, H.F. and S. Diana Anggraeni, The optimal number of options used in multiple-choice test format for national examinations in Indonesia. Humanities & Social Sciences Reviews, 2020. **8**(2): p. 824-834.
105. Enders, N., R. Gaschler, and V. Kubik, Online quizzes with closed questions in formal assessment: How elaborate feedback can promote learning. Psychology Learning & Teaching, 2021. **20**(1): p. 91-106.

106. Pelánek, R., A classification framework for practice exercises in adaptive learning systems. IEEE Transactions on Learning Technologies, 2020. **13**(4): p. 734-747.
107. Klefstad, B., et al. Learning Outcomes and a Taxonomy as a Starting Point for creating digital Multiple-choice Tests. in *Seminar. net*. 2010.
108. Tuah, N.A.A. and L. Naing, Is online assessment in higher education institutions during COVID-19 pandemic reliable? Siriraj Medical Journal, 2021. **73**(1): p. 61-68.
109. Reedy, A.K., Rethinking online learning design to enhance the experiences of Indigenous higher education students. Australasian Journal of Educational Technology, 2019. **35**(6): p. 132-149.
110. Zeri, F., et al., Evidence-based teaching in contact lenses education: Teaching and learning strategies. Contact Lens and Anterior Eye, 2023: p. 101822.
111. Reavy, K. and S. Tavernier, Nurses reclaiming ownership of their practice: implementation of an evidence-based practice model and process. The Journal of Continuing Education in Nursing, 2008. **39**(4): p. 166-172.
112. Ashayeri, I., et al. Implementation of a novel data-driven approach to optimise UK offsite housing delivery. in *IOP Conference Series: Earth and Environmental Science*. 2022. IOP Publishing.
113. Cooper, H., et al., Developing an evidence base for interdisciplinary learning: a systematic review. Journal of advanced nursing, 2001. **35**(2): p. 228-237.
114. Means, B., et al., Evaluation of evidence-based practices in online learning: A meta-analysis and review of online learning studies. 2009.
115. Radović, S., et al., Analysing students' self-assessment practice in a distance education environment: Student behaviour, accuracy, and task-related characteristics. Journal of Computer Assisted Learning, 2023.
116. Ifenthaler, D., C. Schumacher, and J. Kuzilek, Investigating students' use of self-assessments in higher education using learning analytics. Journal of Computer Assisted Learning, 2023. **39**(1): p. 255-268.
117. Sáiz-Manzanares, M.C., et al., Using Eye Tracking Technology to Analyse Cognitive Load in Multichannel Activities in University Students. International Journal of Human–Computer Interaction, 2023: p. 1-19.
118. Goh, Y.L., et al., Prediction of students' academic performance by K-means clustering. Science Proceedings Series, 2020. **2**(1): p. 1-6.
119. Syakur, M., et al. Integration k-means clustering method and elbow method for identification of the best customer profile cluster. in *IOP conference series: materials science and engineering*. 2018. IOP Publishing. DOI: 10.1088/1757-899X/336/1/012017.
120. Gligorea, I., et al., Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review. Education Sciences, 2023. **13**(12): p. 1216. DOI: 10.3390/educsci13121216.
121. Khosravi, H. and K.M. Cooper. Using learning analytics to investigate patterns of performance and engagement in large classes. in *Proceedings of the 2017 acm sigcse technical symposium on computer science education*. 2017.
122. Pham, D.T., S.S. Dimov, and C.D. Nguyen, Selection of K in K-means clustering. Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, 2005. **219**(1): p. 103-119.
123. Cui, M., Introduction to the k-means clustering algorithm based on the elbow method. Accounting, Auditing and Finance, 2020. **1**(1): p. 5-8.
124. Vankayalapati, R., et al., K-Means Algorithm for Clustering of Learners Performance Levels Using Machine Learning Techniques. Revue d'Intelligence Artificielle, 2021. **35**(1).
125. Farida, A. and N.A. Sudibyo, Implementation of the K-Means Algorithm on Learning Outcomes and Self-Regulated Learning. Union: Jurnal Ilmiah Pendidikan Matematika, 2022. **10**(2): p. 147-154.
126. Wang, Z., Higher education management and student achievement assessment method based on clustering algorithm. Computational Intelligence and Neuroscience, 2022. **2022**.
127. Alamri, H.A., S. Watson, and W. Watson, Learning technology models that support personalization within blended learning environments in higher education. TechTrends, 2021. **65**: p. 62-78.

128. Przymuszała, P., et al., Guidelines on writing multiple choice questions: a well-received and effective faculty development intervention. SAGE Open, 2020. **10**(3): p. 2158244020947432.
129. Nunnally, J.C., An overview of psychological measurement. Clinical diagnosis of mental disorders: A handbook, 1978: p. 97-146.
130. Davis, J.A., A partial coefficient for Goodman and Kruskal's gamma. Journal of the American Statistical Association, 1967. **62**(317): p. 189-193.
131. Fabrigar, L.R., et al., Evaluating the use of exploratory factor analysis in psychological research. Psychological methods, 1999. **4**(3): p. 272.
132. Spearman, C., " General Intelligence" Objectively Determined and Measured. 1961.
133. Park, H.M., Comparing group means: t-tests and one-way ANOVA using Stata, SAS, R, and SPSS. 2009.
134. Sainani, K.L., The value of scatter plots. PM&R, 2016. **8**(12): p. 1213-1217.
135. Tarrant, M. and J. Ware, Impact of item-writing flaws in multiple-choice questions on student achievement in high-stakes nursing assessments. Medical education, 2008. **42**(2): p. 198-206.
136. Black, P., Assessment, learning theories and testing systems. Learners, learning and assessment, 1999: p. 118-134.
137. Rogers, W.T. and D. Harley, An empirical comparison of three-and four-choice items and tests: susceptibility to testwiseness and internal consistency reliability. Educational and Psychological Measurement, 1999. **59**(2): p. 234-247.
138. Raykov, Y.P., et al., What to do when K-means clustering fails: a simple yet principled alternative algorithm. PloS one, 2016. **11**(9): p. e0162259. DOI: 10.1371/journal.pone.0162259.
139. Sharifi, N., Perception and Practice of English Language Teachers about Assessment in Afghanistan. ICoCSPA 2021, 2021: p. 123.
140. Heil, J. and D. Ifenthaler, Online Assessment in Higher Education: A Systematic Review. Online Learning, 2023. **27**(1). DOI: 10.24059/olj.v27i1.3398.
141. Upchurch, A.M., et al., Access to Online Formative Assessments in Lower-Division Undergraduate Biology Courses: Investigating Barriers to Student Engagement. CBE—Life Sciences Education, 2022. **21**(4): p. ar80. DOI: 10.1187/cbe.22-05-0098.
142. Beaudoin, L. and L. Avanthey, How to help digital-native students to successfully take control of their learning: A return of 8 years of experience on a computer science e-learning platform in higher education. Education and Information Technologies, 2023. **28**(5): p. 5421-5451.
143. Nguyen, K.A., C. Lucas, and D. Leadbeatter, Student Generation and Peer Review of Examination Questions in the Dental Curriculum: Enhancing Student Engagement and Learning. European Journal of Dental Education, 2020. **24**(3): p. 548-558. DOI: 10.1111/eje.12536.
144. Brown, A., The role of test-taker feedback in the test development process: Test-takers' reactions to a tape-mediated test of proficiency in spoken Japanese. Language testing, 1993. **10**(3): p. 277-301.
145. Scully, D., Constructing multiple-choice items to measure higher-order thinking. Practical Assessment, Research, and Evaluation, 2019. **22**(1): p. 4. DOI: 10.7275/swgt-rj52.
146. Hess, K., *Rigor by Design, Not Chance: Deeper Thinking Through Actionable Instruction and Assessment*. 2023: ASCD.
147. Nash, J. and K. Krauss. Method for aligning MCQ assessment with cognitive skills and learning objectives. 2015. Paper presented on 44th Conference of the Southern African computer ....
148. Aikaula, N., S. Kimura, and Y. Namba, Medical licensure examination for the visually impaired in Japan. 2004.
149. JOHNSON, F.R., *The reliability and concurrent validity of multiple-choice tests derived by four distractor selection procedures*. 1976: Kansas State University.
150. Saito, H., K. Arita, and I. Nasu, Can be the multiple-choice question an objective rating system?[J]. Medical Education Japan, 1982. **13**(4): p. 251-255.
151. Mitani, K., Quantitative analysis of the objective" X2 type" question in the new national board examination of Japan. Medical Education, 1996: p. 235-240.
152. Moore, S., et al., Crowdsourcing the Evaluation of Multiple-Choice Questions Using Item-Writing Flaws and Bloom's Taxonomy. 2023. DOI: 10.1145/3573051.3593396.

153. Hall, B.M., Designing Multiple-Choice Questions.
154. Tractenberg, R.E., The assessment evaluation rubric: Promoting learning and learner-centered teaching through assessment in face-to-face or distanced higher education. Education Sciences, 2021. **11**(8): p. 441.
155. Sudakova, N.E., et al., Online formative assessment in higher education: bibliometric analysis. Education Sciences, 2022. **12**(3): p. 209.
156. Pachler, N., et al., Formative e-Assessment: Practitioner Cases. Computers & Education, 2010. **54**(3): p. 715-721. DOI: 10.1016/j.compedu.2009.09.032.
157. Al-Hamad, N., et al., Enhancing educational outcomes through strategic human resources (hr) initiatives: Emphasizing faculty development, diversity, and leadership excellence. Education, 2023: p. 1-11.
158. Ohshima, N., Using H. 264 Codec Remote Conference System to Realize Credit Transfer of Global MOT Course at Yamaguchi University and ASEAN Universities. The Educational Review, USA, 2021. **5**(9): p. 367-372. DOI: 10.26855/er.2021.09.006.
159. Mohan, S., *Feasibility study of Hybrid Cloud Adoption in Education and Manufacturing*. 2013, The Ohio State University.
160. Charidimou, D., D. Politis, and V. Aleksić, Multilingual Conversational Communication Tools for Distance Learning. 2020.
161. Hahn, M.G., et al., A systematic review of the effects of automatic scoring and automatic feedback in educational settings. IEEE Access, 2021. **9**: p. 108190-108198.
162. Zhou, X., C.J.M. Smith, and H. Al-Samarraie, Digital Technology Adaptation and Initiatives: A Systematic Review of Teaching and Learning During COVID-19. Journal of Computing in Higher Education, 2023: p. 1-22.
163. Lockman, A.S. and B.R. Schirmer, Online Instruction in Higher Education: Promising, Research-Based, and Evidence-Based Practices. Journal of Education and e-Learning Research, 2020. **7**(2): p. 130-152. DOI: 10.20448/journal.509.2020.72.130.152.
164. Pollock, N.B., Student performance and perceptions of anatomy and physiology across face-to-face, hybrid, and online teaching lab styles. Advances in Physiology Education, 2022. **46**(3): p. 453-460.
165. Borgavakar, S.P. and A. Shrivastava, Evaluating student's performance using k-means clustering. Int. J. Eng. Res. Technol, 2017. **6**(05): p. 114-116.
166. Bowen, F., et al., Revealing underlying factors of absenteeism: A machine learning approach. Frontiers in Psychology, 2022. **13**: p. 958748.
167. da Silva, L.M., et al., A literature review on intelligent services applied to distance learning. Education Sciences, 2021. **11**(11): p. 666.
168. MacQueen, J.B., On the Asymptotic Behavior of k-means. Defense Technical Information Center, 1965. **10**. DOI: DOI: 10.21236/AD0629518.
169. MacQueen, J. Some methods for classification and analysis of multivariate observations. in *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*. 1967. Oakland, CA, USA.
170. Nanda, S., B. Mahanty, and M. Tiwari, Clustering Indian stock market data for portfolio management. Expert Systems with Applications, 2010. **37**(12): p. 8793-8798. DOI: 10.1016/j.eswa.2010.06.026.
171. Sinaga, K.P. and M.-S. Yang, Unsupervised K-means clustering algorithm. IEEE access, 2020. **8**: p. 80716-80727.
172. Lu, J.-F., et al., Hierarchical initialization approach for K-Means clustering. Pattern Recognition Letters, 2008. **29**(6): p. 787-795. DOI: 10.1016/j.patrec.2007.12.009.
173. Ketchen, D.J. and C.L. Shook, The application of cluster analysis in strategic management research: an analysis and critique. Strategic management journal, 1996. **17**(6): p. 441-458.
174. Permadi, V.A., S.P. Tahalea, and R.P. Agusdin, K-Means and Elbow Method for Cluster Analysis of Elementary School Data. PROGRES PENDIDIKAN, 2023. **4**(1): p. 50-57.
175. Martin, F., et al., A meta-analysis on the effects of synchronous online learning on cognitive and affective educational outcomes. International Review of Research in Open and Distributed Learning, 2021. **22**(3): p. 205-242.
176. Mahesh, B., Machine learning algorithms-a review. International Journal of Science and Research (IJSR).[Internet], 2020. **9**(1): p. 381-386.
177. Romero, C. and S. Ventura, Educational data mining: A survey from 1995 to 2005. Expert systems with applications, 2007. **33**(1): p. 135-146.

178. Baker, R. and G. Siemens, Learning analytics and educational data mining. Cambridge Handbook of the Leaning Sciences, 2014: p. 253-272.
179. Tremblay, K., D. Lalancette, and D. Roseveare, Assessment of Higher Education Learning Outcomes: Feasibility Study Report, Volume 1–Design and Implementation. Paris, France: Organisation for Economic Co-operation and Development, 2012. **1**.
180. Rahman, M.A. and M.Z. Islam, A hybrid clustering technique combining a novel genetic algorithm with K-Means. Knowledge-Based Systems, 2014. **71**: p. 345-365. DOI: 10.1016/j.knosys.2014.08.011.
181. Baleni, Z.G., Online Formative Assessment in Higher Education: Its Pros and Cons. Electronic Journal of e-Learning, 2015. **13**(4): p. pp228-236-pp228-236.

Appendix

1.
Catalogue

CSV		Fase to Face		Online	
All		2nd Quarter		3rd Quarter	
		Writing Assignment	Multiple Choice Question	Writing Assignment	Multiple Choice Question
2019	Yoshida	RD2019_Q2_Yoshida_WRT	RD2019_Q2_Yoshida_MCQ	RD2019_Q3_Yoshida_WRT	RD2019_Q3_Yoshida_MCQ
	Tokiwa	RD2019_Q2_Tokiwa_WRT	RD2019_Q2_Tokiwa_MCQ	RD2019_Q3_Tokiwa_WRT	RD2019_Q3_Tokiwa_MCQ
2020	Yoshida	RD2020_Q2_Yoshida_WRT	RD2020_Q2_Yoshida_MCQ	RD2020_Q3_Yoshida_WRT	RD2020_Q3_Yoshida_MCQ
	Tokiwa	RD2020_Q2_Tokiwa_WRT	RD2020_Q2_Tokiwa_MCQ	RD2020_Q3_Tokiwa_WRT	RD2020_Q3_Tokiwa_MCQ

Number of students

CSV		Fase to Face		Online	
Remove row including "0 cell"		2nd Quarter		3rd Quarter	
		Writing Assignment	Multiple Choice Question	Writing Assignment	Multiple Choice Question
2019	Yoshida	rem0_RD2019_Q2_Yoshida_WRT	rem0_RD2019_Q2_Yoshida_MCQ	rem0_RD2019_Q3_Yoshida_WRT	rem0_RD2019_Q3_Yoshida_MCQ
	Tokiwa	rem0_RD2019_Q2_Tokiwa_WRT	rem0_RD2019_Q2_Tokiwa_MCQ	rem0_RD2019_Q3_Tokiwa_WRT	rem0_RD2019_Q3_Tokiwa_MCQ
2020	Yoshida	rem0_RD2020_Q2_Yoshida_WRT	rem0_RD2020_Q2_Yoshida_MCQ	rem0_RD2020_Q3_Yoshida_WRT	rem0_RD2020_Q3_Yoshida_MCQ
	Tokiwa	rem0_RD2020_Q2_Tokiwa_WRT	rem0_RD2020_Q2_Tokiwa_MCQ	rem0_RD2020_Q3_Tokiwa_WRT	rem0_RD2020_Q3_Tokiwa_MCQ
CSV		Fase to Face		Online	
All		2nd Quarter		3rd Quarter	
		Writing Assignment	Multiple Choice Question	Writing Assignment	Multiple Choice Question

2019	Yos hida	RD2019_Q2_Yo shida_WRT	RD2019_Q2_Yo shida_MCQ	RD2019_Q3_Yo shida_WRT	RD2019_Q3_Yo shida_MCQ
	Toki wa	RD2019_Q2_To kiwa_WRT	RD2019_Q2_To kiwa_MCQ	RD2019_Q3_To kiwa_WRT	RD2019_Q3_To kiwa_MCQ
2020	Yos hida	RD2020_Q2_Yo shida_WRT	RD2020_Q2_Yo shida_MCQ	RD2020_Q3_Yo shida_WRT	RD2020_Q3_Yo shida_MCQ
	Toki wa	RD2020_Q2_To kiwa_WRT	RD2020_Q2_To kiwa_MCQ	RD2020_Q3_To kiwa_WRT	RD2020_Q3_To kiwa_MCQ

CSV		Fase to Face		Online	
All		2nd Quarter		3rd Quarter	
		Writing Assignment	Multiple Choice Question	Writing Assignment	Multiple Choice Question
2019	Yos hida	RD2019_Q2_Yo shida_WRT	RD2019_Q2_Yo shida_MCQ	RD2019_Q3_Yo shida_WRT	RD2019_Q3_Yo shida_MCQ
	Toki wa	RD2019_Q2_To kiwa_WRT	RD2019_Q2_To kiwa_MCQ	RD2019_Q3_To kiwa_WRT	RD2019_Q3_To kiwa_MCQ
2020	Yos hida	RD2020_Q2_Yo shida_WRT	RD2020_Q2_Yo shida_MCQ	RD2020_Q3_Yo shida_WRT	RD2020_Q3_Yo shida_MCQ
	Toki wa	RD2020_Q2_To kiwa_WRT	RD2020_Q2_To kiwa_MCQ	RD2020_Q3_To kiwa_WRT	RD2020_Q3_To kiwa_MCQ

		2019		2020	
All		2nd Quarter	3rd Quarter	2nd Quarter	3rd Quarter
Yoshi da	Tota l	85	42	93	41
	4	28	28	24	26
	1	57	14	61	14
	2	0	0	0	1
Toki wa	Tota l	194	137	174	135
	4	72	61	70	64
	1	120	76	98	66
	2	2	0	0	5

CSV		Fase to Face		Online	
All		2nd Quarter		3rd Quarter	
		Writing Assignment	Multiple Choice Question	Writing Assignment	Multiple Choice Question
2019	Yos hida	RD2019_Q2_Yo shida_WRT	RD2019_Q2_Yo shida_MCQ	RD2019_Q3_Yo shida_WRT	RD2019_Q3_Yo shida_MCQ
	Toki wa	RD2019_Q2_To kiwa_WRT	RD2019_Q2_To kiwa_MCQ	RD2019_Q3_To kiwa_WRT	RD2019_Q3_To kiwa_MCQ
2020	Yos hida	RD2020_Q2_Yo shida_WRT	RD2020_Q2_Yo shida_MCQ	RD2020_Q3_Yo shida_WRT	RD2020_Q3_Yo shida_MCQ
	Toki wa	RD2020_Q2_To kiwa_WRT	RD2020_Q2_To kiwa_MCQ	RD2020_Q3_To kiwa_WRT	RD2020_Q3_To kiwa_MCQ

		2019		2020	
All		2nd Quarter	3rd Quarter	2nd Quarter	3rd Quarter
Yoshida	Total	85	42	93	41
	4	28	28	24	26
	1	57	14	61	14
	2	0	0	0	1
Tokiwa	Total	194	137	174	135
	4	72	61	70	64
	1	120	76	98	66
	2	2	0	0	5

Standardization

CSV		Fase to Face		Online	
Remove row including "0 cell"		2nd Quarter		3rd Quarter	
		Writing Assignment	Multiple Choice Question	Writing Assignment	Multiple Choice Question
2019	Yoshida	rem0_RD2019_Q2_Yoshida_WRT	rem0_RD2019_Q2_Yoshida_MCQ	rem0_RD2019_Q3_Yoshida_WRT	rem0_RD2019_Q3_Yoshida_MCQ
	Tokiwa	rem0_RD2019_Q2_Tokiwa_WRT	rem0_RD2019_Q2_Tokiwa_MCQ	rem0_RD2019_Q3_Tokiwa_WRT	rem0_RD2019_Q3_Tokiwa_MCQ
2020	Yoshida	rem0_RD2020_Q2_Yoshida_WRT	rem0_RD2020_Q2_Yoshida_MCQ	rem0_RD2020_Q3_Yoshida_WRT	rem0_RD2020_Q3_Yoshida_MCQ
	Tokiwa	rem0_RD2020_Q2_Tokiwa_WRT	rem0_RD2020_Q2_Tokiwa_MCQ	rem0_RD2020_Q3_Tokiwa_WRT	rem0_RD2020_Q3_Tokiwa_MCQ

CSV		Fase to Face		Online	
Standardization		2nd Quarter		3rd Quarter	
		Writing Assignment	Multiple Choice Question	Writing Assignment	Multiple Choice Question

2019	Yoshida	rem0_RD2019_Q2_Yoshida_WRT_stn	rem0_RD2019_Q2_Yoshida_MCQ_stn	rem0_RD2019_Q3_Yoshida_WRT_stn	rem0_RD2019_Q3_Yoshida_MCQ_stn
	Tokiwa	rem0_RD2019_Q2_Tokiwa_WRT_stn	rem0_RD2019_Q2_Tokiwa_MCQ_stn	rem0_RD2019_Q3_Tokiwa_WRT_stn	rem0_RD2019_Q3_Tokiwa_MCQ_stn
2020	Yoshida	rem0_RD2020_Q2_Yoshida_WRT_stn	rem0_RD2020_Q2_Yoshida_MCQ_stn	rem0_RD2020_Q3_Yoshida_WRT_stn	rem0_RD2020_Q3_Yoshida_MCQ_stn
	Tokiwa	rem0_RD2020_Q2_Tokiwa_WRT_stn	rem0_RD2020_Q2_Tokiwa_MCQ_stn	rem0_RD2020_Q3_Tokiwa_WRT_stn	rem0_RD2020_Q3_Tokiwa_MCQ_stn

variable
name list

Before treatment		2nd Quarter		3rd Quarter	
		Writing Assignment	Multiple Choice Question	Writing Assignment	Multiple Choice Question
2019	Yoshida	”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_K”, ”W_Q", ”W_L”	”SN”, ”Y”, ”Student_ID”, ”M_B”, ”M_C”, ”M_F”, ”M_R”, ”M_K”, ”M_Q", ”M_L”	”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_K”, ”W_Z”, ”W_L"	”SN”, ”Y”, ”Student_ID”, ”M_B”, ”M_C”, ”M_F”, ”M_R”, ”M_K”, ”M_Z”, ”M_L"
	Tokiwa	”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_K”, ”W_Q", ”W_L”	”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_K”, ”W_Q", ”W_L”	” ”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_K”, ”W_Z”, ”W_L"	”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_K”, ”W_Z”, ”W_L""
2020	Yoshida	”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_S”, ”W_L", ”WQ”	”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_S”, ”W_L", ”WQ”	”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_S”, ”W_L", ”WQ”	”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_S”, ”W_L", ”WQ”
	Tokiwa	”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_S”, ”W_L", ”WQ”	”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_S”, ”W_L", ”WQ”	”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_S”, ”W_L", ”WQ”	”SN”, ”Y”, ”Student_ID”, ”W_B”, ”W_C”, ”W_F”, ”W_R”, ”W_S”, ”W_L", ”WQ”

variable
name list

After standardization		2nd Quarter		3rd Quarter	
		Writing Assignment	Multiple Choice Question	Writing Assignment	Multiple Choice Question
2019	Yoshida	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”, ”W_K_stn”, ”W_L_stn", ”W_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_R_stn”, ”M_K_stn”, ”M_L_stn", ”M_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”, ”W_K_stn”, ”W_Z_stn”, ”W_L_stn"	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_R_stn”, ”M_K_stn”, ”M_Z_stn”, ”M_L_stn"
	Tokiwa	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”, ”W_K_stn”, ” W_L_stn", ”W_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_R_stn”, ”M_K_stn”, ” M_L_stn", ”M_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”, ”W_K_stn”, ”W_Z_stn”, ”W_L_stn"	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_R_stn”, ”M_K_stn”, ”M_Z_stn”, ”M_L_stn"
2020	Yoshida	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”,”, ”W_S_stn”, ”W_L_stn", ”W_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_R_stn”,”, ”M_S_stn”, ”M_L_stn", ”M_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”, ”W_S_stn”, ”W_L_stn", ”W_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_R_stn”, ”M_S_stn”, ”M_L_stn", ”M_Q_stn”
	Tokiwa	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”,”, ”W_S_stn”, ”W_L_stn", ”W_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_R_stn”,”, ”M_S_stn”, ”M_L_stn", ”M_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”, ”W_S_stn”, ”W_L_stn", ”W_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_R_stn”, ”M_S_stn”, ”M_L_stn", ”M_Q_stn”

		2019		2020	
WRT		2nd Quarter	3rd Quarter	2nd Quarter	3rd Quarter
Yoshi da	Tota l	43	22	62	30
	4	16	14	17	22
	1	27	8	41	7
	2	0	0	4	1
Toki wa	Tota l	110	79	135	100
	4	47	34	53	45
	1	63	45	78	51
	2	0	0	4	4

MCQ		2nd Quarter	3rd Quarter	2nd Quarter	3rd Quarter
Yoshi da	Tota l	53	22	72	30
	4	19	14	20	22
	1	34	8	48	7
	2	0	0	4	1
Toki wa	Tota l	135	80	128	97
	4	52	35	53	44
	1	83	45	71	49
	2	0	0	4	4

pandas、describe( )	
count	Shows the total number.
mean	Shows the average.
std	Standard deviation value
min	Minimum value
25%	First Quantile
50%	Median or Second Quantile
75%	Third Quantile
max	Max : Maximum value

Scatter plot Matrix

CSV		Fase to Face		Online	
Standardization		2nd Quarter		3rd Quarter	
		Writing Assignment	Multiple Choice Question	Writing Assignment	Multiple Choice Question
2019	Yoshida	rem0_RD2019_Q2_Yoshida_WRT_stn	rem0_RD2019_Q2_Yoshida_MCQ_stn	rem0_RD2019_Q3_Yoshida_WRT_stn	rem0_RD2019_Q3_Yoshida_MCQ_stn
	Tokiwa	rem0_RD2019_Q2_Tokiwa_WRT_stn	rem0_RD2019_Q2_Tokiwa_MCQ_stn	rem0_RD2019_Q3_Tokiwa_WRT_stn	rem0_RD2019_Q3_Tokiwa_MCQ_stn
2020	Yoshida	rem0_RD2020_Q2_Yoshida_WRT_stn	rem0_RD2020_Q2_Yoshida_MCQ_stn	rem0_RD2020_Q3_Yoshida_WRT_stn	rem0_RD2020_Q3_Yoshida_MCQ_stn
	Tokiwa	rem0_RD2020_Q2_Tokiwa_WRT_stn	rem0_RD2020_Q2_Tokiwa_MCQ_stn	rem0_RD2020_Q3_Tokiwa_WRT_stn	rem0_RD2020_Q3_Tokiwa_MCQ_stn

After standardization		2nd Quarter		3rd Quarter	
		Writing Assignment	Multiple Choice Question	Writing Assignment	Multiple Choice Question
2019	Yoshida	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”, ”W_K_stn”, ”W_L_stn", ”W_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_R_stn”, ”M_K_stn”, ”M_L_stn", ”M_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”, ”W_K_stn”, ”W_Z_stn”, ”W_L_stn"	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_R_stn”, ”M_K_stn”,”, ”M_Z_stn”, ”M_L_stn"
	Tokiwa	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”, ”W_K_stn”, ”W_L_stn", ”W_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_R_stn”, ”M_K_stn”, ”M_L_stn", ”M_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”, ”W_K_stn”, ”W_Z_stn”, ”W_L_stn"	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_R_stn”, ”M_K_stn”, ”M_Z_stn”, ”M_L_stn"
2020	Yoshida	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”,	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_Rstn”,	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”,	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_Rstn”,

		”W_S_stn”, ”W_L_stn", ”W_Q_stn”	”M_S_stn”, ”M_L_stn", ”M_Q_stn”	”W_S_stn”, ”W_L_stn", ”W_Q_stn”	”M_S_stn”, ”M_L_stn", ”M_Q_stn”
	To ki wa	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”, ”W_S_stn”, ”W_L_stn", ”W_Q_st”	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_Rstn”, ”M_S_stn”, ”M_L_stn", ”M_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”W_B_stn”, ”W_C_stn”, ”W_F_stn”, ”W_R_stn”, ”W_S_stn”, ”W_L_stn", ”W_Q_stn”	”SN”, ”Y”, ”Student_ID”, ”M_B_stn”, ”M_C_stn”, ”M_F_stn”, ”M_Rstn”, ”M_S_stn”, ”M_L_stn", ”M_Q_stn”
SPM_b y_year		Fase to Face		Online	
Standar dizatio n		2nd Quarter		3rd Quarter	
		Writing Assignment	Multiple Choice Question	Writing Assignment	Multiple Choice Question
2019	Yo shi da		Scatter_year_rem0_ RD2019_Q2_Yoshi da_MCQ_stn		Scatter_year_rem0_ RD2019_Q3_Yoshi da_MCQ_stn
	To ki wa		Scatter_year_rem0_ RD2019_Q2_Toki wa_MCQ_stn		Scatter_year_rem0_ RD2019_Q3_Toki wa_MCQ_stn
2020	Yo shi da		Scatter_year_rem0_ RD2020_Q2_Yoshi da_MCQ_stn		Scatter_year_rem0_ RD2020_Q3_Yoshi da_MCQ_stn
	To ki wa		Scatter_year_rem0_ RD2020_Q2_Toki wa_MCQ_stn		Scatter_year_rem0_ RD2020_Q3_Toki wa_MCQ_stn
SPM_b y_all		Fase to Face		Online	
Standar dizatio n		2nd Quarter		3rd Quarter	
		Writing Assignment	Multiple Choice Question	Writing Assignment	Multiple Choice Question
2019	Yo shi da		Scatter_all_rem0_R D2019_Q2_Yoshid a_MCQ_stn		Scatter_all_rem0_R D2019_Q3_Yoshid a_MCQ_stn
	To ki wa		Scatter_all_rem0_R D2019_Q2_Tokiwa _MCQ_stn		Scatter_all_rem0_R D2019_Q3_Tokiwa _MCQ_stn
2020	Yo shi da		Scatter_all_rem0_R D2020_Q2_Yoshid a_MCQ_stn		Scatter_all_rem0_R D2020_Q3_Yoshid a_MCQ_stn

	To ki wa		Scatter_all_rem0_RD2020_Q2_Tokiwa_MCQ_stn		Scatter_all_rem0_RD2020_Q3_Tokiwa_MCQ_stn

Google colab code:

Code Single scatter plot matrix analysis

```
import matplotlib.pyplot as plt
import seaborn as sns

# Create the scatter plots for each pair of variables, with color differentiation by 'Y' and with a regression line.

# Function to create scatter plots with color differentiation and regression line
def create_color_regress_scatter_plots(data, variables, y_variable, plot_path):
  plot_files = {}

  for i in range(len(variables)):
    for j in range(i+1, len(variables)):
      plt.figure(figsize=(8, 6))

      # Using hue for color differentiation based on 'Y'
      sns.scatterplot(data=data, x=variables[i], y=variables[j], hue=y_variable,
palette='viridis')

      # Add a regression line to the plot
      sns.regplot(data=data, x=variables[i], y=variables[j], scatter=False, color='blue')
      plt.title(f'Scatter Plot of {variables[i]} vs {variables[j]} with Regression Line')
      plt.xlabel(variables[i])
      plt.ylabel(variables[j])

      # Save the plot
      file_name = f'color_regress_scatter_{variables[i]}_vs_{variables[j]}.png'
      file_path = plot_path + file_name
      plt.savefig(file_path)
      plt.close()  # Close the figure to avoid displaying it in the notebook
      plot_files[(variables[i], variables[j])] = file_path
  return plot_files

# Create and save the scatter plots with color differentiation and regression line
color_regress_scatter_plot_files = create_color_regress_scatter_plots(data, variables, 'Y',
plot_path)
color_regress_scatter_plot_files
```

Code Scatter plot matrix analysis

```
# Import libraries
import pandas as pd
import seaborn as sns
```

```
import matplotlib.pyplot as plt


# Load the dataset
data_path = '/content/RD2019_Q2_Tokiwa_MCQ.csv' # Replace with the path to CSV file
data = pd.read_csv(data_path)

# Selecting the variables for the scatter diagram matrix
selected_variables = data[["B", "C", "F", "R", "K", "Q", "L"]]

# Plotting the scatter diagram matrix with regression lines
sns.pairplot(selected_variables, kind='reg')

# Adjusting title and displaying the plot
plt.suptitle('Scatter Diagram Matrix for each Lecturer B, C, F, R, K, Q, L', y=1.02)
plt.show()
```

Data Analysis of Educational Evaluation Using K-Means Clustering Method

```
# Google Drive creates a CSV avatar.

# Cluster Analysis with the x-axis labeled "Answer Registration Time [min]" and the y-axis labeled "Score of Multiple-Choice Question [points]". Different colors and markers represent four distinct clusters. "AFLN","Y","WT","MCQ"

import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer

# CSV file path list
file_paths = [
    '/content/drive/MyDrive/CSV /dataset_AF_WT_RD2023_Q2_2_F.csv',
    '/content/drive/MyDrive/CSV/dataset_AF_WT_RD2023_Q2_3_M.csv',
    '/content/drive/MyDrive/CSV/dataset_AF_WT_RD2023_Q2_4_C.csv',
    '/content/drive/MyDrive/ CSV/dataset_AF_WT_RD2023_Q2_5_S.csv',
    '/content/drive/MyDrive/CSV/dataset_AF_WT_RD2023_Q2_6_O.csv',
    '/content/drive/MyDriveCSV /dataset_AF_WT_RD2023_Q2_7_H.csv',
    '/content/drive/MyDrive/CSV/dataset_AF_WT_RD2023_Q2_8_K.csv'
]
# output file name
output_files = [
    'PNG_Elbow_RD2023_Q2_2_F.png',
    'PNG_Elbow_RD2023_Q2_3_M.png',
    'PNG_Elbow_RD2023_Q2_4_C.png',
    'PNG_Elbow_RD2023_Q2_5_S.png',
    'PNG_Elbow_RD2023_Q2_6_O.png',
```

```
    'PNG_Elbow_RD2023_Q2_7_H.png',
    'PNG_Elbow_RD2023_Q2_8_K.png'
]

# Elbow analysis function
def perform_elbow_analysis(file_path, output_file):
    df = pd.read_csv(file_path, encoding='shift-jis')

    # Data Preprocessing
    column_transformer = ColumnTransformer([
        ('onehot', OneHotEncoder(), ['AFLN', 'Y']),
        ('scaler', StandardScaler(), ['WT', 'MCQ'])
    ])
    X = column_transformer.fit_transform(df)

    # Estimating the number of clusters using the elbow method    sse = []
    for k in the range(1, 11):
        kmeans = KMeans(n_clusters=k, random_state=0)
        kmeans.fit(X)
        sse.append(kmeans.inertia_)

    # SSE のグラフをプロット
    plt.figure(figsize=(10, 6))
    plt.plot(range(1, 11), sse, marker='o')
    plt.title('Elbow Method - ' + output_file.split('.')[0].split('_')[-1])
    plt.xlabel('Number of clusters')
    plt.ylabel('SSE')
    plt.grid(True)

    # Save graph as PNG file
    plt.savefig('/content/drive/MyDrive/ PNG_paper/' + output_file)
    plt.close()

# Perform elbow analysis on each file
for file_path and output_file in zip(file_paths, output_files):
    perform_elbow_analysis(file_path, output_file)

## K-means

import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer

# CSV file path list
file_paths = [
    '/content/drive/MyDrive/CSV /dataset_AF_WT_RD2023_Q2_2_F.csv',
    '/content/drive/MyDrive/CSV/dataset_AF_WT_RD2023_Q2_3_M.csv',
```

```
    '/content/drive/MyDrive/CSV/dataset_AF_WT_RD2023_Q2_4_C.csv',
    '/content/drive/MyDrive/ CSV/dataset_AF_WT_RD2023_Q2_5_S.csv',
    '/content/drive/MyDrive/CSV/dataset_AF_WT_RD2023_Q2_6_O.csv',
    '/content/drive/MyDriveCSV /dataset_AF_WT_RD2023_Q2_7_H.csv',
    '/content/drive/MyDrive/CSV/dataset_AF_WT_RD2023_Q2_8_K.csv'
]

# output file name
output_files = [
    'PNG_Elbow_RD2023_Q2_2_F.png',
    'PNG_Elbow_RD2023_Q2_3_M.png',
    'PNG_Elbow_RD2023_Q2_4_C.png',
    'PNG_Elbow_RD2023_Q2_5_S.png',
    'PNG_Elbow_RD2023_Q2_6_O.png',
    'PNG_Elbow_RD2023_Q2_7_H.png',
    'PNG_Elbow_RD2023_Q2_8_K.png'
]

# Clustering and plotting functions
def perform_kmeans_clustering(file_path, output_file):
    df = pd.read_csv(file_path, encoding='shift-jis')

    # Data Preprocessing
    column_transformer = ColumnTransformer([
        ('onehot', OneHotEncoder(), ['AFLN', 'Y']),
        ('scaler', StandardScaler(), ['WT', 'MCQ'])
    ])
    X = column_transformer.fit_transform(df)

    # k-means clustering
    kmeans = KMeans(n_clusters=4, random_state=0)
    df['cluster'] = kmeans.fit_predict(X)

    # Display number of items for each cluster
    print(df['cluster'].value_counts())

    # Plot graph
    plt.figure(figsize=(10, 6))
colors = ['green', 'darkblue', 'brown', 'orange']
    for i in range(4):
        cluster_data = df[df['cluster'] == i]
        plt.scatter(cluster_data['WT'] / 60, cluster_data['MCQ'], c=colors[i], label= f' Cluster
{i+1}', marker='x')

    plt.title('Cluster Analysis for ' + output_file.split('.')[0].split('_')[-1])
    plt.xlabel('Answer Registration Time [min]')
    plt.ylabel('Score of Multiple-Choice Question [points]')
    plt.legend()
    plt.grid(True)
```

```
    # # Save graph as PNG file
    plt.savefig('/content/drive/MyDrive/Malayphone_Paper4/KLISEE2023/PNG/'
+ output_file)
    plt.show()

# Perform elbow analysis on each file
for file_path and output_file in zip(file_paths, output_files):
    perform_kmeans_clustering(file_path, output_file)
```

Data Set1:
 # RD2019_Q2_Tokiwa_MCQ

SN	Y	B	C	F	R	K	Q	L
2	4	-0.37078	0.784982	-0.5474	0.672769	-1.67034	1.300617	-0.81674
3	4	-1.0294	0.179425	-2.33527	-0.24464	-1.67034	0.009563	-1.85693
6	4	0.946465	0.784982	0.04856	-0.24464	1.014135	-2.57254	0.223447
7	4	0.946465	-1.63725	0.04856	-1.16206	-0.3281	0.009563	-1.85693
8	4	0.287843	0.179425	0.644518	-0.24464	1.014135	-1.28149	1.263634
9	4	0.287843	0.784982	-1.14336	-0.24464	1.014135	0.009563	0.223447
10	4	0.287843	0.784982	1.240476	-0.24464	1.014135	0.009563	-0.81674
11	4	0.946465	-1.03169	1.240476	-0.24464	-0.3281	0.009563	1.263634
12	4	0.287843	-1.63725	1.240476	-0.24464	-0.3281	0.009563	0.223447
13	4	0.287843	0.784982	-1.14336	-1.16206	1.014135	0.009563	1.263634
14	4	0.946465	0.784982	-1.14336	0.672769	1.014135	1.300617	0.223447
15	4	-1.0294	1.39054	-0.5474	-0.24464	-0.3281	-1.28149	-0.81674
20	4	0.287843	0.784982	0.644518	-0.24464	1.014135	0.009563	0.223447
23	4	0.287843	-0.42613	-1.14336	-1.16206	1.014135	1.300617	0.223447
24	4	-1.0294	0.179425	1.240476	0.672769	1.014135	0.009563	0.223447
25	4	0.287843	1.996098	-0.5474	0.672769	-0.3281	0.009563	0.223447
27	4	-0.37078	0.784982	0.644518	-1.16206	-3.01258	-2.57254	-0.81674
29	4	0.946465	-1.63725	-0.5474	0.672769	-1.67034	0.009563	0.223447
30	4	-0.37078	0.179425	1.240476	0.672769	-1.67034	0.009563	0.223447
31	4	0.946465	1.39054	0.644518	0.672769	-1.67034	0.009563	0.223447
32	4	0.287843	0.179425	-1.73932	-2.07947	-1.67034	1.300617	0.223447
33	4	-0.37078	-1.63725	0.04856	-0.24464	1.014135	0.009563	0.223447
34	4	-1.68803	0.784982	-1.73932	0.672769	-1.67034	-1.28149	1.263634
35	4	0.287843	0.179425	1.836434	0.672769	-0.3281	0.009563	0.223447
36	4	-1.0294	-1.03169	0.04856	0.672769	1.014135	0.009563	0.223447
37	4	-1.68803	-1.63725	1.240476	-0.24464	1.014135	0.009563	0.223447
38	4	-1.68803	-1.03169	0.644518	-1.16206	-0.3281	0.009563	0.223447
39	4	0.287843	0.179425	-0.5474	0.672769	1.014135	-1.28149	1.263634
41	4	0.287843	-1.63725	0.04856	0.672769	-1.67034	1.300617	1.263634
44	4	0.287843	0.179425	-1.14336	0.672769	-0.3281	-2.57254	0.223447
46	4	0.287843	1.39054	0.04856	0.672769	1.014135	1.300617	1.263634

47	4	0.287843	0.179425	0.04856	0.672769	-1.67034	0.009563	0.223447
48	4	-0.37078	-1.03169	3.028351	0.672769	-0.3281	0.009563	0.223447
49	4	0.287843	-1.03169	-0.5474	0.672769	-0.3281	1.300617	0.223447
50	4	-3.66389	-1.03169	1.240476	0.672769	-1.67034	0.009563	0.223447
51	4	0.946465	-2.24281	-0.5474	0.672769	-0.3281	-1.28149	0.223447
52	4	0.946465	-1.03169	1.836434	0.672769	-0.3281	-1.28149	-1.85693
53	4	-0.37078	0.179425	0.644518	-0.24464	-0.3281	0.009563	0.223447
54	4	0.946465	1.39054	0.04856	-0.24464	-1.67034	-1.28149	0.223447
57	4	0.287843	0.179425	1.240476	0.672769	-1.67034	0.009563	0.223447
58	4	0.287843	-1.03169	-1.14336	0.672769	1.014135	-1.28149	0.223447
59	4	0.946465	-1.63725	0.04856	0.672769	1.014135	0.009563	0.223447
60	4	0.287843	-1.63725	-0.5474	-0.24464	-0.3281	1.300617	1.263634
61	4	-0.37078	0.179425	1.240476	-1.16206	1.014135	-1.28149	-1.85693
63	4	0.287843	0.179425	0.04856	-1.16206	-1.67034	0.009563	1.263634
65	4	-0.37078	1.39054	1.240476	0.672769	-0.3281	0.009563	0.223447
66	4	-2.34665	-1.03169	-1.14336	0.672769	-0.3281	0.009563	1.263634
67	4	0.287843	-0.42613	-1.73932	-0.24464	-0.3281	1.300617	-1.85693
68	4	0.287843	-1.63725	0.04856	-1.16206	1.014135	-1.28149	-0.81674
69	4	0.287843	0.784982	-0.5474	0.672769	-1.67034	0.009563	0.223447
71	4	0.946465	0.784982	-1.14336	0.672769	-1.67034	-1.28149	0.223447
72	4	0.287843	0.784982	-0.5474	-0.24464	-0.3281	1.300617	1.263634
74	1	0.287843	0.784982	-1.73932	0.672769	1.014135	0.009563	1.263634
75	1	0.946465	-1.63725	-0.5474	0.672769	1.014135	-2.57254	1.263634
76	1	0.946465	0.784982	-1.14336	-1.16206	-0.3281	-1.28149	1.263634
77	1	0.946465	0.179425	1.240476	0.672769	1.014135	0.009563	0.223447
78	1	0.946465	1.996098	-0.5474	-0.24464	1.014135	1.300617	0.223447
79	1	0.287843	-1.63725	2.432393	0.672769	-0.3281	1.300617	0.223447
81	1	-1.0294	-1.03169	-0.5474	0.672769	1.014135	0.009563	1.263634
83	1	0.946465	0.179425	0.644518	-0.24464	1.014135	1.300617	-1.85693
84	1	0.946465	0.179425	1.240476	0.672769	1.014135	1.300617	0.223447
85	1	-0.37078	1.39054	-0.5474	0.672769	-0.3281	0.009563	0.223447
88	1	0.946465	0.179425	0.644518	0.672769	1.014135	1.300617	1.263634
89	1	-0.37078	0.179425	-1.14336	0.672769	1.014135	1.300617	-0.81674
90	1	-1.0294	0.784982	0.644518	0.672769	1.014135	1.300617	1.263634
91	1	0.946465	0.784982	-0.5474	-0.24464	-0.3281	0.009563	-0.81674
92	1	-2.34665	1.39054	0.04856	-0.24464	-0.3281	0.009563	-1.85693
94	1	-0.37078	0.179425	0.644518	0.672769	-0.3281	0.009563	0.223447
95	1	-1.0294	0.784982	-0.5474	-0.24464	1.014135	0.009563	-1.85693
97	1	0.287843	0.179425	-0.5474	0.672769	-0.3281	1.300617	1.263634
99	1	0.287843	0.179425	-1.14336	-1.16206	-0.3281	0.009563	0.223447
101	1	-1.0294	0.784982	0.04856	0.672769	-0.3281	0.009563	0.223447
102	1	0.946465	0.179425	1.836434	-2.99688	-0.3281	-1.28149	-0.81674
103	1	0.287843	0.179425	-1.14336	0.672769	1.014135	1.300617	-0.81674
104	1	-3.00527	-1.63725	0.04856	-0.24464	-0.3281	-1.28149	-0.81674
106	1	-0.37078	0.179425	0.04856	-0.24464	1.014135	0.009563	-0.81674

107	1	0.946465	0.179425	-1.14336	-0.24464	1.014135	0.009563	0.223447
109	1	-0.37078	0.179425	0.644518	0.672769	1.014135	0.009563	1.263634
111	1	0.287843	0.179425	0.644518	0.672769	1.014135	0.009563	-1.85693
112	1	0.946465	0.179425	0.644518	0.672769	-0.3281	1.300617	0.223447
113	1	-0.37078	0.179425	0.644518	0.672769	1.014135	1.300617	1.263634
114	1	0.946465	0.784982	0.644518	0.672769	1.014135	-1.28149	-0.81674
115	1	0.287843	0.784982	0.04856	0.672769	1.014135	0.009563	0.223447
116	1	0.946465	0.784982	-0.5474	0.672769	1.014135	1.300617	1.263634
117	1	0.946465	0.784982	-0.5474	0.672769	1.014135	0.009563	0.223447
118	1	-0.37078	0.179425	1.240476	-1.16206	-0.3281	0.009563	0.223447
120	1	-4.32252	0.179425	0.04856	-5.74912	-0.3281	1.300617	0.223447
121	1	-1.0294	0.179425	0.644518	0.672769	1.014135	1.300617	1.263634
122	1	0.287843	0.179425	0.644518	0.672769	1.014135	0.009563	1.263634
124	1	0.946465	0.784982	-0.5474	0.672769	1.014135	0.009563	1.263634
125	1	0.946465	0.179425	-2.93123	0.672769	-1.67034	1.300617	1.263634
126	1	-0.37078	1.39054	0.04856	0.672769	1.014135	-1.28149	1.263634
127	1	-0.37078	-1.03169	0.644518	0.672769	-1.67034	0.009563	0.223447
128	1	0.287843	-0.42613	-0.5474	-1.16206	-0.3281	-1.28149	1.263634
132	1	0.946465	1.39054	0.04856	0.672769	-1.67034	0.009563	0.223447
133	1	-0.37078	1.39054	-0.5474	0.672769	-0.3281	0.009563	0.223447
135	1	0.946465	0.784982	0.04856	-1.16206	-0.3281	0.009563	0.223447
136	1	-1.68803	0.179425	1.836434	-1.16206	-0.3281	-1.28149	-0.81674
138	1	-0.37078	1.39054	0.04856	0.672769	1.014135	1.300617	0.223447
139	1	0.287843	-2.24281	0.04856	0.672769	-0.3281	1.300617	-0.81674
143	1	0.287843	-1.63725	-0.5474	0.672769	-1.67034	-1.28149	-1.85693
145	1	0.287843	0.784982	0.644518	0.672769	-0.3281	-1.28149	-0.81674
146	1	0.946465	1.39054	-1.14336	0.672769	-0.3281	0.009563	-1.85693
147	1	0.946465	0.179425	-1.14336	0.672769	-1.67034	-1.28149	-1.85693
148	1	0.287843	-1.03169	1.836434	-0.24464	1.014135	-1.28149	-1.85693
150	1	0.287843	0.179425	-0.5474	0.672769	-0.3281	0.009563	0.223447
151	1	0.946465	0.784982	0.644518	-1.16206	1.014135	0.009563	-0.81674
152	1	0.287843	-0.42613	-0.5474	-0.24464	1.014135	0.009563	-0.81674
155	1	0.946465	-0.42613	-0.5474	0.672769	-0.3281	0.009563	0.223447
156	1	0.287843	-1.63725	0.04856	-1.16206	1.014135	-1.28149	-0.81674
157	1	0.946465	0.784982	0.644518	0.672769	-0.3281	1.300617	0.223447
158	1	-0.37078	0.179425	-0.5474	0.672769	-0.3281	1.300617	-0.81674
159	1	0.287843	0.179425	-1.73932	-2.07947	-0.3281	1.300617	1.263634
160	1	-0.37078	-1.03169	-0.5474	-0.24464	-0.3281	0.009563	1.263634
163	1	-0.37078	-1.63725	0.644518	-0.24464	1.014135	0.009563	-1.85693
164	1	-1.68803	-2.24281	0.644518	-1.16206	-0.3281	-2.57254	-1.85693
165	1	0.287843	1.39054	0.644518	0.672769	-0.3281	0.009563	1.263634
166	1	0.946465	0.179425	1.240476	-1.16206	1.014135	0.009563	-0.81674
167	1	0.946465	-1.03169	-1.14336	-2.07947	1.014135	0.009563	0.223447
168	1	0.946465	-1.03169	0.04856	-0.24464	1.014135	0.009563	-1.85693
169	1	-2.34665	-0.42613	-1.73932	0.672769	1.014135	-1.28149	0.223447

170	1	0.946465	-1.63725	-1.73932	0.672769	1.014135	1.300617	-1.85693
172	1	-1.0294	-1.63725	0.04856	-2.07947	-0.3281	0.009563	-0.81674
174	1	-1.0294	0.179425	0.644518	0.672769	-0.3281	0.009563	0.223447
175	1	0.287843	1.39054	0.644518	0.672769	-0.3281	0.009563	0.223447
177	1	0.287843	0.179425	0.04856	0.672769	1.014135	1.300617	1.263634
178	1	-2.34665	-0.42613	0.04856	-0.24464	-0.3281	0.009563	0.223447
181	1	-1.68803	0.179425	0.644518	-2.07947	-1.67034	0.009563	-1.85693
182	1	0.946465	1.39054	-0.5474	0.672769	-0.3281	1.300617	0.223447
184	1	0.287843	0.784982	0.04856	0.672769	-0.3281	0.009563	1.263634
187	1	-0.37078	-1.03169	0.644518	-0.24464	-1.67034	-1.28149	-0.81674
190	1	0.946465	0.179425	1.836434	-1.16206	-0.3281	1.300617	0.223447
191	1	-0.37078	0.179425	0.04856	0.672769	1.014135	0.009563	0.223447
192	1	0.287843	-0.42613	-1.14336	0.672769	-0.3281	1.300617	-0.81674
193	1	-0.37078	-0.42613	-0.5474	-2.99688	1.014135	-1.28149	-1.85693

 # RD2019_Q2_Yoshida_MCQ

SN	Y	B	C	F	R	K	Q	L
1	4	0.195962	0.234993	0.347861	0.688478	-0.44491	-0.02748	-0.04717
2	4	-1.28775	0.234993	-0.28788	0.688478	0.942163	-1.48405	-0.04717
3	4	-2.02961	-0.95116	-0.92363	-1.9179	-0.44491	-0.02748	-1.29708
5	4	-1.28775	-0.95116	0.347861	-0.61471	0.942163	-0.02748	-0.04717
6	4	-0.5459	0.82807	-0.92363	-1.9179	-1.83198	-0.02748	1.20275
7	4	0.93782	1.421147	-0.28788	-0.61471	0.942163	1.429089	1.20275
8	4	0.195962	-1.54424	0.983607	0.688478	0.942163	-0.02748	1.20275
9	4	0.93782	-1.54424	-0.92363	0.688478	0.942163	-0.02748	-0.04717
10	4	0.195962	0.82807	0.983607	0.688478	-0.44491	1.429089	-0.04717
11	4	0.93782	0.234993	0.347861	0.688478	-3.21906	1.429089	-1.29708
12	4	0.195962	-0.35808	0.983607	0.688478	-1.83198	-0.02748	1.20275
13	4	-3.51333	0.82807	0.347861	0.688478	0.942163	-0.02748	1.20275
15	4	0.93782	1.421147	0.983607	0.688478	0.942163	-0.02748	-1.29708
16	4	-0.5459	0.82807	-0.28788	0.688478	-0.44491	-0.02748	-0.04717
20	4	0.93782	-0.35808	-0.92363	0.688478	-1.83198	-0.02748	-1.29708
21	4	0.93782	-0.95116	-0.92363	-0.61471	-0.44491	-0.02748	-0.04717
23	4	0.195962	-1.54424	-0.28788	0.688478	0.942163	-0.02748	1.20275
24	4	0.195962	2.014224	-0.28788	0.688478	0.942163	-0.02748	-0.04717
25	4	-0.5459	-0.95116	-0.28788	0.688478	0.942163	-0.02748	-0.04717

29	1	0.195962	0.82807	0.983607	0.688478	0.942163	-0.02748	1.20275
30	1	0.195962	-1.54424	-2.19512	-1.9179	-0.44491	-0.02748	-0.04717
31	1	-0.5459	-0.95116	-0.28788	0.688478	0.942163	-0.02748	-1.29708
32	1	0.93782	0.234993	-2.19512	-1.9179	-0.44491	-0.02748	-0.04717
33	1	0.93782	0.234993	1.619352	-0.61471	-0.44491	-0.02748	-0.04717
35	1	0.195962	-0.95116	0.983607	-1.9179	0.942163	1.429089	-1.29708
38	1	-1.28775	0.82807	-0.92363	-0.61471	0.942163	-2.94063	-1.29708
39	1	0.195962	-0.95116	1.619352	0.688478	0.942163	1.429089	1.20275
40	1	0.195962	0.82807	0.347861	0.688478	-0.44491	1.429089	-2.547
42	1	-0.5459	-0.95116	-1.55938	0.688478	-0.44491	-0.02748	-0.04717
45	1	0.93782	0.234993	-0.28788	0.688478	0.942163	-1.48405	-0.04717
49	1	0.93782	-0.95116	0.983607	0.688478	-0.44491	-0.02748	-0.04717
50	1	0.93782	0.82807	0.983607	0.688478	0.942163	1.429089	1.20275
52	1	-0.5459	-0.35808	-0.92363	0.688478	0.942163	1.429089	1.20275
53	1	0.93782	-2.13732	0.347861	-1.9179	-0.44491	-1.48405	-1.29708
54	1	-2.02961	1.421147	0.347861	0.688478	-0.44491	-1.48405	-0.04717
56	1	0.195962	0.82807	-0.28788	0.688478	0.942163	-0.02748	-0.04717
57	1	0.93782	1.421147	0.347861	-1.9179	-0.44491	1.429089	1.20275
59	1	-2.02961	-0.35808	-0.28788	0.688478	0.942163	-0.02748	-0.04717
60	1	-1.28775	0.234993	0.983607	0.688478	-0.44491	-0.02748	1.20275
62	1	0.93782	0.234993	-0.92363	-0.61471	-0.44491	-0.02748	-0.04717
63	1	0.195962	0.82807	0.347861	0.688478	0.942163	-1.48405	-0.04717
64	1	-0.5459	0.82807	-1.55938	-1.9179	-0.44491	-1.48405	1.20275
65	1	0.93782	0.82807	0.347861	0.688478	-1.83198	1.429089	-1.29708
67	1	-0.5459	0.234993	1.619352	0.688478	-0.44491	-1.48405	-0.04717
72	1	0.93782	-1.54424	-0.28788	-0.61471	-0.44491	-0.02748	1.20275
73	1	0.195962	0.82807	0.347861	0.688478	0.942163	-1.48405	1.20275
74	1	-1.28775	0.82807	-0.28788	0.688478	-0.44491	-0.02748	-0.04717
79	1	0.93782	0.82807	0.983607	0.688478	-1.83198	-0.02748	1.20275
80	1	0.93782	-0.95116	0.347861	-1.9179	-0.44491	-0.02748	-1.29708
81	1	0.195962	-1.54424	1.619352	-0.61471	-0.44491	-0.02748	-2.547

82	1	0.93782	-0.95116	-2.83087	-0.61471	0.942163	1.429089	-0.04717
83	1	0.195962	0.82807	0.983607	0.688478	-0.44491	1.429089	-0.04717
85	1	-0.5459	0.234993	-0.28788	-0.61471	0.942163	-1.48405	-0.04717

RD2019_Q3_Tokiwa_MCQ

SN	Y	B	C	F	R	K	Z	Q
1	4	0.73864	-1.72953	-0.55386	-0.82136	0.854882	0.957451	1.217161
4	4	0.73864	0.140232	-0.98826	-1.49185	0.854882	1.227155	0
5	4	0.73864	0.140232	0.314938	1.19013	0.854882	0.957451	1.217161
6	4	0.73864	0.140232	-1.42265	-3.50334	0.854882	-1.73959	-1.21716
7	4	-0.00935	0.763484	1.618132	-0.15086	0.854882	1.227155	1.217161
10	4	0.73864	0.140232	0.314938	1.19013	-3.16809	-0.39107	-1.21716
12	4	-2.25332	0.140232	-2.72585	-2.16235	-0.48611	-0.66078	-1.21716
13	4	-0.75734	-1.10627	0.314938	-0.15086	-0.48611	0.687746	0
14	4	0.73864	-2.35278	-0.55386	0.519634	0.854882	-0.66078	0
16	4	-0.75734	-0.48302	-0.11946	-0.82136	-0.48611	-1.20018	-1.21716
17	4	0.73864	-1.10627	-0.55386	1.19013	-0.48611	0.957451	-1.21716
18	4	-1.50533	0.140232	0.749336	-0.15086	0.854882	0.148337	1.217161
19	4	-0.00935	1.386737	0.314938	-0.15086	-0.48611	-0.12137	1.217161
22	4	-0.00935	0.763484	0.314938	-0.15086	-0.48611	0.687746	0
23	4	-0.75734	0.140232	0.749336	-0.15086	0.854882	0.957451	1.217161
25	4	0.73864	0.763484	0.749336	-0.15086	-0.48611	0.687746	1.217161
29	4	-0.00935	0.763484	-1.42265	-0.15086	0.854882	-0.93048	-1.21716
30	4	-0.75734	0.763484	0.314938	1.19013	0.854882	1.227155	1.217161
31	4	-0.00935	-0.48302	0.749336	0.519634	0.854882	0.148337	0
32	4	-0.75734	0.763484	0.749336	0.519634	-1.8271	0.957451	0
33	4	0.73864	0.763484	0.749336	0.519634	0.854882	-0.66078	0
34	4	-0.00935	-1.72953	0.749336	-0.82136	0.854882	-0.66078	-1.21716
35	4	0.73864	0.763484	-1.42265	-0.82136	-0.48611	0.687746	0
37	4	-0.00935	0.140232	1.183734	0.519634	-0.48611	-0.66078	-2.43432
38	4	-0.00935	-1.10627	-0.11946	0.519634	0.854882	0.148337	-1.21716
39	4	0.73864	0.140232	-0.11946	-0.82136	0.854882	-0.93048	0

41	4	0.73864	0.763484	1.618132	1.19013	-0.48611	1.227155	1.217161
43	4	0.73864	-1.72953	0.314938	-0.15086	-0.48611	0.418042	-1.21716
45	4	0.73864	0.140232	-0.55386	0.519634	-0.48611	1.227155	0
48	4	-0.75734	0.140232	-0.11946	-0.15086	-0.48611	0.957451	0
50	4	-0.75734	0.763484	0.314938	0.519634	0.854882	-0.39107	0
52	4	0.73864	1.386737	0.749336	-0.15086	0.854882	0.148337	0
53	4	0.73864	0.763484	-1.42265	-1.49185	0.854882	-0.93048	0
54	4	-0.00935	1.386737	1.183734	-0.15086	0.854882	0.148337	0
60	4	-0.00935	-1.10627	1.618132	-1.49185	0.854882	-1.20018	0
62	1	-0.75734	0.763484	-0.55386	0.519634	-0.48611	-2.0093	0
63	1	-0.00935	0.763484	0.314938	-0.15086	0.854882	0.148337	0
64	1	-0.75734	0.140232	-0.11946	-0.15086	0.854882	-0.66078	-2.43432
65	1	0.73864	0.763484	0.314938	1.19013	-0.48611	0.418042	0
66	1	0.73864	0.140232	-2.72585	-2.16235	-0.48611	-2.0093	-1.21716
67	1	-0.75734	0.763484	1.618132	1.19013	0.854882	0.687746	0
68	1	-0.75734	0.140232	-1.42265	0.519634	0.854882	0.418042	0
69	1	-0.75734	-0.48302	-0.55386	-0.15086	-0.48611	-0.93048	0
70	1	-0.75734	0.763484	-1.42265	-2.16235	-0.48611	-1.20018	-1.21716
71	1	0.73864	0.763484	0.749336	-0.82136	-1.8271	-1.20018	1.217161
73	1	-0.00935	0.763484	0.314938	-0.15086	-0.48611	0.418042	0
78	1	-0.75734	-1.10627	0.314938	0.519634	-1.8271	1.227155	1.217161
79	1	0.73864	1.386737	-0.11946	0.519634	-1.8271	-0.93048	-1.21716
81	1	-0.75734	0.763484	0.314938	0.519634	-0.48611	0.687746	1.217161
82	1	-0.75734	-0.48302	0.314938	-0.15086	0.854882	0.957451	0
83	1	-2.25332	-1.10627	-0.55386	-0.15086	0.854882	-0.66078	-1.21716
87	1	0.73864	0.763484	1.618132	1.19013	0.854882	-0.12137	1.217161
88	1	0.73864	-1.10627	-0.55386	0.519634	-0.48611	0.687746	-1.21716
89	1	-2.25332	-1.72953	-2.29145	-0.82136	0.854882	-2.0093	0
90	1	-0.75734	-0.48302	-0.98826	-0.82136	-1.8271	0.957451	-1.21716
92	1	0.73864	0.763484	1.618132	1.19013	0.854882	0.957451	1.217161
95	1	0.73864	-2.35278	0.314938	0.519634	-1.8271	-1.46989	0
101	1	0.73864	0.140232	-0.11946	1.19013	-0.48611	-0.93048	-1.21716

103	1	-0.75734	-1.10627	-2.29145	-0.15086	-0.48611	-1.73959	0
104	1	-0.00935	0.140232	0.749336	1.19013	0.854882	-2.0093	1.217161
105	1	0.73864	0.140232	0.314938	0.519634	0.854882	-0.66078	-1.21716
106	1	0.73864	1.386737	-0.55386	1.19013	0.854882	-0.93048	0
107	1	0.73864	0.140232	1.618132	-2.16235	0.854882	-1.46989	0
108	1	0.73864	-1.10627	-0.11946	1.19013	-0.48611	1.227155	-1.21716
109	1	0.73864	0.763484	-0.11946	1.19013	-1.8271	1.227155	1.217161
110	1	-0.00935	-1.10627	0.749336	1.19013	-1.8271	-0.93048	1.217161
112	1	-0.00935	0.763484	0.314938	0.519634	0.854882	0.957451	0
113	1	0.73864	-1.10627	-0.55386	1.19013	0.854882	-0.93048	1.217161
115	1	0.73864	0.763484	0.749336	0.519634	-0.48611	0.687746	0
118	1	0.73864	0.140232	0.314938	-0.15086	-0.48611	1.227155	-2.43432
119	1	0.73864	0.140232	-0.98826	-0.15086	0.854882	-0.39107	0
120	1	0.73864	-1.10627	-1.42265	-0.82136	-1.8271	1.227155	1.217161
124	1	-0.75734	0.763484	0.749336	1.19013	0.854882	0.687746	1.217161
125	1	0.73864	0.763484	1.618132	1.19013	0.854882	1.227155	1.217161
126	1	-5.24528	0.763484	-0.11946	-0.82136	0.854882	-0.39107	0
127	1	0.73864	-2.35278	-0.11946	-0.15086	-1.8271	-0.93048	1.217161
128	1	-1.50533	-1.72953	-0.55386	-1.49185	0.854882	0.957451	0
129	1	0.73864	-1.72953	-0.98826	-1.49185	-0.48611	1.227155	0
132	1	0.73864	1.386737	0.314938	0.519634	-0.48611	1.227155	1.217161
134	1	0.73864	1.386737	0.314938	-0.15086	0.854882	0.418042	1.217161

RD2019_Q3_Yoshida_MCQ

SN	Y	B	C	F	R	K	Z	Q
1	4	-1.18308	-0.99478	-1.34025	-0.13969	0.759468	0.096875	1.352729
2	4	-0.54825	1.249854	-1.81582	-0.13969	0.759468	-0.25833	-0.06442
3	4	0.721387	0.127536	-0.86468	-0.90796	-1.81104	-2.38958	-2.8987
4	4	0.086566	0.688695	0.086468	-0.90796	0.759468	0.096875	1.352729
5	4	0.721387	-0.43362	-0.3891	0.628587	-0.52579	0.807292	-0.06442
6	4	0.086566	-0.43362	-2.29139	-0.90796	0.759468	-1.32396	-0.06442
7	4	-1.18308	-0.43362	0.562039	1.396861	-1.81104	0.807292	-0.06442
8	4	-3.08754	-3.23942	0.562039	-0.13969	0.759468	-0.25833	-0.06442
9	4	-1.8179	0.127536	-0.3891	-1.67623	-0.52579	0.807292	-0.06442
10	4	0.721387	0.127536	1.03761	1.396861	-0.52579	-1.32396	-0.06442
11	4	0.086566	0.127536	1.988753	-2.44451	0.759468	-0.25833	-0.06442
12	4	0.086566	-0.43362	0.086468	-0.13969	0.759468	0.452084	-0.06442
13	4	0.721387	0.127536	0.086468	0.628587	0.759468	-0.96875	-0.06442
14	4	0.721387	0.127536	1.03761	1.396861	-0.52579	1.517709	-0.06442
15	1	-0.54825	0.127536	1.513182	0.628587	0.759468	0.452084	-1.48156

16	1	0.721387	1.249854	0.086468	0.628587	-1.81104	-0.96875	-0.06442
17	1	0.721387	0.127536	0.562039	-0.13969	0.759468	1.517709	1.352729
18	1	0.721387	0.127536	-0.3891	1.396861	0.759468	-0.25833	-0.06442
19	1	0.721387	1.249854	-0.86468	-0.13969	-0.52579	0.452084	-1.48156
20	1	0.721387	1.249854	0.086468	0.628587	0.759468	0.452084	1.352729
21	1	0.086566	0.688695	0.086468	-0.13969	0.759468	1.517709	1.352729
22	1	0.721387	-1.55594	0.562039	-0.90796	-1.81104	-0.96875	-0.06442

RD2020_Q2_Tokiwa_MCQ

SN	Y	B	C	F	R	S	Q	L
1	4	0.813647	-1.05899	-0.93752	0.962652	0.117041	-0.42411	1.414716
2	4	0.813647	1.804764	1.335249	0.962652	1.05337	-0.42411	0.021765
3	4	0.813647	1.804764	1.335249	0.962652	1.05337	1.004474	1.414716
4	4	0.813647	-1.05899	1.335249	0.962652	1.05337	-0.42411	1.414716
5	4	-1.05725	-0.10441	0.426143	-0.51303	0.117041	1.004474	-1.37119
6	4	0.190013	0.372885	1.335249	0.962652	1.05337	-0.42411	1.414716
7	4	0.190013	1.804764	-0.93752	-0.51303	0.117041	1.004474	0.021765
8	4	-0.43362	-0.5817	-0.93752	0.962652	1.05337	-0.42411	1.414716
9	4	-1.05725	-0.5817	1.335249	0.962652	1.05337	-0.42411	0.021765
10	4	0.190013	0.372885	1.335249	0.962652	1.05337	1.004474	1.414716
11	4	-4.17542	0.850178	-0.48296	0.962652	1.05337	-0.42411	1.414716
12	4	0.813647	-0.5817	-0.02841	-0.51303	1.05337	-1.8527	1.414716
13	4	0.190013	0.850178	-0.93752	-4.20224	1.05337	1.004474	0.021765
14	4	0.813647	0.850178	-0.93752	-0.51303	1.05337	1.004474	0.021765
15	4	0.813647	0.850178	-0.93752	0.224811	0.117041	1.004474	0.021765
16	4	-0.43362	-1.05899	-1.84662	0.962652	-0.81929	-0.42411	0.021765
17	4	-0.43362	0.850178	0.426143	0.224811	0.117041	-0.42411	0.021765
18	4	0.813647	-0.10441	-1.39207	-1.25087	0.117041	1.004474	-1.37119
19	4	0.813647	-0.5817	-0.02841	0.224811	0.117041	-0.42411	-1.37119
20	4	0.813647	-0.10441	-0.93752	-1.25087	-0.81929	-3.28128	-1.37119
21	4	-0.43362	0.372885	0.426143	0.224811	1.05337	1.004474	1.414716
22	4	-0.43362	0.850178	-0.48296	0.224811	1.05337	1.004474	0.021765
23	4	0.813647	-0.5817	-0.48296	0.224811	0.117041	-0.42411	0.021765
24	4	0.813647	-0.10441	-1.84662	-1.98871	-0.81929	-0.42411	0.021765
25	4	0.813647	-0.5817	0.426143	-0.51303	0.117041	-0.42411	0.021765
26	4	0.813647	1.327471	0.880696	0.962652	-0.81929	-1.8527	0.021765
27	4	0.190013	0.372885	-0.02841	0.224811	0.117041	1.004474	0.021765
28	4	-1.05725	1.327471	-0.48296	-1.25087	-1.75562	-0.42411	-1.37119
29	4	0.813647	0.850178	0.426143	-1.25087	1.05337	1.004474	0.021765
30	4	0.813647	-0.10441	1.335249	0.962652	1.05337	-0.42411	-1.37119
31	4	-0.43362	-0.10441	1.335249	0.962652	1.05337	-0.42411	0.021765
32	4	-2.92816	-0.5817	-0.93752	0.224811	-0.81929	-1.8527	0.021765
33	4	-0.43362	-0.10441	0.880696	-0.51303	0.117041	1.004474	0.021765
34	4	0.813647	-0.5817	-0.48296	-0.51303	1.05337	-0.42411	-1.37119
35	4	0.813647	0.372885	-0.48296	-0.51303	-1.75562	-0.42411	0.021765

36	4	0.190013	-0.10441	-0.48296	0.224811	0.117041	1.004474	0.021765
37	4	-0.43362	-0.5817	-0.93752	-0.51303	0.117041	-0.42411	-1.37119
38	4	-0.43362	-2.01358	-1.39207	-0.51303	-1.75562	-0.42411	0.021765
39	4	0.813647	-0.10441	-0.93752	-0.51303	1.05337	-0.42411	0.021765
40	4	-2.30452	0.372885	0.426143	0.224811	-0.81929	1.004474	0.021765
41	4	-1.68089	0.850178	-0.93752	0.224811	1.05337	-0.42411	0.021765
42	4	-1.68089	0.372885	0.880696	-0.51303	0.117041	1.004474	0.021765
43	4	-1.68089	0.372885	-0.48296	-1.98871	-1.75562	1.004474	0.021765
44	4	-1.05725	-0.10441	1.335249	0.224811	-1.75562	1.004474	0.021765
45	4	0.813647	-0.5817	-0.48296	-0.51303	0.117041	1.004474	0.021765
46	4	0.190013	-0.10441	0.426143	-0.51303	-0.81929	-0.42411	-1.37119
47	4	0.813647	0.372885	-0.48296	-1.25087	0.117041	1.004474	0.021765
48	4	0.813647	-0.5817	-0.02841	0.962652	-0.81929	-1.8527	1.414716
49	4	0.813647	-0.5817	0.880696	0.224811	0.117041	1.004474	0.021765
50	4	0.813647	-0.5817	-0.02841	0.962652	1.05337	1.004474	0.021765
51	4	0.813647	1.804764	1.335249	0.962652	1.05337	-0.42411	0.021765
52	4	-1.05725	0.372885	0.426143	0.962652	-1.75562	1.004474	0.021765
53	4	-1.05725	-0.10441	0.426143	0.224811	1.05337	1.004474	0.021765
54	2	-2.92816	-0.5817	-0.02841	0.224811	0.117041	1.004474	0.021765
55	2	-2.30452	-2.49087	-1.84662	-1.98871	-0.81929	-0.42411	-2.76414
56	2	-0.43362	-1.05899	-1.39207	-1.98871	0.117041	-1.8527	-1.37119
57	2	-1.68089	-0.5817	-1.39207	-0.51303	1.05337	-0.42411	0.021765
58	1	0.813647	1.804764	1.335249	0.962652	-0.81929	-0.42411	1.414716
59	1	0.190013	0.372885	1.335249	0.962652	1.05337	1.004474	1.414716
60	1	0.813647	-0.5817	-0.02841	0.962652	-0.81929	-0.42411	1.414716
61	1	0.190013	0.850178	0.426143	0.962652	0.117041	1.004474	0.021765
62	1	0.813647	1.804764	0.880696	0.962652	-0.81929	-0.42411	1.414716
63	1	0.190013	0.372885	0.426143	0.962652	0.117041	1.004474	0.021765
64	1	-0.43362	-0.10441	-0.02841	-1.25087	1.05337	-3.28128	1.414716
65	1	-0.43362	0.372885	1.335249	0.962652	1.05337	-0.42411	1.414716
66	1	0.813647	1.804764	1.335249	0.962652	1.05337	-0.42411	1.414716
67	1	0.813647	-0.10441	-0.02841	-0.51303	1.05337	1.004474	1.414716
68	1	0.190013	-1.05899	-0.48296	-1.25087	-1.75562	1.004474	0.021765
69	1	0.813647	1.804764	1.335249	0.962652	0.117041	-0.42411	0.021765
70	1	0.813647	-0.5817	-1.84662	-1.25087	-0.81929	-1.8527	-1.37119
71	1	0.190013	-0.10441	1.335249	0.962652	0.117041	-0.42411	0.021765
72	1	0.190013	-0.10441	1.335249	0.962652	1.05337	-0.42411	1.414716
73	1	0.813647	1.327471	1.335249	0.962652	1.05337	-0.42411	0.021765
74	1	0.813647	1.804764	1.335249	0.962652	1.05337	1.004474	0.021765
75	1	0.190013	0.850178	-0.93752	0.962652	-1.75562	-0.42411	0.021765
76	1	0.813647	-0.5817	-1.84662	0.962652	1.05337	-0.42411	1.414716
77	1	0.813647	1.804764	1.335249	0.962652	1.05337	1.004474	1.414716
78	1	0.813647	1.804764	1.335249	0.962652	1.05337	-0.42411	0.021765
79	1	0.190013	-0.10441	1.335249	0.962652	-0.81929	-0.42411	0.021765
80	1	0.813647	-0.10441	-0.48296	-0.51303	-1.75562	1.004474	1.414716

81	1	0.190013	-0.10441	0.880696	0.224811	1.05337	1.004474	0.021765
82	1	-0.43362	-0.5817	0.880696	0.224811	0.117041	-0.42411	0.021765
83	1	-0.43362	-2.96817	1.335249	0.962652	1.05337	-0.42411	1.414716
84	1	-0.43362	-1.05899	0.880696	0.224811	0.117041	1.004474	0.021765
85	1	0.813647	0.372885	0.880696	-0.51303	-1.75562	1.004474	0.021765
86	1	0.813647	-0.10441	0.880696	0.962652	-0.81929	-0.42411	0.021765
87	1	-0.43362	-0.5817	1.335249	0.962652	1.05337	-0.42411	1.414716
88	1	0.813647	-0.10441	-0.48296	0.224811	-0.81929	-0.42411	0.021765
89	1	0.190013	1.804764	1.335249	0.224811	1.05337	1.004474	1.414716
90	1	0.813647	-0.5817	-0.02841	-0.51303	0.117041	1.004474	0.021765
91	1	-0.43362	0.372885	-0.02841	0.224811	0.117041	1.004474	0.021765
92	1	-0.43362	-2.01358	-1.84662	-4.20224	1.05337	-1.8527	-1.37119
93	1	-1.68089	-1.53629	-2.30117	0.224811	-1.75562	-0.42411	1.414716
94	1	-0.43362	-0.10441	-1.39207	0.224811	-0.81929	1.004474	-1.37119
95	1	0.190013	-0.5817	-0.93752	0.224811	-0.81929	-0.42411	-1.37119
96	1	-1.68089	0.372885	0.880696	0.962652	1.05337	-0.42411	0.021765
97	1	-0.43362	0.372885	-0.02841	0.962652	-1.75562	-1.8527	0.021765
98	1	0.190013	-0.5817	-0.93752	-1.25087	-0.81929	1.004474	0.021765
99	1	0.190013	0.850178	0.880696	-1.98871	-1.75562	1.004474	-1.37119
100	1	0.813647	0.372885	0.426143	0.224811	1.05337	-0.42411	-1.37119
101	1	0.190013	0.850178	1.335249	0.962652	1.05337	1.004474	0.021765
102	1	0.190013	-0.10441	-0.02841	-0.51303	-1.75562	1.004474	-1.37119
103	1	0.190013	-2.01358	-1.39207	-1.25087	1.05337	-0.42411	0.021765
104	1	0.813647	-1.05899	-1.39207	0.224811	1.05337	-0.42411	0.021765
105	1	0.813647	0.850178	1.335249	0.224811	-0.81929	-0.42411	1.414716
106	1	0.813647	-0.10441	-0.02841	-0.51303	0.117041	1.004474	0.021765
107	1	-0.43362	-0.5817	-1.84662	-1.98871	-0.81929	-0.42411	-1.37119
108	1	0.813647	0.850178	-0.02841	-0.51303	-0.81929	-0.42411	1.414716
109	1	-1.68089	0.372885	0.426143	0.224811	-0.81929	1.004474	0.021765
110	1	0.813647	1.327471	-0.48296	-0.51303	0.117041	-0.42411	0.021765
111	1	0.813647	0.372885	0.880696	0.224811	-0.81929	1.004474	1.414716
112	1	0.190013	-0.10441	-0.02841	0.962652	0.117041	1.004474	-1.37119
113	1	-0.43362	-2.01358	-1.39207	0.962652	1.05337	-0.42411	-1.37119
114	1	0.813647	0.372885	-0.48296	0.224811	-1.75562	-1.8527	0.021765
115	1	-0.43362	-0.5817	-0.93752	-0.51303	-1.75562	-1.8527	-1.37119
116	1	0.190013	-0.5817	-1.39207	0.962652	0.117041	1.004474	0.021765
117	1	-1.68089	-1.53629	-0.93752	-0.51303	-0.81929	-0.42411	-1.37119
118	1	-0.43362	-2.01358	-0.02841	0.224811	-0.81929	-0.42411	0.021765
119	1	-2.92816	0.372885	-0.02841	-1.25087	0.117041	-0.42411	0.021765
120	1	0.813647	-0.10441	-0.48296	-0.51303	0.117041	1.004474	-1.37119
121	1	0.813647	0.372885	-0.02841	0.224811	1.05337	1.004474	-1.37119
122	1	-1.05725	-1.53629	-1.39207	-1.25087	-0.81929	1.004474	-2.76414
123	1	0.813647	0.372885	0.426143	-0.51303	0.117041	-0.42411	0.021765
124	1	0.813647	0.372885	0.426143	-0.51303	1.05337	1.004474	0.021765
125	1	-1.05725	-0.10441	-0.48296	-0.51303	1.05337	-0.42411	0.021765

126	1	0.813647	0.372885	-0.48296	0.224811	-1.75562	-1.8527	0.021765
127	1	0.813647	-2.96817	-0.02841	0.224811	-0.81929	-1.8527	-1.37119
128	1	-0.43362	-0.10441	-0.48296	0.224811	-1.75562	1.004474	-2.76414

RD2020_Q2_Yoshida_MCQ

SN	Y	B	C	F	R	S	Q	L
1	4	0.087223	0.057157	-2.08742	-1.08168	-0.77152	-1.63835	1.81605
2	4	0.087223	0.057157	1.000817	1.208941	0.154303	1.01246	0.313112
3	4	-0.61056	1.232951	-0.5433	1.208941	-1.69734	-0.31294	0.313112
4	4	-0.61056	0.057157	-0.02859	0.445399	0.154303	-1.63835	0.313112
5	4	-1.30834	0.645054	1.515523	0.445399	-0.77152	-0.31294	-1.18983
6	4	0.785003	0.645054	-0.02859	0.445399	0.154303	1.01246	0.313112
7	4	0.785003	1.232951	1.000817	0.445399	0.154303	-0.31294	0.313112
8	4	-0.61056	0.645054	-1.57271	-0.31814	0.154303	-0.31294	0.313112
9	4	-0.61056	0.057157	-1.05801	-1.84523	0.154303	-0.31294	0.313112
10	4	0.785003	0.057157	-0.02859	-0.31814	1.080123	-1.63835	-1.18983
11	4	0.087223	-0.53074	-1.57271	0.445399	1.080123	1.01246	-1.18983
12	4	-0.61056	0.057157	2.030229	1.208941	1.080123	1.01246	1.81605
13	4	-2.00612	-2.29443	-0.02859	-4.13585	0.154303	1.01246	0.313112
14	4	0.087223	-0.53074	1.515523	0.445399	-1.69734	-0.31294	-2.69276
15	4	0.785003	0.057157	1.000817	-0.31814	1.080123	-0.31294	0.313112
16	4	-0.61056	1.820848	0.486111	0.445399	0.154303	1.01246	-1.18983
17	4	0.087223	0.645054	0.486111	1.208941	-0.77152	1.01246	1.81605
18	4	0.785003	0.645054	-0.5433	-1.08168	-0.77152	1.01246	0.313112
19	4	0.087223	-0.53074	-0.5433	0.445399	1.080123	-0.31294	-1.18983
20	4	0.785003	0.057157	-0.02859	-0.31814	1.080123	-0.31294	0.313112
21	2	0.785003	0.645054	-1.05801	0.445399	1.080123	-0.31294	0.313112
22	2	-0.61056	1.232951	1.515523	-0.31814	-1.69734	1.01246	0.313112
23	2	-1.30834	0.057157	0.486111	1.208941	1.080123	1.01246	-1.18983
24	2	0.785003	0.645054	2.030229	1.208941	1.080123	1.01246	-1.18983
25	1	-2.7039	-1.11864	-1.05801	-1.84523	1.080123	1.01246	-1.18983
26	1	-2.00612	0.057157	-0.02859	-0.31814	0.154303	-1.63835	-1.18983
27	1	-0.61056	0.645054	1.000817	0.445399	-1.69734	1.01246	1.81605
28	1	0.087223	0.645054	0.486111	-0.31814	0.154303	1.01246	1.81605
29	1	-2.00612	-0.53074	-1.05801	-0.31814	-1.69734	1.01246	0.313112

30	1	0.785003	0.057157	-0.02859	0.445399	-1.69734	-0.31294	0.313112
31	1	0.785003	1.232951	1.515523	0.445399	0.154303	1.01246	0.313112
32	1	0.785003	2.408745	1.000817	0.445399	0.154303	-0.31294	-1.18983
33	1	0.785003	0.057157	-0.5433	-0.31814	1.080123	-0.31294	0.313112
34	1	-2.7039	-2.29443	0.486111	-0.31814	-1.69734	-0.31294	-1.18983
35	1	-1.30834	-0.53074	0.486111	-0.31814	0.154303	-0.31294	0.313112
36	1	0.087223	-0.53074	0.486111	-1.08168	-0.77152	-1.63835	0.313112
37	1	0.087223	1.232951	1.515523	0.445399	-0.77152	-0.31294	1.81605
38	1	0.785003	0.057157	0.486111	0.445399	0.154303	-0.31294	0.313112
39	1	-3.40168	-0.53074	-1.57271	0.445399	-0.77152	-2.96375	-2.69276
40	1	0.785003	1.232951	0.486111	-0.31814	0.154303	1.01246	0.313112
41	1	0.785003	0.057157	-1.05801	-0.31814	-1.69734	-0.31294	0.313112
42	1	0.785003	0.057157	-1.05801	-0.31814	-1.69734	-1.63835	-1.18983
43	1	-0.61056	-0.53074	0.486111	-1.08168	-0.77152	1.01246	0.313112
44	1	-0.61056	0.057157	0.486111	-0.31814	1.080123	1.01246	-1.18983
45	1	0.785003	-0.53074	-0.02859	0.445399	0.154303	1.01246	-1.18983
46	1	0.785003	0.057157	-0.5433	-1.08168	1.080123	-0.31294	0.313112
47	1	-1.30834	-1.70653	-0.5433	-2.60877	-1.69734	1.01246	0.313112
48	1	0.785003	-0.53074	-0.5433	-0.31814	1.080123	-1.63835	0.313112
49	1	0.785003	-1.11864	-0.02859	1.208941	0.154303	-0.31294	-1.18983
50	1	0.785003	-1.11864	-0.5433	-0.31814	0.154303	1.01246	0.313112
51	1	0.785003	0.057157	1.000817	0.445399	1.080123	1.01246	0.313112
52	1	0.785003	0.645054	-0.5433	-0.31814	-1.69734	-0.31294	1.81605
53	1	0.785003	0.645054	-1.05801	0.445399	1.080123	-0.31294	-1.18983
54	1	0.087223	0.645054	1.000817	1.208941	-1.69734	-0.31294	0.313112
55	1	0.087223	-0.53074	-1.57271	-1.08168	0.154303	-0.31294	-1.18983
56	1	0.785003	0.645054	-0.5433	0.445399	0.154303	-1.63835	0.313112
57	1	0.785003	0.645054	-0.5433	1.208941	0.154303	-0.31294	0.313112
58	1	0.785003	0.057157	1.000817	1.208941	1.080123	1.01246	0.313112
59	1	0.087223	0.057157	-1.57271	0.445399	1.080123	1.01246	0.313112
60	1	0.785003	-0.53074	2.030229	1.208941	1.080123	1.01246	0.313112

61	1	0.785003	-1.70653	-1.05801	-0.31814	1.080123	-0.31294	0.313112
62	1	0.087223	0.057157	-0.02859	-1.84523	0.154303	1.01246	1.81605
63	1	0.785003	0.645054	2.030229	1.208941	1.080123	-0.31294	0.313112
64	1	0.785003	-0.53074	-0.5433	-0.31814	1.080123	-1.63835	0.313112
65	1	0.785003	0.645054	-0.5433	0.445399	0.154303	-0.31294	0.313112
66	1	0.785003	-2.29443	-0.5433	-1.08168	0.154303	1.01246	0.313112
67	1	-1.30834	0.057157	-0.5433	-0.31814	0.154303	-1.63835	0.313112
68	1	0.087223	0.645054	-0.5433	-0.31814	-0.77152	-0.31294	0.313112
69	1	0.087223	0.645054	0.486111	1.208941	-1.69734	-0.31294	0.313112
70	1	0.087223	-0.53074	-0.02859	1.208941	1.080123	1.01246	0.313112
71	1	0.785003	-4.05812	-1.57271	-1.08168	-0.77152	-1.63835	-1.18983
72	1	-0.61056	0.645054	-0.5433	1.208941	1.080123	1.01246	-1.18983

RD2020_Q3_Tokiwa_MCQ

SN	Y	B	C	F	R	S	Q	L
1	4	-0.21441	0.105053	-1.26876	-1.95016	-0.28895	-0.88794	-1.39285
2	4	0.363301	0.105053	1.377899	1.028823	-0.28895	1.092064	1.451494
3	4	-0.21441	0.105053	0.93679	1.028823	1.045718	0.102062	1.451494
4	4	-1.36982	0.671173	1.377899	1.028823	-0.28895	1.092064	1.451494
5	4	0.363301	0.105053	1.377899	1.028823	1.045718	1.092064	1.451494
6	4	0.363301	-0.46107	-0.38654	0.284078	1.045718	0.102062	1.451494
7	4	-0.79212	-1.02719	1.377899	1.028823	-0.28895	1.092064	1.451494
8	4	0.363301	0.105053	1.377899	1.028823	-0.28895	1.092064	1.451494
9	4	0.363301	-1.02719	-1.26876	-1.20541	1.045718	-0.88794	0.029323
10	4	0.363301	0.671173	-0.38654	0.284078	-0.28895	0.102062	1.451494
11	4	0.363301	0.671173	1.377899	0.284078	1.045718	0.102062	0.029323
12	4	0.363301	1.803413	1.377899	1.028823	-0.28895	1.092064	0.029323
13	4	0.363301	1.803413	1.377899	1.028823	1.045718	0.102062	-1.39285
14	4	-0.21441	1.803413	1.377899	1.028823	-1.62361	1.092064	1.451494
15	4	0.363301	1.803413	1.377899	1.028823	1.045718	1.092064	0.029323
16	4	-0.21441	0.105053	-0.38654	-1.20541	1.045718	1.092064	1.451494
17	4	0.94101	0.671173	-1.26876	1.028823	-0.28895	1.092064	-1.39285
18	4	0.363301	0.105053	0.93679	0.284078	1.045718	-1.87794	0.029323
19	4	0.94101	0.671173	-1.26876	1.028823	-0.28895	1.092064	-1.39285
20	4	0.363301	-1.02719	0.05457	-0.46067	1.045718	1.092064	0.029323
21	4	0.363301	-0.46107	0.05457	-0.46067	-0.28895	1.092064	0.029323
22	4	0.363301	0.105053	-1.70987	-0.46067	-0.28895	1.092064	-1.39285
23	4	0.363301	-1.02719	-0.38654	-0.46067	-0.28895	0.102062	-1.39285
24	4	-0.21441	-0.46107	0.05457	0.284078	-0.28895	0.102062	1.451494
25	4	0.363301	0.671173	0.49568	0.284078	1.045718	1.092064	0.029323

26	4	0.94101	0.671173	-1.26876	1.028823	-0.28895	1.092064	0.029323
27	4	0.363301	0.105053	0.05457	1.028823	1.045718	0.102062	1.451494
28	4	0.363301	1.803413	1.377899	1.028823	1.045718	0.102062	0.029323
29	4	0.363301	0.105053	0.05457	-1.20541	1.045718	-1.87794	0.029323
30	4	0.363301	-0.46107	0.49568	0.284078	-0.28895	0.102062	1.451494
31	4	0.363301	-0.46107	-1.70987	0.284078	-0.28895	1.092064	0.029323
32	4	-1.36982	0.105053	0.49568	-0.46067	1.045718	0.102062	0.029323
33	4	0.363301	-0.46107	-1.26876	0.284078	1.045718	0.102062	0.029323
34	4	0.363301	-0.46107	-1.26876	-1.20541	-0.28895	0.102062	0.029323
35	4	-1.94753	-0.46107	-1.26876	-1.95016	1.045718	0.102062	0.029323
36	4	0.94101	0.671173	0.05457	-0.46067	1.045718	0.102062	-1.39285
37	4	0.363301	-1.02719	0.49568	-0.46067	1.045718	0.102062	0.029323
38	4	0.94101	-0.46107	0.05457	-1.20541	1.045718	0.102062	0.029323
39	4	0.363301	0.671173	0.49568	-1.20541	-0.28895	-0.88794	-1.39285
40	4	-0.21441	-1.02719	-0.38654	-0.46067	1.045718	0.102062	0.029323
41	4	0.94101	0.105053	0.05457	0.284078	-0.28895	0.102062	0.029323
42	4	0.363301	-1.02719	-0.82765	0.284078	-0.28895	0.102062	0.029323
43	4	0.363301	-0.46107	0.05457	-0.46067	1.045718	0.102062	0.029323
44	4	0.363301	-1.02719	-0.82765	-0.46067	1.045718	0.102062	0.029323
45	2	0.363301	-2.15943	0.49568	-2.6949	-0.28895	0.102062	0.029323
46	2	0.363301	-0.46107	-1.26876	-0.46067	1.045718	0.102062	0.029323
47	2	0.363301	1.803413	-0.38654	1.028823	-0.28895	-0.88794	0.029323
48	2	0.363301	-0.46107	-1.26876	1.028823	-0.28895	-1.87794	0.029323
49	1	0.363301	-1.59331	0.49568	-0.46067	-0.28895	0.102062	0.029323
50	1	0.363301	-1.59331	0.49568	-0.46067	-0.28895	0.102062	1.451494
51	1	0.363301	-1.59331	0.49568	-0.46067	-0.28895	1.092064	1.451494
52	1	0.363301	-0.46107	-0.38654	1.028823	-0.28895	1.092064	1.451494
53	1	-0.79212	-0.46107	-1.26876	0.284078	-0.28895	1.092064	0.029323
54	1	0.363301	-1.59331	0.05457	1.028823	-0.28895	1.092064	-1.39285
55	1	-4.25837	-0.46107	-0.82765	0.284078	-0.28895	-1.87794	0.029323
56	1	-0.79212	0.105053	0.05457	1.028823	-0.28895	1.092064	1.451494
57	1	-0.79212	1.237293	-1.26876	0.284078	-0.28895	1.092064	0.029323
58	1	-1.94753	-1.02719	-1.26876	0.284078	-2.95828	-0.88794	0.029323
59	1	0.363301	1.803413	0.49568	0.284078	-0.28895	0.102062	1.451494
60	1	-1.94753	0.105053	-0.38654	-1.20541	-0.28895	1.092064	0.029323
61	1	0.94101	-0.46107	-0.82765	0.284078	-2.95828	0.102062	-1.39285
62	1	0.363301	0.105053	-0.82765	0.284078	-1.62361	-0.88794	0.029323
63	1	0.94101	0.105053	0.93679	0.284078	-0.28895	-0.88794	1.451494
64	1	0.363301	1.803413	0.93679	1.028823	-0.28895	1.092064	1.451494
65	1	-2.52524	-1.02719	-0.82765	0.284078	1.045718	1.092064	0.029323
66	1	0.363301	-1.59331	-1.70987	1.028823	1.045718	-1.87794	0.029323
67	1	0.363301	-0.46107	0.93679	-0.46067	-0.28895	-1.87794	0.029323
68	1	0.363301	0.105053	-1.70987	-0.46067	-0.28895	-1.87794	-1.39285
69	1	-0.79212	0.671173	-0.38654	-1.95016	1.045718	-0.88794	-1.39285
70	1	0.363301	0.105053	-0.82765	-1.20541	-0.28895	-1.87794	0.029323

71	1	0.94101	-1.02719	0.49568	0.284078	1.045718	0.102062	0.029323
72	1	-0.79212	0.671173	1.377899	0.284078	1.045718	-1.87794	0.029323
73	1	0.363301	-0.46107	-0.38654	-1.95016	-2.95828	-1.87794	-1.39285
74	1	0.363301	1.803413	1.377899	1.028823	1.045718	1.092064	0.029323
75	1	0.363301	-1.02719	-1.26876	-1.20541	1.045718	-0.88794	0.029323
76	1	0.363301	1.803413	1.377899	1.028823	-0.28895	0.102062	0.029323
77	1	0.94101	0.671173	1.377899	1.028823	-0.28895	-1.87794	0.029323
78	1	0.363301	0.105053	0.49568	0.284078	1.045718	0.102062	0.029323
79	1	-3.68066	0.671173	-0.82765	-0.46067	-0.28895	1.092064	0.029323
80	1	0.363301	1.803413	1.377899	1.028823	1.045718	0.102062	-1.39285
81	1	-3.68066	-2.15943	0.05457	-1.95016	-1.62361	-0.88794	-1.39285
82	1	0.363301	0.105053	0.49568	0.284078	-2.95828	0.102062	0.029323
83	1	0.94101	0.671173	0.49568	0.284078	-0.28895	0.102062	0.029323
84	1	0.363301	-2.15943	-1.70987	1.028823	1.045718	-1.87794	1.451494
85	1	-0.79212	1.237293	1.377899	1.028823	-0.28895	-0.88794	0.029323
86	1	0.94101	0.671173	-0.38654	-1.95016	-0.28895	0.102062	-1.39285
87	1	0.94101	1.803413	1.377899	1.028823	-0.28895	1.092064	-1.39285
88	1	0.363301	0.671173	-1.26876	1.028823	-0.28895	1.092064	-1.39285
89	1	0.363301	0.671173	1.377899	0.284078	-1.62361	0.102062	-2.81502
90	1	0.94101	0.671173	1.377899	1.028823	-1.62361	1.092064	-1.39285
91	1	-0.79212	-0.46107	0.93679	-1.20541	-0.28895	0.102062	-1.39285
92	1	0.363301	-1.59331	-0.38654	0.284078	-0.28895	-1.87794	0.029323
93	1	-1.94753	0.105053	0.49568	-1.20541	-0.28895	-1.87794	-1.39285
94	1	-0.79212	-0.46107	-0.82765	-3.43965	-1.62361	0.102062	-1.39285
95	1	-0.79212	-0.46107	-1.70987	0.284078	-1.62361	0.102062	0.029323
96	1	0.363301	-0.46107	0.49568	-0.46067	1.045718	-0.88794	1.451494
97	1	0.363301	0.105053	-0.38654	-0.46067	1.045718	-0.88794	0.029323

RD2020_Q3_Yoshida_MCQ

SN	Y	B	C	F	R	S	Q	L
1	4	0.383893	0.198825	0.454655	0.530161	0.603023	-0.08639	-1.54282
2	4	0.383893	0.198825	-0.86531	1.287534	0.603023	-0.08639	0.237356
3	4	0.383893	-0.46393	0.014666	0.530161	0.603023	-0.08639	0.237356
4	4	0.383893	0.198825	0.454655	0.530161	0.603023	-0.08639	-1.54282
5	4	0.383893	-1.12668	-1.74529	-0.22721	-0.90453	1.209416	0.237356
6	4	-0.29357	-0.46393	0.454655	0.530161	-0.90453	1.209416	0.237356
7	4	0.383893	-1.12668	1.334632	-0.22721	-0.90453	-0.08639	-1.54282
8	4	0.383893	-0.46393	1.334632	-1.74196	-0.90453	-1.38219	0.237356
9	4	0.383893	-0.46393	0.894644	-0.22721	0.603023	1.209416	0.237356
10	4	0.383893	-0.46393	0.894644	-0.22721	0.603023	-1.38219	0.237356
11	4	-3.68086	-0.46393	0.454655	0.530161	-0.90453	-0.08639	-1.54282
12	4	0.383893	0.861576	0.454655	-1.74196	-0.90453	-0.08639	0.237356
13	4	0.383893	-1.78943	0.454655	0.530161	0.603023	-0.08639	0.237356
14	4	-0.29357	0.198825	0.454655	0.530161	-0.90453	1.209416	0.237356
15	4	0.383893	1.524327	-0.86531	1.287534	0.603023	-0.08639	0.237356

16	4	1.061351	0.861576	-2.62527	1.287534	0.603023	-0.08639	0.237356
17	4	-0.29357	0.861576	-1.74529	-0.22721	0.603023	1.209416	0.237356
18	4	-0.29357	0.198825	0.014666	0.530161	0.603023	1.209416	0.237356
19	4	0.383893	0.198825	0.454655	0.530161	0.603023	-0.08639	0.237356
20	4	0.383893	-1.12668	0.894644	-0.22721	0.603023	1.209416	-1.54282
21	4	0.383893	1.524327	0.014666	-0.98458	0.603023	-0.08639	0.237356
22	4	-3.0034	0.861576	0.894644	-0.22721	0.603023	1.209416	2.017529
23	2	1.061351	0.861576	-0.42532	-0.98458	0.603023	-0.08639	0.237356
24	1	0.383893	2.187078	1.334632	1.287534	0.603023	1.209416	2.017529
25	1	0.383893	-2.45218	-0.86531	-3.2567	-0.90453	-2.67799	-1.54282
26	1	0.383893	0.198825	0.894644	-0.22721	0.603023	-0.08639	0.237356
27	1	0.383893	-1.12668	-0.42532	-0.98458	-0.90453	-1.38219	-1.54282
28	1	-0.97102	0.198825	-1.74529	0.530161	-3.91965	-0.08639	0.237356
29	1	0.383893	0.861576	-0.42532	0.530161	0.603023	-1.38219	0.237356
30	1	-0.97102	-0.46393	-0.42532	0.530161	0.603023	-1.38219	2.017529

Data Set2 for K-means:
###dataset_AF_WT_RD2023_Q2_2_F

SN	Y	Start	Ending	WT	MCQ	L_Achiev
1	4	16:32	16:55	23	26	4
2	4	12:01	12:04	3	30	4
3	4	13:37	15:37	120	30	4
4	4	19:57	20:28	31	28	4
5	4	12:19	12:23	4	28	4
6	4	12:23	13:21	58	30	3
7	4	0:55	0:57	2	30	4
8	4	16:28	17:01	33	28	4
9	4	18:47	19:09	22	30	2.5
10	4	18:05	18:09	4	30	4
11	4	16:03	16:51	48	28	3
12	4	23:15	23:18	3	28	4
13	4	15:57	15:58	1	28	3
14	4	19:07	19:14	7	28	4
15	4	16:53	17:14	21	30	4
16	4	19:11	19:30	19	30	3.5
17	4	16:56	16:58	2	30	4
18	4	17:08	17:12	4	26	3
19	4	23:05	23:19	14	28	4
20	4	18:25	18:26	1	30	4
21	4	20:23	20:53	30	26	3
22	4	12:18	12:26	8	30	4
23	4	20:16	20:18	2	28	4
24	4	17:43	17:44	1	30	3.5
25	4	16:04	16:23	19	26	4
26	4	21:13	21:23	10	30	4

27	4	16:17	16:18	1	28	4
28	4	16:15	16:24	9	30	4
29	4	17:55	17:57	2	30	3.5
30	4	11:49	12:09	20	28	4
31	4	22:52	22:59	7	30	4
32	4	22:28	22:30	2	26	3
33	4	16:00	16:02	2	30	4
34	4	13:18	13:19	1	28	3
35	4	13:00	13:01	1	30	3
36	4	10:57	10:59	2	30	3
37	4	16:32	16:35	3	30	3
38	4	16:57	17:13	16	30	4
39	4	16:02	16:04	2	30	4
40	4	16:29	17:12	43	28	4
41	4	16:00	16:01	1	30	3
42	4	18:36	18:39	3	30	3
43	4	10:39	11:04	25	30	4
44	4	18:47	18:55	8	30	4
45	4	11:46	11:48	2	28	3
46	4	12:46	12:57	11	30	4
47	4	18:19	19:26	67	30	2.5
48	4	16:55	17:17	22	30	3
49	4	17:20	17:43	23	30	3
50	4	19:17	19:22	5	28	3
51	4	17:52	17:54	2	30	3
52	4	12:57	13:08	11	30	4
53	4	19:25	19:32	7	24	3
54	4	22:43	22:58	15	30	4
55	4	22:20	23:05	45	28	4
56	4	16:21	16:25	4	30	3
57	4	17:03	17:05	2	26	3
58	4	16:35	16:40	5	30	3
59	4	19:16	19:18	2	30	3
60	4	13:47	14:21	34	28	4
61	4	16:24	16:29	5	30	3
62	4	16:03	16:26	23	26	4
63	4	16:21	16:34	13	30	2.5
64	4	20:40	20:43	3	26	3
65	4	20:46	20:49	3	30	3.5
66	4	16:15	16:25	10	28	3
67	4	22:44	22:47	3	26	3
68	4	15:42	16:04	22	30	3
69	4	23:07	23:17	10	28	3
70	4	17:42	17:55	13	26	4
71	4	18:52	18:55	3	24	4

72	4	16:58	17:02	4	30	3
73	4	12:18	12:20	2	30	4
74	4	17:37	17:56	19	30	2.5
75	4	10:29	11:02	33	30	3
76	4	0:12	0:18	6	28	3
77	4	19:38	19:39	1	30	4
78	4	16:01	16:08	7	24	3
79	4	17:07	17:20	13	30	3
80	4	16:56	16:58	2	20	2.5
81	4	0:23	0:47	24	28	3
82	4	16:01	16:30	29	30	3
83	4	10:01	10:04	3	22	2
84	4	16:04	16:15	11	30	3.5
85	4	20:50	21:36	46	30	3
86	4	18:59	19:12	13	30	4
87	4	14:58	15:04	6	30	4
88	4	14:19	14:54	35	26	3
89	4	16:03	16:14	11	24	3
90	4	17:32	17:55	23	30	4
91	2	15:38	15:53	15	30	3
92	2	16:00	16:15	15	28	4
93	2	16:49	17:07	18	26	4
94	2	0:44	0:51	7	28	3
95	2	16:18	16:30	12	30	3.5
96	2	5:47	6:13	26	28	3
97	2	17:43	18:25	42	28	4
98	2	21:58	22:46	48	28	3
99	2	16:31	16:36	5	24	3
100	2	16:01	16:14	13	28	4
101	2	16:00	16:01	1	30	4
102	2	16:05	16:10	5	28	4
103	2	0:03	0:31	28	30	4
104	1	16:59	17:13	14	30	4
105	1	16:34	16:36	2	30	3
106	1	8:45	8:47	2	28	3
107	1	13:02	13:24	22	26	2.5
108	1	17:01	18:14	73	24	3
109	1	16:03	16:48	45	30	3.5
110	1	21:46	21:47	1	30	3
111	1	17:18	17:19	1	28	4
112	1	16:09	16:11	2	26	4
113	1	11:19	12:08	49	26	2.5
114	1	11:32	11:34	2	30	4
115	1	17:50	17:51	1	30	4
116	1	17:50	17:55	5	30	4

117	1	3:36	3:46	10	30	3.5
118	1	16:10	16:21	11	30	2.5
119	1	10:51	10:59	8	30	4
120	1	22:53	22:59	6	24	3
121	1	18:11	18:22	11	26	3
122	1	16:16	16:47	31	26	4
123	1	16:00	16:04	4	30	3.5
124	1	19:57	20:06	9	26	3
125	1	17:01	17:19	18	28	4
126	1	22:43	23:09	26	28	4
127	1	0:11	0:12	1	28	4
128	1	17:40	17:50	10	28	3
129	1	17:56	18:02	6	28	3
130	1	19:16	19:20	4	26	3
131	1	18:19	18:20	1	18	3
132	1	21:00	21:04	4	30	4
133	1	19:33	19:34	1	22	4
134	1	17:49	17:50	1	30	2.5
135	1	21:45	21:55	10	28	3
136	1	19:05	19:06	1	28	3
137	1	9:33	10:00	27	28	3
138	1	10:26	11:29	63	28	3
139	1	20:29	20:37	8	28	4
140	1	22:25	22:29	4	30	4
141	1	21:05	21:13	8	30	3.5
142	1	19:00	19:13	13	30	3
143	1	20:16	20:24	8	30	4
144	1	19:05	19:13	8	30	4
145	1	16:12	17:52	100	28	3
146	1	16:14	16:27	13	30	4
147	1	3:00	3:04	4	20	3
148	1	16:12	17:05	53	28	4
149	1	16:04	16:35	31	28	3
150	1	21:21	21:38	17	30	2
151	1	21:54	21:55	1	24	3.5
152	1	18:41	19:10	29	30	4
153	1	14:16	14:24	8	28	4
154	1	20:38	20:47	9	30	3
155	1	20:53	20:56	3	28	4
156	1	18:42	18:55	13	30	3
157	1	16:20	16:23	3	30	3
158	1	17:13	17:32	19	28	3
159	1	18:29	18:46	17	30	3
160	1	18:24	18:26	2	26	3
161	1	14:49	15:29	40	26	3

162	1	18:13	18:20	7	24	3
163	1	15:02	15:04	2	30	3
164	1	18:12	18:22	10	24	3.5
165	1	16:52	17:07	15	24	4
166	1	17:39	17:42	3	28	3
167	1	18:07	18:07	0	30	4
168	1	17:43	18:01	18	28	3
169	1	17:02	17:17	15	20	3
170	1	19:02	19:07	5	28	3
171	1	12:37	12:41	4	28	3
172	1	14:56	15:38	42	28	4
173	1	20:53	21:07	14	28	4
174	1	20:24	20:43	19	26	4
175	4	16:16	16:48	32	28	3
176	4	21:41	21:52	11	30	4
177	4	16:04	16:24	20	30	3
178	4	17:50	18:28	38	30	3
179	4	1:13	1:38	25	30	4
180	4	15:37	15:46	9	30	3
181	4	16:01	16:23	22	30	4
182	4	16:57	17:06	9	28	4
183	4	17:03	17:07	4	30	4
184	4	20:46	20:47	1	30	3
185	4	17:12	17:17	5	30	4
186	4	16:21	16:24	3	30	3
187	4	17:00	17:07	7	30	4
188	4	16:08	16:17	9	20	3
189	4	18:09	18:15	6	30	4
190	4	18:04	18:10	6	30	3
191	4	22:28	22:31	3	30	4
192	4	21:46	22:12	26	24	4
193	4	16:01	16:19	18	30	3.5
194	4	8:25	9:00	35	30	3
195	4	21:25	21:45	20	30	4
196	4	22:14	22:20	6	30	3
197	4	19:37	19:44	7	28	4
198	4	14:08	15:05	57	30	4
199	4	17:35	17:57	22	30	3
200	4	16:10	16:14	4	30	4
201	4	16:13	17:06	53	30	3
202	4	17:33	17:47	14	30	3
203	4	16:05	16:13	8	30	4
204	4	16:01	16:14	13	30	4
205	4	16:01	16:19	18	30	3.5
206	4	16:03	16:15	12	26	3

207	4	16:07	16:26	19	30	3
208	4	21:35	21:43	8	30	4
209	4	16:06	16:38	32	30	3.5
210	4	16:58	17:03	5	24	3.5
211	4	16:02	16:15	13	30	3
212	4	18:21	18:33	12	28	4
213	2	16:11	16:40	29	28	4
214	2	15:20	16:02	42	28	3.5
215	2	11:14	11:20	6	22	4
216	2	16:16	16:28	12	28	3
217	1	16:10	16:57	47	30	3.5
218	1	14:20	16:01	101	28	3
219	1	21:02	21:07	5	30	3
220	1	13:12	13:13	1	30	4
221	1	13:32	13:35	3	30	4
222	1	20:13	20:16	3	28	3
223	1	21:10	21:21	11	30	3
224	1	22:40	22:52	12	30	3
225	1	12:55	12:57	2	30	4
226	1	16:36	16:45	9	28	3
227	1	22:42	22:43	1	30	3
228	1	16:03	16:14	11	26	3.5
229	1	16:04	16:37	33	30	4
230	1	11:33	11:50	17	30	4
231	1	19:54	20:27	33	30	4
232	1	16:08	16:22	14	26	4
233	1	17:07	17:18	11	28	3.5
234	1	10:28	10:43	15	30	3.5
235	1	14:55	14:55	0	26	4
236	1	16:08	16:10	2	30	4
237	1	16:01	16:05	4	30	4
238	1	16:04	16:06	2	30	4
239	1	18:21	18:29	8	30	3
240	1	16:32	16:40	8	30	3
241	1	17:06	17:33	27	30	4
242	1	18:02	18:10	8	28	3
243	1	20:44	20:47	3	28	4
244	1	16:23	16:41	18	28	3
245	1	9:47	9:49	2	28	3
246	1	17:02	17:04	2	28	4
247	1	15:13	15:41	28	28	3
248	1	21:37	21:45	8	30	3

dataset_AF_WT_RD2023_Q2_3_M

SN	Y	Start	Ending	WT	MCQ	L_Achiev

1	4	16:32	17:31	59	18	4
2	4	16:49	16:53	4	24	3
3	4	16:07	17:29	82	30	4
4	4	22:40	23:05	25	22	3
5	4	17:25	17:26	1	30	4
6	4	16:02	17:30	88	30	3
7	4	16:25	16:30	5	24	4
8	4	0:17	0:20	3	24	3.5
9	4	12:50	12:54	4	24	3
10	4	16:18	16:22	4	28	4
11	4	16:21	16:21	0	18	3
12	4	19:46	20:10	24	26	4
13	4	18:35	18:37	2	24	4
14	4	18:18	18:22	4	22	3
15	4	19:42	19:59	17	22	4
16	4	20:57	20:58	1	30	3
17	4	16:49	16:53	4	24	4
18	4	19:29	19:37	8	20	3
19	4	16:48	16:53	5	24	4
20	4	19:51	19:52	1	26	3.5
21	4	17:42	17:46	4	30	3.5
22	4	16:26	16:31	5	30	3
23	4	13:38	13:49	11	24	4
24	4	20:43	20:45	2	24	4
25	4	15:54	16:17	23	24	4
26	4	15:48	15:50	2	14	3
27	4	11:09	11:28	19	22	4
28	4	16:51	16:54	3	22	4
29	4	18:08	18:21	13	30	3
30	4	11:54	12:18	24	22	3
31	4	16:00	16:01	1	24	4
32	4	18:47	18:49	2	22	3
33	4	12:54	13:08	14	22	4
34	4	11:26	11:30	4	22	3
35	4	16:08	16:09	1	14	3
36	4	18:26	18:34	8	26	4
37	4	16:40	16:41	1	22	3
38	4	17:43	18:00	17	26	4
39	4	16:00	16:01	1	24	3
40	4	18:45	18:48	3	30	3
41	4	11:51	12:07	16	22	4
42	4	22:24	22:58	34	30	3
43	4	14:58	15:00	2	20	3
44	4	13:07	13:09	2	22	4
45	4	17:53	18:26	33	22	3

46	4	16:26	16:31	5	20	3
47	4	16:14	16:24	10	30	3
48	4	13:57	14:02	5	20	3
49	4	0:40	0:46	6	22	1
50	4	13:31	13:34	3	22	4
51	4	10:07	10:14	7	22	3
52	4	22:58	23:00	2	18	4
53	4	20:02	20:39	37	20	4
54	4	16:38	16:41	3	30	4
55	4	21:10	21:12	2	22	3
56	4	13:26	13:29	3	30	4
57	4	21:02	21:06	4	22	4
58	4	10:51	10:56	5	22	3
59	4	22:26	22:27	1	24	4
60	4	9:26	9:30	4	22	3.5
61	4	19:39	19:41	2	30	2
62	4	16:30	16:45	15	20	3
63	4	20:48	20:50	2	20	3
64	4	15:19	15:45	26	26	3
65	4	23:06	23:21	15	26	3
66	4	23:28	23:38	10	26	4
67	4	22:44	22:49	5	14	4
68	4	22:46	22:58	12	20	3
69	4	13:52	13:53	1	24	3
70	4	19:49	20:07	18	26	4
71	4	21:18	21:23	5	22	3
72	4	12:14	12:15	1	20	4
73	4	3:29	3:36	7	26	3.5
74	4	14:34	14:38	4	22	2.5
75	4	21:40	21:46	6	26	3
76	4	17:56	18:36	40	24	3
77	4	22:39	22:40	1	26	3
78	4	19:27	20:02	35	22	3
79	4	19:56	20:02	6	18	3
80	4	10:00	10:07	7	22	4
81	4	1:17	1:32	15	24	3
82	4	5:47	5:48	1	24	3
83	4	14:50	15:09	19	30	4
84	2	17:29	17:30	1	30	3
85	2	0:09	0:25	16	30	4
86	2	18:58	19:02	4	20	3
87	2	16:03	16:29	26	22	4
88	2	8:52	9:18	26	24	3
89	2	19:36	19:41	5	18	4
90	2	20:27	20:29	2	22	2

91	2	21:57	22:03	6	8	3
92	2	19:03	19:04	1	30	4
93	2	20:56	21:46	50	22	3.5
94	2	16:46	16:50	4	20	3
95	2	11:13	11:25	12	30	4
96	2	16:46	16:49	3	30	4
97	2	1:09	1:31	22	24	4
98	2	23:36	23:45	9	24	4
99	1	18:02	18:05	3	30	4
100	1	17:03	17:04	1	30	3.5
101	1	19:34	19:55	21	20	4
102	1	21:02	21:53	51	18	3
103	1	20:13	20:27	14	24	4
104	1	16:17	16:24	7	24	4
105	1	16:01	16:08	7	24	3.5
106	1	18:05	18:08	3	18	3
107	1	10:31	10:33	2	30	4
108	1	21:41	21:43	2	30	4
109	1	19:01	19:02	1	20	4
110	1	16:28	16:31	3	30	2.5
111	1	16:13	16:26	13	10	3
112	1	16:04	16:06	2	30	3
113	1	10:57	11:02	5	30	4
114	1	12:00	12:04	4	16	4
115	1	16:00	16:04	4	30	3
116	1	16:55	17:21	26	22	3
117	1	11:11	11:30	19	14	4
118	1	17:26	17:26	0	24	3.5
119	1	21:26	21:28	2	14	3
120	1	21:26	21:27	1	14	3
121	1	17:28	17:38	10	12	3
122	1	17:00	17:03	3	14	3
123	1	19:50	20:02	12	26	3.5
124	1	19:50	20:15	25	22	3.5
125	1	18:37	18:41	4	12	3.5
126	1	10:15	10:21	6	22	3
127	1	13:56	14:00	4	22	2.5
128	1	16:55	17:08	13	22	3
129	1	12:48	12:57	9	14	4
130	1	17:51	18:38	47	22	3
131	1	15:46	15:50	4	20	3
132	1	19:57	20:18	21	26	3
133	1	16:22	16:26	4	12	4
134	1	0:32	0:37	5	26	4
135	1	21:00	21:25	25	30	3

136	1	20:08	20:19	11	16	3
137	1	21:20	21:28	8	30	4
138	1	19:44	19:47	3	26	3.5
139	1	16:28	16:59	31	14	4
140	1	13:29	13:36	7	16	3
141	1	16:29	17:24	55	24	4
142	1	16:30	16:58	28	22	3
143	1	15:27	15:36	9	24	2
144	1	15:25	15:33	8	20	3.5
145	1	16:19	16:22	3	16	3
146	1	19:09	19:27	18	20	4
147	1	21:08	21:57	49	24	4
148	1	10:21	10:40	19	12	3
149	1	22:39	22:52	13	22	2
150	1	18:41	18:42	1	22	4
151	1	12:48	13:15	27	18	4
152	1	20:31	20:33	2	30	3
153	1	15:01	15:23	22	24	3
154	1	19:12	19:21	9	20	4
155	1	11:14	11:30	16	22	4
156	1	23:10	23:29	19	22	3
157	1	11:44	12:22	38	22	3
158	1	22:30	22:55	25	22	3
159	1	16:13	16:37	24	16	3
160	1	1:59	2:11	12	18	4
161	1	22:54	22:58	4	22	4
162	1	16:13	16:35	22	26	3
163	1	18:09	18:17	8	20	3
164	1	16:22	17:10	48	24	3
165	1	16:25	16:29	4	24	3
166	1	18:56	18:59	3	22	3
167	1	21:42	21:47	5	18	4
168	1	22:20	22:25	5	24	4
169	4	22:50	22:58	8	24	3
170	4	12:24	13:00	36	24	4
171	4	19:11	19:31	20	20	3
172	4	17:56	17:59	3	20	3
173	4	11:56	12:50	54	24	3
174	4	22:25	22:56	31	20	4
175	4	19:34	19:37	3	22	4
176	4	16:07	16:22	15	26	4
177	4	22:32	22:46	14	26	3.5
178	4	19:35	19:53	18	22	4
179	4	16:32	16:35	3	26	3
180	4	16:06	16:16	10	26	4

181	4	21:00	21:01	1	24	3
182	4	19:15	19:21	6	26	4
183	4	16:26	16:32	6	30	3.5
184	4	13:11	13:22	11	26	3
185	4	22:55	22:56	1	22	4
186	4	16:01	16:24	23	22	4
187	4	16:54	16:56	2	26	3
188	4	21:30	21:50	20	24	4
189	4	22:51	22:53	2	22	3
190	4	21:00	21:01	1	26	3
191	4	19:22	19:26	4	24	4
192	4	22:10	22:57	47	22	3
193	4	16:31	16:36	5	26	4
194	4	17:53	18:00	7	20	3
195	4	16:49	16:53	4	26	3.5
196	4	16:00	16:21	21	22	4
197	4	16:37	16:41	4	22	3
198	4	16:10	16:21	11	26	3
199	4	16:57	17:11	14	26	3
200	4	16:23	16:40	17	24	3
201	4	16:02	16:20	18	24	3
202	4	16:36	17:08	32	22	4
203	2	20:16	20:20	4	30	4
204	2	20:45	21:07	22	22	3
205	2	15:30	15:32	2	18	4
206	2	16:02	16:15	13	18	3
207	1	21:59	22:14	15	26	3
208	1	22:52	22:59	7	20	3
209	1	12:16	12:18	2	24	3.5
210	1	22:48	22:50	2	30	3
211	1	22:05	22:27	22	22	4
212	1	19:44	19:46	2	20	1
213	1	18:24	18:26	2	22	3
214	1	22:28	22:45	17	22	3
215	1	22:29	22:30	1	26	3
216	1	16:07	16:14	7	20	3
217	1	22:26	22:46	20	30	3
218	1	16:17	16:37	20	28	3
219	1	16:28	16:57	29	24	2.5
220	1	11:16	11:24	8	24	4
221	1	17:58	18:07	9	22	3
222	1	18:13	18:16	3	16	4
223	1	17:50	18:02	12	22	3
224	1	17:21	17:22	1	22	3
225	1	12:52	13:09	17	26	3

226	1	18:35	18:39	4	20	2.5
227	1	16:26	16:32	6	22	4
228	1	16:06	16:07	1	26	4
229	1	16:09	16:12	3	22	4
230	1	16:03	16:12	9	24	4
231	1	16:40	17:22	42	30	3
232	1	22:01	22:49	48	26	3
233	1	16:24	16:29	5	30	3
234	1	17:29	17:38	9	8	4
235	1	19:00	19:20	20	24	3
236	1	21:34	21:37	3	22	4
237	1	16:04	16:04	0	18	3
238	1	16:08	16:10	2	24	4
239	1	16:02	16:18	16	30	3
240	1	21:53	22:08	15	24	3

dataset_AF_WT_RD2023_Q2_4_C

SN	Y	Start	Ending	WT	MCQ	L_Achiev
1	4	16:22	16:36	14	20	4
2	4	17:48	18:05	17	22	3.3
3	4	19:27	19:31	4	30	4
4	4	18:50	19:17	27	28	3.5
5	4	17:34	17:38	4	30	4
6	4	14:12	15:16	64	30	3
7	4	11:34	12:04	30	22	4
8	4	6:13	6:20	7	28	4
9	4	20:34	20:37	3	30	3
10	4	16:32	16:38	6	24	4
11	4	13:14	13:15	1	26	3
12	4	19:34	19:36	2	26	4
13	4	17:35	17:36	1	22	3
14	4	19:23	19:25	2	30	4
15	4	13:22	13:23	1	22	4
16	4	0:04	0:16	12	16	3.3
17	4	16:50	16:52	2	30	4
18	4	17:52	17:53	1	26	3
19	4	13:52	13:54	2	26	4
20	4	16:28	16:31	3	30	3
21	4	17:22	17:24	2	22	3.8
22	4	22:33	22:38	5	24	3
23	4	16:24	16:26	2	22	4
24	4	12:58	13:01	3	12	4
25	4	20:54	20:56	2	30	3
26	4	16:47	16:48	1	30	3.5
27	4	16:22	16:30	8	30	3

28	4	19:06	19:07	1	22	4
29	4	21:14	21:15	1	22	4
30	4	13:27	14:04	37	22	4
31	4	11:17	11:18	1	22	3
32	4	11:55	12:00	5	24	4
33	4	17:28	17:31	3	30	4
34	4	16:35	16:42	7	30	3
35	4	16:00	16:02	2	28	3
36	4	17:30	17:33	3	22	3.3
37	4	13:27	13:29	2	28	3.8
38	4	11:58	12:00	2	26	3
39	4	16:28	16:40	12	26	3
40	4	21:39	21:50	11	28	4
41	4	22:02	22:02	0	28	3
42	4	16:00	16:23	23	28	3.3
43	4	16:00	16:02	2	28	4
44	4	0:02	0:03	1	30	3
45	4	11:34	11:43	9	24	4
46	4	2:22	2:30	8	30	3
47	4	15:52	15:57	5	28	3
48	4	13:14	13:28	14	26	4
49	4	16:40	16:42	2	28	3
50	4	20:38	20:50	12	28	3
51	4	18:13	18:30	17	30	3
52	4	15:25	15:36	11	28	3
53	4	13:21	13:23	2	24	3
54	4	22:22	22:22	0	24	4
55	4	11:48	11:56	8	30	4
56	4	16:38	16:41	3	30	4
57	4	0:23	0:24	1	28	3
58	4	6:25	6:28	3	26	3
59	4	12:45	12:47	2	30	4
60	4	22:26	22:33	7	22	4
61	4	16:00	16:02	2	28	3.3
62	4	20:42	21:01	19	26	3
63	4	16:58	17:00	2	30	2.5
64	4	21:33	21:47	14	28	3
65	4	22:29	22:35	6	22	3
66	4	15:49	15:59	10	28	2.8
67	4	22:25	22:28	3	26	3
68	4	17:36	17:40	4	28	4
69	4	9:00	9:01	1	28	4
70	4	23:21	23:27	6	28	2
71	4	20:39	20:41	2	28	3
72	4	18:29	18:38	9	30	4

73	4	23:19	23:21	2	26	2.5
74	4	3:07	3:11	4	30	3.5
75	4	21:09	21:27	18	30	2.5
76	4	16:21	16:33	12	26	3
77	4	22:26	22:35	9	28	3
78	4	22:19	22:21	2	20	2
79	4	13:30	13:45	15	26	3
80	4	18:09	18:32	23	28	3
81	4	16:02	16:10	8	16	2
82	4	22:38	22:56	18	26	3
83	4	13:47	14:00	13	24	3
84	4	20:14	20:19	5	30	3
85	4	14:38	14:40	2	24	4
86	4	20:38	20:58	20	26	3
87	4	16:34	16:38	4	22	3.3
88	4	16:36	16:39	3	30	4
89	2	21:26	21:27	1	30	3.3
90	2	8:27	8:29	2	30	4
91	2	11:13	11:17	4	26	3
92	2	16:39	17:30	51	28	4
93	2	22:33	23:25	52	24	4
94	2	19:48	19:52	4	26	4
95	2	19:57	20:05	8	24	3
96	2	16:18	16:20	2	16	3.3
97	2	20:59	21:13	14	30	4
98	2	16:53	17:07	14	30	3
99	2	16:04	16:39	35	30	3
100	2	6:14	6:19	5	22	4
101	2	16:01	16:05	4	26	4
102	2	11:09	11:18	9	24	4
103	1	20:24	20:40	16	30	4
104	1	12:05	12:12	7	30	3.8
105	1	15:14	16:01	47	30	4
106	1	6:39	6:50	11	26	3.5
107	1	18:16	19:01	45	22	2.8
108	1	0:35	1:01	26	26	4
109	1	19:55	19:56	1	28	3
110	1	16:04	16:13	9	24	3
111	1	16:01	16:07	6	30	4
112	1	18:02	18:28	26	26	4
113	1	12:11	12:17	6	30	4
114	1	10:50	10:54	4	30	4
115	1	10:38	11:04	26	26	4
116	1	10:45	11:00	15	30	2.8
117	1	10:26	10:32	6	20	3

118	1	16:01	16:03	2	30	3.3
119	1	10:37	10:39	2	30	3
120	1	22:35	22:38	3	16	3
121	1	16:05	16:10	5	12	3
122	1	16:48	16:50	2	22	4
123	1	16:00	16:04	4	30	3
124	1	22:12	22:20	8	24	2
125	1	17:48	17:51	3	26	4
126	1	18:12	18:12	0	26	3.5
127	1	8:36	8:37	1	30	4
128	1	0:46	0:47	1	30	3
129	1	12:13	12:36	23	28	3
130	1	17:11	17:17	6	18	3
131	1	12:38	12:40	2	28	3
132	1	15:37	15:46	9	26	3.5
133	1	18:09	18:12	3	22	4
134	1	16:57	16:58	1	26	3
135	1	0:11	0:27	16	28	4
136	1	17:09	17:11	2	22	3
137	1	9:10	9:18	8	26	3
138	1	22:54	22:56	2	18	3
139	1	23:18	23:29	11	28	4
140	1	13:18	13:28	10	30	3
141	1	15:17	15:22	5	28	3
142	1	16:59	17:05	6	30	4
143	1	13:11	13:23	12	30	4
144	1	18:03	18:15	12	26	4
145	1	16:18	16:30	12	26	4
146	1	16:30	16:47	17	28	3
147	1	16:31	16:41	10	20	3
148	1	21:35	22:17	42	26	2
149	1	17:51	17:56	5	26	3
150	1	19:00	19:15	15	24	4
151	1	21:59	22:19	20	24	4
152	1	16:38	16:40	2	20	4
153	1	21:19	21:30	11	28	2
154	1	18:56	19:01	5	28	3
155	1	15:52	16:01	9	30	3
156	1	19:53	19:55	2	20	3
157	1	18:20	18:22	2	28	3
158	1	18:36	20:36	120	28	3
159	1	23:04	23:17	13	26	3
160	1	10:50	11:03	13	24	2.8
161	1	22:21	23:02	41	28	3
162	1	21:25	21:37	12	30	4

163	1	10:33	10:37	4	20	4
164	1	21:37	21:43	6	18	4
165	1	17:31	18:05	34	28	3
166	1	17:56	18:46	50	22	3
167	1	16:06	16:07	1	28	3.3
168	1	22:31	22:35	4	30	3
169	1	16:42	16:59	17	20	4
170	1	14:05	15:49	104	26	3.3
171	4	16:03	16:07	4	26	3
172	4	9:54	10:06	12	30	3.5
173	4	18:05	18:11	6	28	3
174	4	19:01	19:03	2	26	4
175	4	21:38	22:09	31	24	3
176	4	14:55	15:10	15	30	3
177	4	16:36	16:44	8	24	3
178	4	16:29	16:42	13	30	4
179	4	9:21	9:22	1	30	4
180	4	3:06	3:44	38	30	4
181	4	16:20	16:21	1	28	4
182	4	13:58	13:59	1	30	3
183	4	18:16	18:21	5	30	3.5
184	4	21:06	21:51	45	28	3
185	4	14:42	14:44	2	30	4
186	4	22:52	22:54	2	30	3
187	4	19:18	19:20	2	30	3
188	4	22:41	22:45	4	26	2.5
189	4	16:02	16:05	3	28	4
190	4	21:01	21:21	20	30	3
191	4	22:32	22:34	2	28	3
192	4	21:57	22:05	8	30	3
193	4	16:00	16:04	4	28	4
194	4	12:08	12:17	9	30	4
195	4	16:03	16:27	24	28	3
196	4	14:02	14:03	1	30	4
197	4	11:46	12:17	31	30	3
198	4	16:02	16:07	5	28	3
199	4	18:14	18:21	7	30	3.5
200	4	16:04	16:08	4	28	3
201	4	16:12	16:36	24	24	4
202	4	16:00	16:03	3	26	3
203	4	20:43	20:48	5	30	3
204	4	16:44	16:54	10	28	3.3
205	4	16:04	16:26	22	30	3
206	4	16:32	16:35	3	28	3
207	4	19:45	20:01	16	26	4

208	2	16:13	16:16	3	30	4
209	2	15:43	16:09	26	28	3
210	2	12:50	12:53	3	30	3
211	2	14:58	15:06	8	30	4
212	2	16:03	16:10	7	30	3
213	1	14:47	15:39	52	30	3
214	1	15:28	15:41	13	30	3
215	1	21:43	21:45	2	30	3
216	1	12:33	12:40	7	30	3
217	1	12:01	12:10	9	28	4
218	1	14:21	14:23	2	28	2.3
219	1	20:55	21:20	25	26	3
220	1	16:29	16:29	0	30	4
221	1	16:00	16:06	6	22	2
222	1	11:47	11:49	2	30	2.8
223	1	17:00	17:07	7	24	3
224	1	16:16	16:32	16	28	3
225	1	12:51	12:52	1	24	4
226	1	17:56	18:07	11	28	3.3
227	1	16:27	16:31	4	24	4
228	1	16:24	16:44	20	26	3
229	1	13:39	13:44	5	26	3.5
230	1	12:52	13:06	14	30	3
231	1	21:04	21:13	9	24	3.5
232	1	13:52	13:54	2	28	3.8
233	1	16:56	16:58	2	26	4
234	1	17:13	17:14	1	26	4
235	1	16:06	16:07	1	30	4
236	1	22:26	22:33	7	30	3
237	1	16:05	16:08	3	30	4
238	1	7:15	7:19	4	30	4
239	1	9:53	9:57	4	26	3
240	1	17:52	18:02	10	28	3
241	1	22:24	22:27	3	24	4
242	1	16:02	16:02	0	30	3
243	1	19:44	19:46	2	22	3
244	1	16:16	16:19	3	26	4
245	1	16:06	16:20	14	24	3
246	1	20:01	20:03	2	24	3

dataset_AF_WT_RD2023_Q2_5_S

SN	Y	Start	Ending	WT	MCQ	L_Achiev
1	4	17:44	17:56	12	20	4
2	4	17:20	17:21	1	22	3.6
3	4	13:20	13:32	12	26	4

4	4	14:57	15:55	58	26	3.4
5	4	13:43	13:47	4	28	4
6	4	14:04	14:20	16	26	3
7	4	14:41	14:52	11	22	4
8	4	22:52	22:57	5	20	3.4
9	4	20:59	21:08	9	28	3
10	4	16:04	16:08	4	28	4
11	4	10:43	10:45	2	28	3
12	4	13:38	13:46	8	24	4
13	4	22:10	22:11	1	24	3
14	4	19:30	19:42	12	28	4
15	4	18:34	18:49	15	18	4
16	4	0:22	0:59	37	22	4
17	4	16:28	16:30	2	22	3.6
18	4	20:57	20:58	1	22	3
19	4	11:48	11:50	2	16	2
20	4	16:02	16:49	47	26	3
21	4	17:26	17:27	1	24	4
22	4	19:55	19:57	2	18	4
23	4	14:24	14:26	2	24	3
24	4	21:33	21:41	8	16	4
25	4	19:56	19:59	3	28	3.4
26	4	12:02	12:03	1	28	3.4
27	4	11:51	12:05	14	28	3.6
28	4	19:54	19:56	2	20	4
29	4	17:38	17:40	2	24	4
30	4	23:01	23:15	14	20	3.8
31	4	13:44	13:45	1	24	3
32	4	11:16	11:34	18	12	4
33	4	22:18	22:19	1	20	4
34	4	14:42	16:02	80	20	3
35	4	16:02	16:07	5	28	3
36	4	20:30	20:31	1	18	3.4
37	4	11:58	12:01	3	22	4
38	4	16:20	16:25	5	28	3
39	4	16:19	16:26	7	20	3
40	4	15:35	15:46	11	24	4
41	4	16:52	16:55	3	26	3
42	4	1:59	2:10	11	20	3
43	4	16:00	16:06	6	24	3
44	4	0:21	0:23	2	26	3
45	4	21:24	21:26	2	28	4
46	4	22:50	22:59	9	26	3
47	4	22:04	22:06	2	22	3
48	4	23:21	23:37	16	20	4

49	4	5:48	6:00	12	24	4
50	4	9:52	10:02	10	18	3
51	4	15:32	15:33	1	20	4
52	4	22:03	22:05	2	26	3
53	4	16:26	16:39	13	20	3.2
54	4	18:15	18:19	4	18	3
55	4	22:23	22:37	14	18	3
56	4	1:52	2:17	25	20	4
57	4	16:00	16:06	6	28	4
58	4	12:12	13:44	92	20	3
59	4	13:11	13:13	2	28	3
60	4	19:45	19:46	1	28	4
61	4	19:03	19:06	3	26	3
62	4	0:09	0:10	1	24	4
63	4	16:09	16:14	5	28	3.2
64	4	16:32	16:32	0	28	3
65	4	0:07	0:23	16	24	3
66	4	14:51	15:04	13	20	3
67	4	13:14	13:44	30	16	3
68	4	1:22	1:25	3	22	3
69	4	19:59	20:02	3	26	4
70	4	21:56	22:01	5	20	4
71	4	11:35	13:05	90	20	3.4
72	4	16:23	16:24	1	30	3
73	4	19:56	20:26	30	22	4
74	4	22:37	22:42	5	20	2.6
75	4	17:23	17:24	1	20	3.2
76	4	2:56	2:58	2	22	3.4
77	4	21:56	22:14	18	28	3
78	4	16:49	16:50	1	22	3
79	4	22:19	22:35	16	22	3
80	4	15:58	16:00	2	22	2
81	4	20:47	22:00	73	20	3
82	4	16:08	16:23	15	22	3
83	4	12:57	13:01	4	16	2.6
84	4	17:40	18:14	34	20	3
85	4	14:16	14:20	4	22	2.6
86	4	18:34	18:47	13	28	3
87	4	16:18	16:19	1	20	4
88	4	11:41	11:56	15	28	3
89	4	16:38	16:40	2	28	3.8
90	2	16:53	17:02	9	28	3
91	2	16:34	16:49	15	28	4
92	2	15:00	15:02	2	18	3
93	2	17:15	17:34	19	24	4

94	2	20:22	20:31	9	20	3
95	2	9:35	9:52	17	20	4
96	2	5:20	5:35	15	16	2.8
97	2	17:08	17:43	35	28	4
98	2	19:10	19:14	4	22	3.2
99	2	22:29	22:49	20	22	3
100	2	16:06	16:12	6	30	4
101	2	16:20	17:04	44	22	4
102	2	18:52	19:16	24	20	3
103	1	18:13	18:18	5	26	4
104	1	13:36	13:46	10	26	3
105	1	16:51	16:53	2	20	2.6
106	1	19:23	20:27	64	22	2
107	1	13:23	13:31	8	24	4
108	1	18:04	18:05	1	22	3
109	1	16:08	16:14	6	20	4
110	1	16:02	16:08	6	24	4
111	1	18:27	18:49	22	18	2.8
112	1	17:05	17:08	3	28	4
113	1	21:08	21:10	2	28	4
114	1	15:14	15:16	2	20	4
115	1	19:32	20:06	34	28	3
116	1	16:19	16:38	19	22	3
117	1	16:00	16:01	1	18	4
118	1	16:37	16:43	6	28	4
119	1	11:06	11:07	1	28	3
120	1	16:37	16:42	5	20	4
121	1	17:42	17:45	3	28	3.2
122	1	16:17	17:04	47	20	3.6
123	1	11:06	11:07	1	28	3.8
124	1	18:27	18:27	0	28	3.8
125	1	16:45	17:21	36	24	3
126	1	13:20	13:24	4	18	3
127	1	17:34	17:42	8	22	3
128	1	16:25	16:30	5	22	3.2
129	1	20:49	20:55	6	18	3.6
130	1	18:20	18:22	2	18	3.6
131	1	20:29	21:08	39	22	2.8
132	1	16:23	16:38	15	16	3
133	1	16:21	16:36	15	20	3
134	1	16:18	16:40	22	24	3
135	1	23:03	23:04	1	22	4
136	1	21:03	21:05	2	30	3
137	1	13:58	14:06	8	18	3
138	1	16:19	16:25	6	28	4

139	1	19:25	19:34	9	28	4
140	1	19:39	19:46	7	22	3.8
141	1	16:22	16:37	15	22	4
142	1	16:16	16:53	37	16	3.2
143	1	17:56	18:25	29	20	3
144	1	21:04	21:07	3	22	3
145	1	18:29	18:48	19	24	4
146	1	18:52	18:53	1	16	4
147	1	13:00	13:05	5	24	4
148	1	22:18	22:26	8	24	2
149	1	17:26	17:44	18	22	3
150	1	12:39	12:44	5	26	4
151	1	17:48	17:58	10	28	3
152	1	17:42	17:43	1	24	3.4
153	1	13:45	13:47	2	26	3
154	1	13:46	13:47	1	16	3
155	1	22:27	22:54	27	24	3.4
156	1	22:19	22:27	8	20	3
157	1	18:14	18:18	4	20	3
158	1	4:16	4:17	1	18	4
159	1	13:11	13:36	25	20	4
160	1	15:00	15:43	43	22	3
161	1	18:44	18:46	2	20	3
162	1	19:23	19:35	12	20	2
163	1	17:09	17:16	7	22	3
164	1	16:52	16:56	4	18	3
165	1	13:34	13:40	6	22	4
166	1	22:06	22:30	24	18	3.8
167	1	13:10	13:11	1	20	4
168	4	0:33	0:46	13	22	3
169	4	12:25	12:51	26	18	3.4
170	4	19:31	19:37	6	20	3
171	4	21:43	22:01	18	26	3
172	4	19:12	19:19	7	28	3
173	4	16:02	16:34	32	10	3
174	4	16:31	16:36	5	22	4
175	4	18:48	18:50	2	22	4
176	4	22:38	22:40	2	22	4
177	4	14:18	14:24	6	20	2.6
178	4	17:50	17:52	2	22	3
179	4	18:46	18:50	4	22	3.2
180	4	17:37	17:39	2	22	2
181	4	19:44	20:04	20	22	4
182	4	11:38	11:44	6	28	3
183	4	22:09	22:11	2	24	3

184	4	0:33	0:37	4	24	3
185	4	16:29	16:31	2	24	4
186	4	20:58	21:06	8	24	3
187	4	23:01	23:14	13	22	3
188	4	21:56	22:11	15	24	3.2
189	4	16:41	16:43	2	24	3
190	4	21:26	21:30	4	22	4
191	4	16:12	17:04	52	24	3
192	4	17:49	17:52	3	22	4
193	4	20:48	21:25	37	22	3
194	4	16:31	16:37	6	24	3
195	4	19:29	19:31	2	22	3.6
196	4	16:16	16:29	13	24	4
197	4	16:28	16:36	8	20	3
198	4	18:19	18:41	22	22	4
199	4	16:02	16:18	16	20	3
200	4	23:15	23:20	5	22	3
201	4	16:05	16:18	13	22	3
202	4	9:34	9:45	11	20	3
203	4	16:15	16:16	1	22	3
204	4	21:19	21:42	23	26	4
205	2	16:32	16:50	18	30	4
206	2	15:44	16:29	45	24	3
207	2	23:00	23:16	16	16	4
208	2	22:27	22:43	16	20	3
209	1	13:51	14:10	19	18	3.2
210	1	13:43	14:17	34	20	3
211	1	22:16	22:21	5	20	3
212	1	18:55	18:58	3	20	3
213	1	23:45	23:46	1	24	4
214	1	19:53	19:55	2	22	2
215	1	18:06	18:08	2	22	3
216	1	22:33	22:46	13	28	3
217	1	13:04	13:04	0	20	4
218	1	16:08	16:15	7	24	3
219	1	15:22	15:23	1	20	2.8
220	1	16:06	16:20	14	22	4
221	1	18:05	18:20	15	16	3
222	1	12:37	12:42	5	24	4
223	1	20:22	20:30	8	22	3
224	1	16:42	16:47	5	10	4
225	1	16:17	16:39	22	20	3
226	1	14:02	14:05	3	24	3.8
227	1	21:57	22:13	16	26	2.8
228	1	19:57	20:01	4	18	3.6

229	1	16:08	16:11	3	22	4
230	1	16:10	16:12	2	24	4
231	1	16:10	16:12	2	24	4
232	1	16:50	16:53	3	18	3
233	1	21:43	22:14	31	26	3
234	1	16:49	16:58	9	18	4
235	1	20:44	22:17	93	24	4
236	1	20:29	20:39	10	20	4
237	1	21:37	21:45	8	20	2.6
238	1	22:05	22:26	21	20	4
239	1	19:14	19:22	8	20	3
240	1	16:40	16:41	1	20	4
241	1	18:58	20:48	110	22	3
242	1	23:00	23:09	9	22	3

dataset_AF_WT_RD2023_Q2_6_O

SN	Y	Start	Ending	WT	MCQ	L_Achiev
1	4	21:09	21:15	6	16	4
2	4	13:28	13:30	2	18	3.3
3	4	12:53	13:33	40	20	4
4	4	19:15	19:51	36	28	4
5	4	17:04	17:13	9	18	4
6	4	17:05	17:20	15	12	3
7	4	11:29	12:06	37	18	4
8	4	0:43	0:48	5	18	2.7
9	4	20:00	20:07	7	14	2.7
10	4	18:46	18:51	5	18	4
11	4	18:55	18:57	2	16	3
12	4	15:12	15:22	10	18	3
13	4	16:34	16:53	19	16	4
14	4	14:22	16:08	106	20	4
15	4	21:00	21:21	21	16	3
16	4	17:46	17:47	1	18	4
17	4	20:47	20:55	8	18	3
18	4	11:46	12:17	31	18	3
19	4	18:08	18:10	2	22	3
20	4	16:10	16:23	13	18	4
21	4	19:47	19:51	4	10	3
22	4	13:32	13:34	2	18	4
23	4	14:47	14:47	0	20	4
24	4	18:17	18:34	17	16	3.7
25	4	17:59	18:01	2	14	3.3
26	4	17:42	17:49	7	16	4
27	4	20:29	20:32	3	18	4
28	4	15:40	15:43	3	18	4

29	4	21:49	22:12	23	18	4
30	4	12:13	12:15	2	18	3
31	4	12:00	12:08	8	10	4
32	4	22:31	22:34	3	22	4
33	4	14:20	14:22	2	18	3
34	4	14:43	15:41	58	22	3
35	4	1:09	1:10	1	16	3
36	4	22:18	22:18	0	14	2.7
37	4	13:23	13:27	4	20	4
38	4	23:27	23:29	2	12	3
39	4	11:46	11:56	10	14	3
40	4	22:23	22:32	9	18	4
41	4	17:28	17:31	3	12	3
42	4	23:34	23:39	5	20	4
43	4	10:45	10:48	3	14	3
44	4	19:48	19:49	1	22	3
45	4	10:50	10:51	1	16	4
46	4	19:10	19:20	10	22	3
47	4	18:35	18:43	8	12	3
48	4	11:17	11:32	15	22	3
49	4	14:31	14:48	17	14	3
50	4	14:13	14:20	7	18	3.3
51	4	14:06	14:09	3	20	3
52	4	22:25	22:51	26	16	3.7
53	4	22:43	22:45	2	20	4
54	4	15:50	15:53	3	14	4
55	4	14:21	14:25	4	22	4
56	4	15:40	16:16	36	26	3
57	4	12:21	12:27	6	16	3.3
58	4	21:32	21:34	2	22	4
59	4	19:11	20:16	65	16	4
60	4	23:08	23:10	2	14	3
61	4	17:04	17:07	3	16	3
62	4	14:50	14:51	1	18	3
63	4	22:40	22:46	6	12	3
64	4	20:13	20:26	13	16	3
65	4	14:46	14:57	11	22	3.3
66	4	17:16	17:23	7	16	4
67	4	21:57	22:17	20	22	4
68	4	10:10	10:24	14	16	2.3
69	4	20:53	20:55	2	22	3
70	4	22:41	23:11	30	18	4
71	4	13:59	14:04	5	14	3
72	4	15:30	15:31	1	20	3.3
73	4	22:39	22:57	18	18	3

74	4	17:06	17:07	1	18	3
75	4	22:29	22:40	11	18	3
76	4	20:23	20:28	5	12	2
77	4	1:27	1:29	2	22	3
78	4	21:54	21:58	4	22	3
79	4	16:47	16:51	4	14	3.3
80	4	16:26	16:28	2	18	3
81	4	22:17	22:36	19	14	3
82	4	12:15	12:21	6	14	4
83	4	16:58	16:59	1	10	3
84	4	12:16	12:19	3	14	4
85	2	19:15	19:16	1	18	3.3
86	2	22:00	22:24	24	18	4
87	2	13:59	14:02	3	20	3
88	2	17:20	17:36	16	20	4
89	2	9:05	9:07	2	18	3
90	2	17:03	17:18	15	20	3
91	2	21:58	22:00	2	10	3.3
92	2	17:59	18:26	27	16	3
93	2	17:46	18:07	21	22	3.7
94	2	20:05	20:24	19	16	3
95	2	17:02	17:31	29	16	4
96	2	18:44	18:49	5	14	4
97	2	17:09	17:25	16	8	4
98	2	17:07	17:36	29	14	3.7
99	1	18:53	19:03	10	18	4
100	1	14:48	15:37	49	22	4
101	1	13:38	13:51	13	16	2.7
102	1	17:14	18:11	57	18	2.3
103	1	15:09	15:25	16	16	4
104	1	21:26	21:28	2	18	3
105	1	14:49	14:56	7	10	4
106	1	14:46	15:00	14	20	4
107	1	21:32	21:34	2	20	4
108	1	13:09	13:16	7	24	4
109	1	21:54	22:03	9	18	4
110	1	14:31	14:38	7	20	4
111	1	22:17	22:20	3	16	2
112	1	17:11	17:13	2	16	3
113	1	18:53	18:59	6	18	4
114	1	10:57	11:05	8	22	4
115	1	14:00	14:39	39	16	3
116	1	11:04	11:08	4	16	4
117	1	19:34	19:35	1	16	3
118	1	17:49	18:08	19	14	3

119	1	20:14	20:28	14	12	4
120	1	10:43	10:45	2	24	3.3
121	1	0:14	0:16	2	14	3
122	1	19:40	19:42	2	14	3
123	1	13:28	13:30	2	16	3
124	1	21:03	21:10	7	22	3
125	1	17:18	17:20	2	22	3.3
126	1	16:06	16:11	5	14	3.7
127	1	21:44	21:52	8	18	3.7
128	1	22:52	22:56	4	16	4
129	1	22:05	22:10	5	22	3
130	1	14:18	15:08	50	16	3
131	1	14:54	15:10	16	24	3.7
132	1	14:11	15:23	72	18	3
133	1	14:52	15:14	22	22	3
134	1	16:39	17:50	71	24	3
135	1	16:25	16:31	6	10	4
136	1	23:23	23:33	10	16	4
137	1	15:37	15:41	4	20	3
138	1	10:30	10:45	15	18	4
139	1	13:58	14:06	8	16	4
140	1	18:10	18:12	2	16	4
141	1	9:14	9:25	11	22	3
142	1	0:40	0:44	4	18	3
143	1	14:26	15:11	45	18	2
144	1	23:15	23:22	7	18	3.3
145	1	17:57	18:08	11	24	3
146	1	19:22	19:48	26	20	4
147	1	13:17	13:21	4	20	4
148	1	16:19	16:26	7	18	3
149	1	17:20	17:32	12	22	3
150	1	15:34	15:58	24	14	4
151	1	18:56	19:44	48	14	3
152	1	14:24	14:47	23	18	3
153	1	11:03	11:19	16	16	3.7
154	1	12:08	12:10	2	22	3
155	1	0:10	0:42	32	16	3
156	1	23:03	23:20	17	14	3
157	1	0:27	0:48	21	12	3
158	1	15:05	15:21	16	16	3
159	1	10:53	11:01	8	16	4
160	1	17:13	17:23	10	16	3
161	1	22:51	22:54	3	20	4
162	1	20:53	21:34	41	20	3
163	1	19:41	20:21	40	24	3

164	1	17:05	17:33	28	22	3.7
165	1	22:41	22:43	2	18	3
166	1	10:54	11:07	13	14	4
167	1	22:18	22:21	3	18	4
168	1	17:03	17:10	7	10	3.7
169	4	23:12	23:19	7	16	3
170	4	13:11	13:58	47	16	3.3
171	4	14:57	15:00	3	14	4
172	4	11:37	11:55	18	16	3.3
173	4	16:09	17:00	51	12	3
174	4	22:23	23:06	43	20	3
175	4	13:47	14:09	22	20	4
176	4	22:17	22:19	2	16	4
177	4	19:22	19:25	3	16	4
178	4	15:16	15:31	15	20	4
179	4	17:00	17:17	17	20	4
180	4	21:34	21:35	1	20	3
181	4	1:30	1:37	7	12	3.3
182	4	17:08	17:22	14	18	3
183	4	21:53	21:59	6	16	4
184	4	10:21	10:24	3	22	3
185	4	20:20	20:35	15	12	3
186	4	22:52	22:54	2	24	4
187	4	17:23	17:27	4	20	4
188	4	22:11	22:19	8	16	3
189	4	12:51	13:01	10	18	3
190	4	13:01	13:16	15	26	3
191	4	11:02	11:04	2	22	3
192	4	15:11	15:19	8	20	4
193	4	18:14	18:17	3	20	3
194	4	18:26	18:39	13	18	4
195	4	15:00	15:23	23	20	3
196	4	19:01	19:09	8	20	3
197	4	10:27	10:33	6	18	3.3
198	4	17:24	17:25	1	20	4
199	4	17:02	17:13	11	20	3
200	4	22:59	23:07	8	14	3
201	4	19:57	19:59	2	14	3
202	4	17:23	17:49	26	20	3
203	4	22:12	22:18	6	20	3.7
204	4	10:27	10:36	9	18	4
205	2	17:01	17:02	1	20	4
206	2	19:25	20:02	37	18	3
207	2	6:47	7:02	15	14	4
208	2	17:35	17:52	17	20	3

209	1	22:49	22:58	9	20	3
210	1	12:35	12:37	2	20	3
211	1	0:23	0:24	1	20	3
212	1	22:13	22:40	27	20	3
213	1	11:16	11:19	3	22	4
214	1	17:34	17:39	5	18	4
215	1	21:14	21:23	9	24	3
216	1	22:32	22:53	21	22	3
217	1	22:30	22:31	1	16	4
218	1	10:14	10:27	13	20	3
219	1	15:04	15:08	4	20	3.7
220	1	17:23	17:37	14	24	3
221	1	10:25	10:28	3	18	3
222	1	12:41	12:45	4	12	3
223	1	21:45	21:46	1	22	3
224	1	21:06	21:17	11	16	4
225	1	22:58	22:59	1	20	3.3
226	1	21:03	21:12	9	18	3.3
227	1	1:08	1:18	10	26	4
228	1	19:48	19:50	2	24	4
229	1	17:01	17:04	3	24	4
230	1	17:00	17:01	1	20	3
231	1	22:48	22:51	3	24	3
232	1	17:43	17:50	7	22	4
233	1	22:18	22:35	17	12	4
234	1	18:43	18:53	10	14	4
235	1	2:09	2:17	8	20	3
236	1	9:41	9:52	11	26	3
237	1	18:33	18:35	2	22	4
238	1	18:10	18:23	13	22	3
239	1	11:18	12:47	89	18	3

dataset_AF_WT_RD2023_Q2_7_H

SN	Y	Start	Ending	WT	MCQ	L_Achiev
1	4	16:33	16:34	1	20	4
2	4	15:21	15:23	2	28	3
3	4	14:52	15:02	10	30	4
4	4	23:22	23:48	26	26	4
5	4	14:14	14:21	7	30	4
6	4	14:52	15:32	40	28	3
7	4	14:44	15:28	44	26	4
8	4	23:08	23:11	3	24	4
9	4	17:21	17:22	1	22	4
10	4	12:19	12:31	12	30	3
11	4	21:01	21:03	2	28	3

12	4	19:56	20:10	14	22	4
13	4	14:35	14:55	20	26	4
14	4	9:24	9:45	21	30	4
15	4	16:01	16:09	8	24	4
16	4	13:11	13:37	26	28	3
17	4	16:32	16:33	1	30	3
18	4	17:24	17:46	22	28	4
19	4	13:25	13:36	11	24	3.5
20	4	16:29	16:30	1	28	4
21	4	20:17	20:21	4	22	3.5
22	4	11:47	11:48	1	30	3
23	4	14:00	14:09	9	30	4
24	4	16:52	16:56	4	26	4
25	4	21:56	21:57	1	26	4
26	4	15:25	15:37	12	26	4
27	4	16:16	16:17	1	28	4
28	4	11:40	12:04	24	28	4
29	4	21:24	21:24	0	26	4
30	4	16:07	16:18	11	30	3
31	4	16:19	16:23	4	26	4
32	4	16:03	16:04	1	28	3
33	4	21:44	21:44	0	26	3.5
34	4	16:07	16:09	2	26	3
35	4	13:32	13:36	4	24	3
36	4	18:48	19:00	12	30	4
37	4	8:17	8:19	2	28	3
38	4	16:06	16:29	23	28	4
39	4	16:18	16:18	0	28	4
40	4	19:35	19:38	3	30	3
41	4	11:40	11:42	2	28	4
42	4	12:26	12:43	17	30	3
43	4	19:55	19:57	2	24	3
44	4	10:58	10:59	1	26	3
45	4	11:14	11:29	15	22	3
46	4	12:17	12:30	13	30	4
47	4	22:55	22:57	2	24	3
48	4	13:12	13:14	2	26	3
49	4	10:03	10:08	5	20	4
50	4	18:11	18:12	1	28	4
51	4	16:02	16:07	5	28	4
52	4	13:03	13:06	3	30	4
53	4	15:00	15:30	30	24	3
54	4	11:29	11:34	5	28	3
55	4	16:57	16:59	2	30	4
56	4	16:09	16:10	1	28	3

57	4	22:55	22:56	1	20	3
58	4	17:40	17:41	1	30	3
59	4	22:30	22:33	3	28	4
60	4	0:00	0:24	24	26	3
61	4	15:54	16:19	25	22	3
62	4	17:35	17:45	10	30	3
63	4	21:30	21:31	1	26	4
64	4	19:51	19:53	2	30	4
65	4	12:52	13:29	37	26	3
66	4	21:45	21:47	2	30	3
67	4	19:42	20:05	23	26	4
68	4	18:11	18:14	3	24	3
69	4	22:10	23:00	50	26	3
70	4	0:49	0:50	1	26	3
71	4	21:44	22:21	37	30	3
72	4	20:23	20:43	20	22	3
73	4	16:27	16:37	10	26	3
74	4	20:38	20:53	15	26	2
75	4	16:16	16:18	2	30	3
76	4	16:04	16:12	8	28	3
77	4	9:40	9:43	3	16	3
78	4	14:58	14:59	1	28	3
79	4	15:31	15:33	2	28	3
80	4	21:05	21:09	4	30	3
81	4	16:44	16:46	2	18	4
82	4	17:21	17:30	9	20	3
83	4	14:13	15:21	68	8	3.5
84	4	16:27	16:28	1	30	4
85	2	18:15	18:16	1	26	4
86	2	21:34	21:36	2	26	4
87	2	14:11	14:11	0	28	2.5
88	2	8:16	8:35	19	22	4
89	2	12:07	12:15	8	26	3
90	2	20:02	20:27	25	18	4
91	2	18:37	18:46	9	20	3
92	2	18:06	18:07	1	30	3
93	2	20:14	20:21	7	30	3
94	2	20:36	20:46	10	22	3
95	2	13:18	13:34	16	26	3
96	2	18:46	18:50	4	30	4
97	2	18:28	18:37	9	24	3
98	2	20:31	20:43	12	22	3
99	2	22:38	23:14	36	22	3
100	1	22:52	23:04	12	26	4
101	1	16:10	16:12	2	30	4

102	1	22:51	22:54	3	24	4
103	1	15:02	15:45	43	20	3
104	1	18:33	19:15	42	26	3
105	1	19:34	19:44	10	22	4
106	1	17:25	17:31	6	26	3
107	1	16:09	16:13	4	30	4
108	1	16:00	16:10	10	26	4
109	1	16:37	17:10	33	24	4
110	1	12:21	12:24	3	30	4
111	1	23:00	23:04	4	30	4
112	1	14:01	14:13	12	28	4
113	1	18:36	18:39	3	30	3
114	1	16:51	16:57	6	20	3
115	1	16:08	16:10	2	30	4
116	1	21:43	21:47	4	30	4
117	1	21:40	21:50	10	20	3
118	1	10:09	10:16	7	14	3
119	1	12:18	12:24	6	30	4
120	1	16:13	16:17	4	30	3
121	1	16:28	16:51	23	28	3
122	1	8:42	8:43	1	22	4
123	1	17:31	17:32	1	28	3.5
124	1	2:22	2:27	5	30	3.5
125	1	17:33	17:35	2	30	4
126	1	10:58	11:11	13	26	3
127	1	15:32	15:44	12	14	3
128	1	14:50	14:52	2	26	3.5
129	1	15:19	15:29	10	18	4
130	1	13:25	13:32	7	28	4
131	1	10:08	10:10	2	20	4
132	1	18:58	19:02	4	28	3
133	1	0:46	1:02	16	24	4
134	1	20:14	20:15	1	20	3
135	1	21:16	21:29	13	26	3
136	1	22:41	22:57	16	26	4
137	1	12:02	12:31	29	22	3
138	1	8:19	8:24	5	30	4
139	1	16:27	16:31	4	30	4
140	1	19:04	19:11	7	28	3.5
141	1	16:18	16:27	9	22	4
142	1	16:18	16:39	21	28	4
143	1	0:32	1:16	44	24	3
144	1	14:01	15:07	66	30	2
145	1	20:32	20:48	16	16	3
146	1	21:04	21:13	9	24	3

147	1	18:24	18:40	16	22	4
148	1	12:10	12:16	6	22	4
149	1	17:15	17:16	1	18	4
150	1	14:42	14:54	12	24	3
151	1	19:06	19:09	3	28	3
152	1	15:32	15:46	14	22	4
153	1	20:38	20:49	11	30	3
154	1	14:56	15:01	5	30	3
155	1	22:15	22:32	17	20	4
156	1	15:54	15:56	2	26	3
157	1	12:19	12:20	1	22	3
158	1	21:32	21:47	15	30	4
159	1	22:57	23:08	11	26	3
160	1	18:59	18:59	0	12	3
161	1	20:49	20:51	2	20	4
162	1	10:08	10:15	7	26	4
163	1	20:32	20:33	1	28	3
164	1	21:25	21:46	21	30	3
165	1	13:50	14:04	14	20	3
166	1	16:14	16:56	42	30	3.5
167	1	22:41	22:42	1	26	3
168	1	18:57	18:58	1	16	4
169	1	23:35	23:38	3	26	4
170	4	21:12	21:14	2	26	3
171	4	12:21	12:32	11	30	3.5
172	4	16:22	16:35	13	28	4
173	4	17:44	17:47	3	24	3
174	4	15:00	15:02	2	24	3
175	4	12:59	13:08	9	30	3
176	4	14:46	14:50	4	30	4
177	4	10:26	10:30	4	30	4
178	4	18:07	18:09	2	26	4
179	4	20:21	20:27	6	20	4
180	4	16:02	16:06	4	28	4
181	4	20:02	20:03	1	26	3
182	4	20:41	20:45	4	26	3.5
183	4	15:16	15:21	5	24	4
184	4	22:05	22:06	1	26	4
185	4	0:09	0:12	3	30	3
186	4	15:05	15:09	4	24	3
187	4	20:02	20:04	2	28	4
188	4	18:24	18:43	19	28	4
189	4	10:44	10:45	1	26	3
190	4	12:30	12:43	13	26	3
191	4	21:08	21:11	3	30	3

192	4	17:19	17:21	2	24	4
193	4	17:53	18:11	18	28	4
194	4	10:51	10:54	3	28	3
195	4	20:49	20:50	1	30	4
196	4	17:58	18:13	15	28	3
197	4	18:23	18:26	3	26	3
198	4	19:06	19:08	2	28	3.5
199	4	18:07	18:27	20	26	4
200	4	16:42	16:56	14	26	3
201	4	16:50	17:01	11	16	4
202	4	16:03	16:06	3	24	3
203	4	17:19	17:24	5	24	3
204	4	17:09	17:12	3	22	3
205	4	21:12	21:18	6	26	3
206	4	21:02	21:04	2	22	4
207	2	11:59	12:03	4	30	4
208	2	15:01	15:47	46	28	3
209	2	19:39	19:43	4	24	4
210	2	14:17	14:57	40	16	3
211	1	15:49	15:55	6	30	3
212	1	14:54	15:45	51	30	3
213	1	21:43	21:47	4	26	3
214	1	13:02	13:08	6	28	4
215	1	10:53	10:55	2	26	4
216	1	19:34	19:42	8	26	2
217	1	21:22	21:27	5	20	3
218	1	11:14	11:27	13	30	3
219	1	11:33	11:37	4	30	4
220	1	16:09	16:14	5	28	3
221	1	16:21	16:23	2	30	3
222	1	17:52	18:05	13	24	3
223	1	16:06	16:10	4	24	3
224	1	2:05	2:07	2	28	4
225	1	15:16	15:30	14	22	3
226	1	16:30	16:44	14	20	3
227	1	23:17	23:22	5	26	3.5
228	1	10:56	11:11	15	24	3
229	1	20:47	20:51	4	26	3
230	1	10:52	10:55	3	24	4
231	1	10:47	10:54	7	24	4
232	1	16:24	16:32	8	26	4
233	1	16:11	16:12	1	30	3
234	1	21:55	22:52	57	28	3
235	1	16:02	16:25	23	30	3
236	1	20:00	21:14	74	26	4

237	1	14:04	14:18	14	24	3
238	1	21:33	21:56	23	20	4
239	1	18:40	18:44	4	22	3
240	1	11:46	11:47	1	24	3
241	1	17:09	17:10	1	24	4
242	1	12:35	12:38	3	26	3

dataset_AF_WT_RD2023_Q2_8_K

SN	Y	Start	Ending	WT	MCQ	L_Achiev
1	4	12:05	12:10	5	30	4
2	4	22:09	22:10	1	30	3.3
3	4	19:15	19:28	13	30	4
4	4	22:18	22:19	1	26	4
5	4	14:06	14:07	1	22	4
6	4	15:15	15:16	1	26	4
7	4	10:11	10:12	1	14	4
8	4	0:41	0:42	1	28	4
9	4	11:11	11:16	5	22	3
10	4	14:55	14:56	1	22	4
11	4	16:37	16:38	1	26	3
12	4	11:12	11:16	4	20	3
13	4	19:38	20:22	44	30	4
14	4	18:13	18:19	6	16	4
15	4	22:27	22:32	5	18	3
16	4	11:06	11:07	1	16	4
17	4	17:11	17:16	5	18	3
18	4	16:24	16:45	21	22	3
19	4	21:51	21:51	0	30	4
20	4	13:44	13:44	0	30	4
21	4	20:45	20:45	0	30	3.7
22	4	20:21	20:28	7	20	3
23	4	11:52	12:06	14	22	4
24	4	17:05	17:07	2	20	4
25	4	21:21	21:21	0	26	3.3
26	4	18:20	18:34	14	22	3.7
27	4	23:10	23:10	0	22	4
28	4	20:40	20:41	1	22	3.7
29	4	10:33	10:34	1	28	3
30	4	2:21	2:22	1	24	3.3
31	4	14:30	14:36	6	22	4
32	4	10:20	10:21	1	24	3
33	4	13:45	13:47	2	22	3
34	4	21:40	21:44	4	28	4
35	4	8:46	8:48	2	18	3

36	4	18:35	18:51	16	18	4
37	4	10:32	10:33	1	30	4
38	4	0:52	0:53	1	30	4
39	4	10:23	10:24	1	24	4
40	4	22:40	22:50	10	30	3
41	4	8:03	8:03	0	28	3
42	4	18:40	18:45	5	18	3
43	4	19:08	19:17	9	24	3
44	4	14:21	14:23	2	16	3.7
45	4	15:45	15:45	0	18	3
46	4	1:59	1:59	0	18	3
47	4	21:22	21:56	34	22	4
48	4	22:08	22:08	0	26	4
49	4	10:03	10:03	0	28	4
50	4	21:11	21:13	2	26	4
51	4	9:36	10:27	51	20	3
52	4	20:59	21:00	1	22	2.7
53	4	17:20	17:21	1	30	4
54	4	12:37	12:38	1	24	3
55	4	17:09	17:10	1	22	4
56	4	19:21	19:22	1	28	3.3
57	4	16:53	17:22	29	24	3
58	4	16:08	16:12	4	28	3
59	4	16:09	16:09	0	22	4
60	4	22:22	22:35	13	30	3
61	4	17:17	17:32	15	28	3
62	4	14:58	15:04	6	28	4
63	4	10:52	10:53	1	28	4
64	4	13:45	14:09	24	22	3
65	4	22:22	22:23	1	20	3
66	4	22:18	22:19	1	24	2.3
67	4	21:42	21:49	7	28	3
68	4	21:58	21:59	1	30	3.3
69	4	22:54	22:58	4	26	3
70	4	22:45	22:53	8	20	3
71	4	21:58	22:11	13	22	3
72	4	14:55	14:57	2	12	2
73	4	8:23	8:25	2	30	4
74	4	10:00	10:01	1	12	2.3
75	4	15:45	16:22	37	24	3
76	4	12:56	12:57	1	24	3.3
77	4	22:49	22:51	2	28	3.7
78	4	11:46	11:48	2	12	4
79	4	16:49	17:06	17	20	3
80	4	21:57	21:58	1	18	3.3

81	4	21:34	21:36	2	24	4
82	2	18:22	18:23	1	30	3.7
83	2	17:56	17:57	1	30	4
84	2	14:43	14:44	1	24	3
85	2	19:59	20:37	38	28	4
86	2	20:05	20:14	9	26	3
87	2	15:45	15:54	9	26	4
88	2	7:53	7:55	2	18	3.7
89	2	14:53	15:06	13	24	3
90	2	16:18	17:24	66	22	3
91	2	20:41	21:29	48	22	3
92	2	20:15	20:39	24	28	4
93	2	22:18	22:24	6	28	4
94	2	10:40	10:44	4	30	3
95	1	14:42	14:43	1	18	4
96	1	12:23	12:43	20	30	4
97	1	13:01	13:07	6	14	2.7
98	1	2:54	2:57	3	24	3
99	1	22:20	22:22	2	26	4
100	1	13:55	13:55	0	26	3
101	1	21:20	21:24	4	24	4
102	1	7:27	7:28	1	22	4
103	1	21:23	21:26	3	22	4
104	1	15:17	15:18	1	30	4
105	1	0:17	0:18	1	30	4
106	1	14:11	14:41	30	24	4
107	1	15:58	16:04	6	26	2.3
108	1	21:04	21:10	6	14	3
109	1	0:37	0:40	3	20	4
110	1	10:42	10:43	1	30	4
111	1	22:47	22:47	0	12	3
112	1	22:01	22:02	1	12	3
113	1	18:36	18:40	4	20	4
114	1	11:17	11:18	1	30	3.3
115	1	12:42	12:55	13	22	4
116	1	11:09	11:10	1	20	2.7
117	1	17:05	17:06	1	22	3.3
118	1	22:06	22:08	2	30	4
119	1	14:18	14:19	1	24	3
120	1	16:16	16:24	8	26	3
121	1	17:27	17:28	1	24	3
122	1	16:42	16:52	10	14	3.7
123	1	16:06	16:16	10	24	4
124	1	21:57	21:57	0	22	4
125	1	21:33	21:33	0	28	2.7

126	1	15:10	15:11	1	22	3
127	1	20:11	20:23	12	14	4
128	1	11:35	12:00	25	20	3
129	1	11:14	11:17	3	24	3
130	1	21:22	21:26	4	12	4
131	1	22:22	22:23	1	26	4
132	1	20:16	20:19	3	28	3
133	1	13:56	14:02	6	18	3
134	1	23:02	23:06	4	18	4
135	1	20:06	20:12	6	28	4
136	1	22:02	22:03	1	30	3.7
137	1	10:29	10:34	5	30	4
138	1	10:37	10:38	1	24	3
139	1	10:06	10:10	4	22	3
140	1	20:19	20:29	10	20	2
141	1	21:02	21:03	1	16	3.3
142	1	14:48	14:55	7	18	3
143	1	12:45	12:49	4	26	4
144	1	11:14	11:16	2	24	4
145	1	19:22	19:23	1	30	4
146	1	21:42	21:44	2	26	3
147	1	9:46	9:46	0	30	3
148	1	14:41	14:59	18	30	4
149	1	12:23	12:25	2	30	3
150	1	13:15	13:16	1	30	2
151	1	14:59	15:00	1	20	3.7
152	1	16:09	16:48	39	22	3
153	1	15:09	15:21	12	20	3
154	1	22:57	23:08	11	26	4
155	1	22:53	22:55	2	26	3
156	1	19:08	19:13	5	28	3
157	1	16:08	16:13	5	18	4
158	1	16:59	17:02	3	30	4
159	1	22:47	22:56	9	30	3
160	1	10:27	10:39	12	28	3
161	1	21:48	22:21	33	24	3
162	1	21:32	21:35	3	28	4
163	1	20:45	20:55	10	22	3
164	1	8:53	8:56	3	20	4
165	1	20:12	20:13	1	12	3.7
166	4	14:33	14:37	4	24	2.3
167	4	13:08	13:23	15	24	3
168	4	15:38	16:34	56	24	4
169	4	18:33	18:39	6	30	3
170	4	10:40	10:47	7	28	3

171	4	11:01	11:03	2	26	4
172	4	18:17	18:18	1	22	4
173	4	15:31	15:36	5	26	4
174	4	10:00	10:07	7	30	4
175	4	17:16	17:16	0	26	4
176	4	12:55	12:56	1	24	3
177	4	14:01	14:04	3	28	3.7
178	4	15:28	15:29	1	14	3
179	4	20:23	20:23	0	24	4
180	4	21:13	21:25	12	30	3
181	4	21:46	21:52	6	28	3
182	4	22:24	22:25	1	28	4
183	4	15:13	15:16	3	30	4
184	4	13:52	13:58	6	28	3
185	4	19:45	19:46	1	30	3
186	4	21:47	21:52	5	28	3
187	4	11:37	11:40	3	26	3
188	4	10:34	10:34	0	30	4
189	4	10:38	11:23	45	26	3
190	4	22:13	22:15	2	28	4
191	4	9:51	10:06	15	30	4
192	4	10:40	10:43	3	26	3
193	4	21:11	21:12	1	28	3.7
194	4	15:13	15:16	3	30	4
195	4	21:46	21:56	10	18	3
196	4	1:51	1:58	7	22	4
197	4	12:26	12:27	1	24	3
198	4	11:36	11:45	9	30	3
199	4	12:09	12:30	21	30	3
200	4	2:28	2:29	1	26	4
201	2	10:56	11:00	4	28	4
202	2	13:20	13:25	5	22	4
203	1	20:54	20:56	2	24	3
204	1	15:00	15:22	22	18	3
205	1	2:47	2:48	1	28	3
206	1	8:02	8:04	2	18	4
207	1	19:33	19:35	2	28	3
208	1	22:29	22:30	1	30	3
209	1	14:58	14:59	1	22	4
210	1	8:59	9:00	1	22	3
211	1	14:52	14:59	7	22	3.3
212	1	21:49	21:51	2	28	3
213	1	12:18	12:21	3	28	3
214	1	13:59	14:00	1	22	4
215	1	23:07	23:08	1	20	3

216	1	21:15	21:45	30	30	4
217	1	12:38	12:55	17	24	3
218	1	21:15	21:16	1	22	4
219	1	18:43	18:44	1	24	3.3
220	1	20:58	21:18	20	30	3
221	1	13:24	13:25	1	28	4
222	1	0:48	0:49	1	18	4
223	1	22:16	22:17	1	18	4
224	1	11:36	11:36	0	22	3
225	1	20:56	20:58	2	30	3
226	1	9:23	9:23	0	22	3
227	1	7:50	8:40	50	22	4
228	1	12:28	12:32	4	22	4
229	1	20:09	20:14	5	18	4
230	1	22:17	22:18	1	18	3
231	1	9:16	9:17	1	26	4
232	1	10:40	10:42	2	18	3
233	1	19:45	19:46	1	30	3