

A novel web-based application to identify multiple intelligence types of high school students and examining the impact of differentiated homework on academic performance

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Highlights

- A web-based platform integrates multiple intelligence assessment, student profiling, differentiated assignment, monitoring, and reporting.
- Mathematics assignments are differentiated according to students' dominant intelligence types while maintaining the same curricular topic.
- The study provides an applied model for integrating digital assessment with technology-supported differentiated learning.

Abstract

This study aimed to develop and implement a web-based system integrating multiple intelligence assessment, student profiling, differentiated mathematics assignments, monitoring, and reporting processes, and to examine changes in students' academic performance. The study was conducted in a science high school in Genç district of Bingöl province during the 2024-2025 academic year, focusing on the topic of "Statistical Research Process" within the scope of ninth-grade mathematics lessons. A quasi-experimental pre-test-post-test control group design was used with a total of 60 students, 30 in the experimental group and 30 in the control group. The dominant intelligence types of the students in the experimental group were determined by analyzing data obtained from the Multiple Intelligence Survey administered via the developed web-based platform, using an algorithm developed within the scope of the research. Subsequently, differentiated mathematics performance assignments were given to the students via the same system according to their determined dominant intelligence types, while the control group continued with their existing teaching and assessment practices. Academic performance scores obtained before and after the application were used to examine changes within and between the groups. Parametric and non-parametric statistical methods were selected according to the distribution characteristics of the data. The findings showed a descriptive increase in academic performance in the experimental group, but within-group variation was not statistically significant. While a decrease in academic performance was observed in the control group, a comparison of the change scores showed a statistically significant difference between the experimental and control groups. The study demonstrates an applied approach to integrating student assessment, intelligence profiling, differentiated assignment, monitoring, and reporting in a web-based learning environment and provides a foundation for further research on technology-assisted differentiated learning.

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Keywords: Multiple intelligence theory, differentiated learning, web-based education, academic performance, high school students

1. Introduction

The rapid development of information and communication technologies has transformed educational environments and created new opportunities for collecting, analyzing, and using student data in

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instructional decision-making. This transformation accelerates the digitalization of learning environments and necessitates the redesign of teaching processes in line with more flexible, data-driven, and individualized structures (Riina vd., 2022). Contemporary educational approaches increasingly emphasize learner-centered instruction, individual differences, continuous monitoring, and data-informed interventions (Darling-Hammond vd., 2020; Hattie, 2023; Ifenthaler vd., 2019; Williamson, 2021). However, the availability of digital technologies does not necessarily result in differentiated learning. In many school settings, assessment results, student information, learning activities, and monitoring processes remain fragmented across separate tools and procedures, making it difficult for teachers to interpret information about students' individual characteristics into differentiated instructional practices and systematically monitor their outcomes (Datnow & Park, 2014; Schildkamp, 2019). Web-based assessment and monitoring systems can provide an infrastructure for collecting student data and supporting feedback and monitoring processes (Çetin & Çetin, 2021; Saracosti vd., 2022). Nevertheless, a major challenge remains: how can information about students' individual characteristics be systematically transformed into differentiated instructional activities within a coherent digital process?

One framework for addressing individual differences in students' abilities is Gardner's Theory of Multiple Intelligences. Rather than viewing intelligence as a single general capability, the theory proposes that individuals may demonstrate different patterns of relative strengths across several intelligence domains. In educational settings, this perspective has been used to diversify learning activities and assessment practices by taking students' relative strengths into account (Armstrong, 2009). However, identifying students' intelligence profiles is only an initial step. The educational value of such information depends on whether identified characteristics can be interpreted into differentiated learning activities and systematically monitored. This issue is particularly relevant in technology-supported educational environments, where assessment, student profiling, instructional assignment, and monitoring can potentially be integrated within a single digital platform.

Previous studies have examined technology-supported learning environments, multiple-intelligence-based instructional practices, and student assessment, but these lines of research have generally been investigated separately. Limited attention has been given to integrated systems that identify students' dominant intelligence types through digital assessment, use these profiles to structure differentiated learning activities, deliver and monitor those activities through a web-based platform, and examine associated changes in academic performance. This gap is particularly relevant in school settings, where assessment, student profiling, assignment design, delivery, monitoring, and performance evaluation are often conducted through separate tools or manual procedures. The proposed study addresses this gap by developing and implementing a web-based platform that connects these processes within a single measurement–profiling–instruction–monitoring cycle. Within the system, students' dominant intelligence types are identified through the web-based administration of the Multiple Intelligence Survey, and mathematics assignments are differentiated according to these profiles and monitored through the platform.

Accordingly, the study addresses two interconnected dimensions. The first concerns the development of a web-based infrastructure that integrates assessment, student profiling, differentiated assignment, monitoring, and reporting. The second concerns the examination of changes in academic performance among students participating in the differentiated assignment process compared with a control group. By combining these dimensions, the study provides an applied example of how educational technologies can be used to connect student assessment with differentiated instructional planning and monitoring.

Main contribution of this study is to develop and implement a web-based system for identifying students' dominant intelligence types and providing mathematics assignments differentiated according to these areas, and to examine changes in academic performance between the experimental and control groups.

1.1. Theoretical Framework: Multiple Intelligences Theory

The theoretical foundation of the study is based on Gardner's Theory of Multiple Intelligences (Gardner, 1993). The theory challenges the view of intelligence as a single, unitary cognitive capacity and proposes that individuals may demonstrate different patterns of relative strengths across multiple domains. From an

educational perspective, the framework emphasizes recognizing these differences and diversifying learning activities accordingly. Armstrong (2009) similarly emphasizes the use of multiple-intelligence-informed activities to diversify classroom practices. In this study, the theory is used as a pedagogical framework for identifying students' relative intelligence profiles and differentiating the format of mathematics assignments according to these profiles. The measurement instrument used in the present study also includes existential intelligence as a ninth domain; this reflects the structure of the selected instrument rather than an attempt in this study to establish an expanded version of Gardner's original framework. The Multiple Intelligences framework is particularly relevant to mathematics education because mathematical learning involves different forms of reasoning, representation, visualization, communication, pattern recognition, and problem solving. Previous studies conducted in Türkiye have reported positive outcomes associated with Multiple Intelligences Theory-based approaches in mathematics education. Yıldırım and Tarım (2008) reported significant effects on mathematics achievement and retention, while Yıldırım et al. (2006) reported positive effects of a Multiple Intelligences Theory-supported cooperative learning approach on mathematics achievement. A meta-analysis by Kaplan et al. (2015) also examined the overall effects of Multiple Intelligences Theory-based instruction on mathematics achievement. These findings support the relevance of differentiated, multiple-intelligence-informed activities as a framework for investigating alternative forms of mathematics learning.

However, identifying students' relative intelligence profiles and using these profiles for instructional purposes are distinct processes. An assessment instrument can provide information about students' perceived or identified strengths, but the educational value of this information depends on how the results are interpreted into instructional decisions. The identified profiles are used as an input for differentiating mathematics assignments within a web-based environment. The system therefore connects assessment with instructional action by transforming students' intelligence profiles into differentiated assignment formats while maintaining the same curricular topic and learning focus. At the same time, Multiple Intelligences Theory should be interpreted cautiously in the context of the present study. Although the framework has been influential in educational practice, questions have been raised concerning its psychometric foundations and the empirical evidence for clearly separable intelligence domains. Therefore, this study does not aim to validate the theory or establish a new psychometric model. Rather, the theory is used as a pedagogical framework for organizing differentiated assignments after students' profiles have been assessed using the selected measurement instrument.

This distinction is important because the purpose of the study is to examine the implementation of an assessment-to-instruction process within a web-based environment, rather than to establish the psychometric validity of Multiple Intelligences Theory.

1.2. Research Gap and Contribution

Previous studies have examined multiple-intelligence-based instructional practices, technology-supported learning environments, and digital student assessment; however, these strands of research have largely been investigated separately. Limited attention has been given to integrated school-based systems that identify students' dominant intelligence types through digital assessment, interpret these profiles into differentiated instructional activities, and monitor the resulting process within the same web-based environment. In many educational settings, assessment, student profiling, assignment design, delivery, monitoring, and academic performance evaluation are still managed through separate tools or manual procedures. This fragmentation may limit the practical use of student-level information in instructional planning and follow-up.

The present study addresses this gap by developing and implementing a web-based platform that connects assessment, student profiling, differentiated assignment, monitoring, and reporting within a single workflow. The platform administers the Multiple Intelligence Survey digitally, identifies students' dominant intelligence types through a researcher-developed algorithm, associates these profiles with differentiated mathematics assignments, and records the subsequent assignment and evaluation processes. The study therefore contributes both a technological model for integrating assessment and instructional monitoring and an empirical examination of changes in academic performance between students participating in the differentiated assignment process and a control group. Rather than treating digital

assessment as an end in itself, the study demonstrates how assessment information can be transformed into a practical instructional action within a web-based educational environment.

1.3. Purpose of the Study

The purpose of this study is to develop and implement a web-based system that identifies students' dominant intelligence types and provides mathematics assignments differentiated according to these areas, and to examine changes in academic performance between the experimental and control groups. Specifically, the study aims to identify students' dominant intelligence types through a web-based assessment process, use these profiles to structure differentiated assignments for a selected ninth-grade mathematics topic, and examine academic performance changes before and after the implementation. The developed web-based system allows for the storage, safe access and interpretation of multidimensional educational data.

1.4. Research Problem

Is the novel web-based application efficient in order to measure of the dominant multiple intelligence types of the students? By using this application, do assignments differentiated to student's dominant intelligence type increase their academic performance?

1.5. Sub-Problems

1. Is there a statistically significant difference between the pretest and posttest academic performance scores of students in the experimental group who received mathematics assignments differentiated according to their dominant intelligence types?
2. Is there a statistically significant difference between the pretest and posttest academic performance scores of students in the control group?
3. Is there a statistically significant difference between the experimental and control groups in terms of their academic performance change scores from pretest to posttest?

2. Methodology

2.1. Research Design

This study employed a quasi-experimental pretest–posttest control group design to examine changes in students' academic performance following the implementation of mathematics assignments differentiated according to their dominant intelligence types. Quasi-experimental designs are appropriate for educational settings in which individual random assignment is not feasible (Creswell & Creswell, 2017). The pretest–posttest control group design enables changes in academic performance to be examined over the implementation period and compared across groups (Büyüköztürk, 2018). Two existing ninth-grade classes at the participating science high school were included in the study. Students were ordered according to their LGS (High School Entrance Examination) placement scores and assigned sequentially to the experimental and control groups. This procedure was used to establish groups with relatively comparable prior academic characteristics; however, it did not constitute random assignment. Therefore, the study was designed and interpreted as a quasi-experimental study, and the possibility of selection bias was considered when interpreting the findings. The experimental group participated in a web-based process in which students' dominant intelligence types were identified through the Multiple Intelligence Survey and mathematics assignments were differentiated according to these areas. The control group continued its regular instructional and assessment practices without the multiple-intelligence-based assignment process. Academic performance scores obtained before and after the implementation were used to examine within-group changes and differences in change scores between the two groups.

2.2. Data Collection Instruments

The primary data collection instrument was the Multiple Intelligence Survey developed by McClellan and Conti (2008). The instrument consists of 27 items organized into three sets of nine items. Each set represents the nine intelligence domains, and participants rank the items from 1 to 9 according to how closely each statement describes them, with 1 indicating the most representative item and 9 the least representative item.

The Turkish adaptation by Babacan and Dilci (2012) was used in the present study. Their adaptation study included 300 participants and reported confirmatory factor analysis results supporting the factor structure of the Turkish form. The reported internal consistency coefficients ranged from .73 to .86 across the intelligence domains. An alpha value of .7 indicates a reliable level (Altunışık vd., 2007). These findings were reported by Babacan and Dilci (2012) as evidence of acceptable validity and reliability of the Turkish form. Accordingly, the instrument was used in the present study to identify students' relative intelligence profiles rather than to establish a new psychometric model. The Turkish form consists of nine intelligence domains: linguistic/verbal, logical-mathematical, visual/spatial, bodily-kinesthetic, musical/rhythmic, interpersonal/social, intrapersonal, naturalistic, and existential intelligence. Participants completed the instrument through the web-based platform developed for the study. The system required a unique ranking from 1 to 9 within each section and generated a warning when an invalid or repeated ranking was entered. The responses were processed by the researcher-developed algorithm to identify the dominant intelligence area according to the scoring procedure described in Section 2.5. In addition to the Multiple Intelligence Survey, mathematics performance scores obtained from official school records were used as the academic performance measure. Scores recorded before the implementation constituted the pretest, whereas scores recorded after the implementation constituted the posttest.

2.3. Participants or Study Group

The study included 60 ninth-grade students enrolled in a science high school. The participants were equally distributed between the experimental group ($n = 30$) and the control group ($n = 30$). Each group included 18 female students (60%) and 12 male students (40%). The participants were enrolled in the two ninth-grade classes available at the school during the study period. Because the study was conducted within an existing school structure, individual random assignment was not feasible. To establish groups with relatively comparable prior academic characteristics, students were ordered according to their LGS placement scores and assigned sequentially to the two groups. This procedure does not constitute random assignment and may introduce selection bias; therefore, the findings should be interpreted within the limits of the quasi-experimental design. The sample size was determined by the number of students enrolled in the two available ninth-grade classes. No a priori power analysis was conducted. Consequently, the findings should be generalized cautiously beyond similar educational contexts. Ethical approval was obtained from the Firat University Social Sciences and Humanities Research Ethics Committee on November 8, 2024 (Approval No. 28739). Permission to conduct the study was also obtained through the Ministry of National Education Research Application and Evaluation System. The application was submitted on November 26, 2024 (Application No. MEB.TT.2024.007907.01), and approval was obtained before data collection.

2.4. Academic Performance Measure

Academic performance was the primary outcome measure of the quasi-experimental component of the study. Performance data for both groups were obtained from official school records with the necessary institutional permission. The measure consisted of a mathematics performance score assigned by the mathematics teacher in accordance with the assessment criteria established by the relevant mathematics department and/or assessment committee at the school. The score recorded before the implementation was treated as the pretest, and the corresponding score recorded after the implementation was treated as the posttest. These scores were part of the school's regular assessment process and were not determined according to students' dominant intelligence types or the differentiated assignments implemented in the experimental group. The same assessment framework was used for both groups, providing a common academic performance indicator. During the intervention, students in the experimental group completed mathematics assignments differentiated according to their identified dominant intelligence types. The assignments addressed the Statistical Research Process topic in the ninth-grade mathematics curriculum and were evaluated by the mathematics teacher using the assessment criteria applied at the school and aligned with relevant Ministry of National Education (MoNE) performance-assessment criteria. Assignment evaluation scores were recorded in the web-based system for monitoring purposes but were not used as the pretest or posttest outcome measure. Thus, assignment scores documented the

implementation process, whereas the teacher-assigned mathematics performance scores obtained from school records served as the outcome measures used in the statistical analyses.

2.5. Web-Based System

A web-based talent tracking platform was developed by the researcher to integrate the assessment, student profiling, differentiated assignment, monitoring, and reporting processes used in the study. The platform was specifically developed for the research and served as the digital environment for administering the Multiple Intelligence Survey, identifying students' dominant intelligence types, distributing differentiated mathematics assignments, and recording assignment-related information. Students completed the Multiple Intelligence Survey through the web-based interface, and their responses were stored in the system database and processed automatically by the researcher-developed algorithm described in Section 2.5.1. Following identification of the dominant intelligence types, the system associated students with the corresponding mathematics assignment types and recorded the assignment distribution. Assignment-related information could subsequently be monitored through the system's reporting interfaces. The platform included separate user roles for students, teachers, and administrators. Students accessed the assessment and assignment functions assigned to them, teachers could review student and assignment information, and administrators could manage relevant system records and users. The overall system flow and user-role structure are presented in Figures 4 and 5. The platform was developed using ASP.NET, Web API, JavaScript, CSS, Bootstrap, and SQL Server, with Microsoft Visual Studio used as the development environment. These technologies provided the infrastructure for the user interfaces, data management, application logic, authentication, and communication among system components. The system also included input validation mechanisms to reduce errors during the ranking-based survey; entries were restricted to values from 1 to 9, and duplicate rankings generated a warning.

2.5.1. Dominant Intelligence Identification Algorithm

The Multiple Intelligence Survey consists of three sections, with three items representing each intelligence domain across the three sections. Participants rank the nine items in each section from 1 to 9 according to how closely each statement represents them. The three ranking values corresponding to the same intelligence domain are then summed to obtain a domain score. Because a lower ranking indicates that an item is more representative of the participant, the intelligence domain with the lowest total score is identified as the dominant intelligence area. The researcher-developed algorithm performs this calculation automatically for each participant after the survey is completed. Table 1 illustrates the ranking structure and the calculation process for a sample participant.

Table 1. Example of dominant intelligence identification based on participant rankings

Item No	Items(A)	Order No	Item No	Items(B)	Order No	Item No	Items(C)	Order No
1	I have an active lifestyle.	6	10	I like playing games outdoors.	6	19	I enjoy working with tools.	7
2	Thinking exercises are beneficial..	3	11	Questions about the meaning of life are important to me.	3	20	I enjoy discussing questions about life.	8
3	I act as part of a group.	9	12	I learn best when I interact with others.	9	21	Extracurricular and club activities are fun.	5
4	Being fair is important to me.	4	13	I am interested in issues related to social justice.	4	22	I learn a subject best if I enjoy it.	9
5	Being systematic helps me succeed..	1	14	People who disrupt order easily annoy me.	1	23	Step-by-step instructions are very helpful to me.	1
6	I enjoy different genres of music.	2	15	I have always been interested in playing a musical instrument.	2	24	I can easily remember song lyrics.	2
7	I try to promote recycling where I live.	8	16	Animals play an important role in my life.	7	25	I find nature walks enjoyable.	3
8	I keep a diary.	5	17	I enjoy writing..	8	26	I am interested in foreign languages.	6
9	I enjoy doing three-dimensional jigsaw puzzles.	7	18	I can visualize objects using the images I have in my mind.	5	27	I can visualize the thoughts in my mind.	4

The algorithm compares the calculated domain scores and assigns the intelligence domain with the lowest total score as the student's dominant intelligence area. Figure 1 presents the logical structure of the algorithm, while Figure 2 illustrates its operational flow within the web-based system.

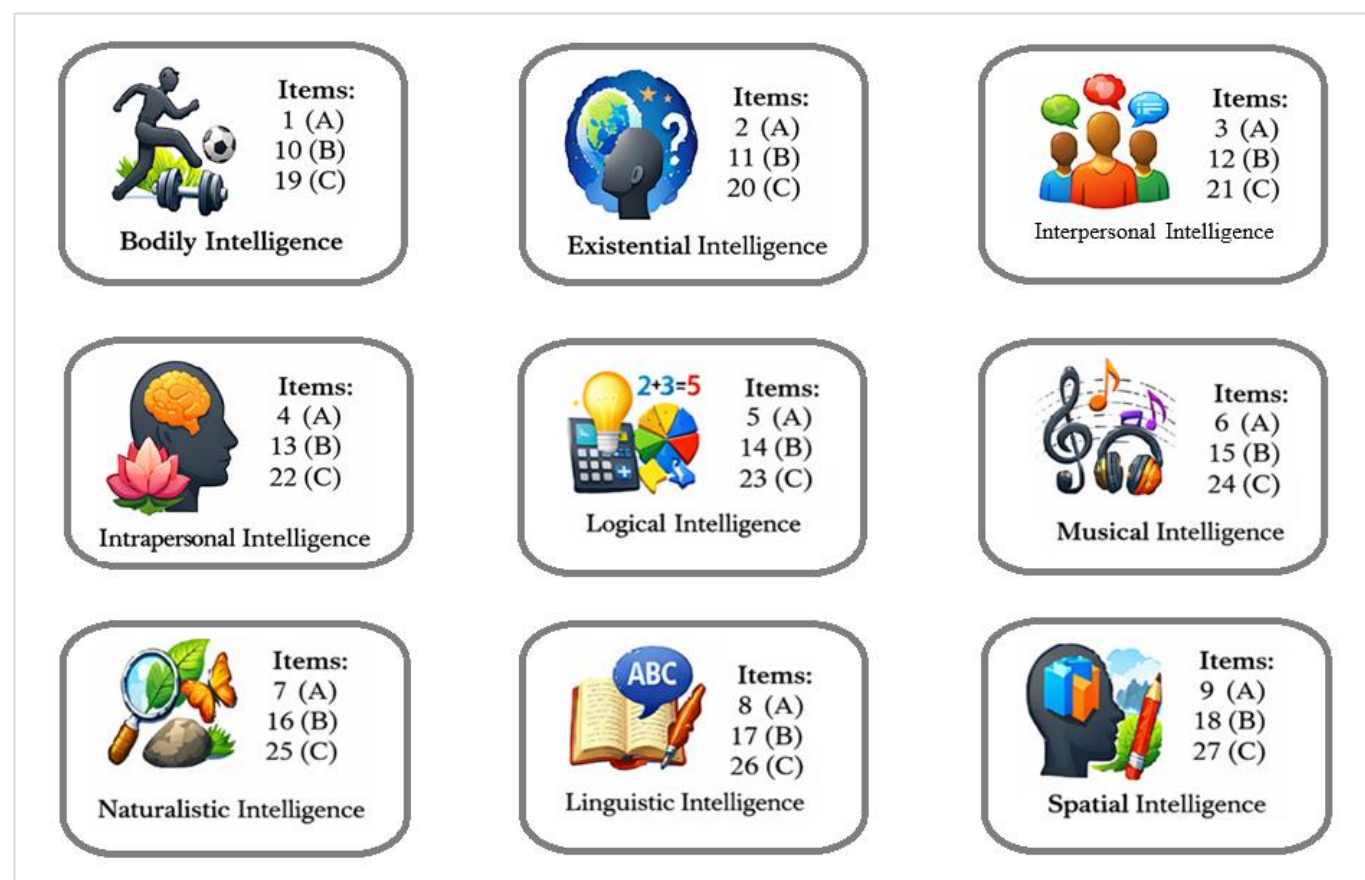
**Figure 1.**Algorithm for identifying dominant intelligence types

Figure 1 presents the logical structure of the algorithm used to process the ranking data and identify the dominant intelligence area. The algorithm automates the calculation that would otherwise require manual comparison of the ranking values across the three sections.

The overall operational flow of the algorithm within the web-based platform is presented in Figure 2. The flowchart illustrates the sequence from student input and ranking validation to the processing of the ranking values and identification of the dominant intelligence area.

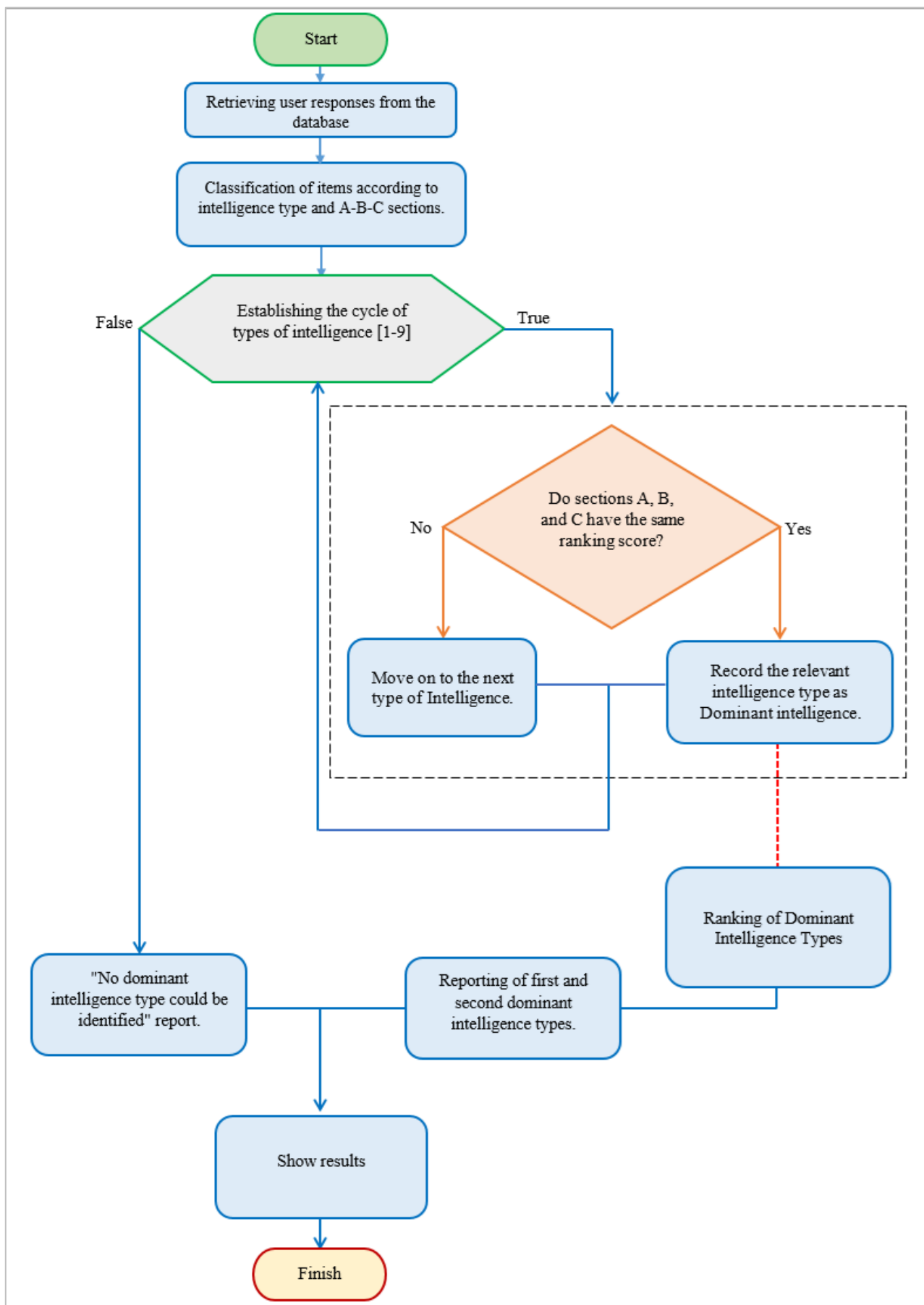


Figure 2. Flowchart of the dominant intelligence identification process

After the dominant intelligence area is identified, the resulting profile is transferred to the assignment-distribution component of the system. The corresponding mathematics assignment is then associated with the student according to the assignment structure described in Section 2.6.

2.5.2. Assignment Distribution and Reporting

Following the identification of students' dominant intelligence types, the web-based system associated each student with the corresponding mathematics assignment type. The assignment pool consisted of tasks designed for the same ninth-grade mathematics topic but differentiated according to the identified intelligence types. The assignment selection process was performed systematically through the platform, and the resulting assignment information was stored in the database. Figure 3 presents an example of the assignment distribution and reporting process, showing the relationship between the identified student profile and the corresponding assignment.

Sequence No.	Participant No	1. Dominant Intelligence Area	2. Dominant Intelligence Area	Subject	TERM PERFORMANCE ASSIGNMENT
1	Participant1	Introverted Intelligence		Statistical Research Process	Within the scope of the Statistical Research Process theme, students will prepare individual statistical research reports according to their area of interest.
2	Participant2	Logical Intelligence		Statistical Research Process	In the learning outcomes covered under the theme of Statistical Research Process, students prepare tables that perform statistical calculations and analyses on a dataset showing temperature changes over the given years.
3	Participant3	Bodily-Kinesthetic Intelligence		Statistical Research Process	In the learning outcomes covered under the theme of Statistical Research Process, students prepare a drama that simulates the statistical research process.
4	Participant4	Visual Intelligence	Bodily-Kinesthetic Intelligence	Statistical Research Process	In the topic of Statistical Research Process, the learning outcomes covered include preparing a poster and visual representation of the statistical research process using the scientific method.
5	Participant5	Musical Intelligence		Statistical Research Process	In the learning outcomes covered under the theme of Statistical Research Process, students will compose a song or rhythmic piece illustrating the steps of statistical research using the scientific method.
6	Participant6	Existential Intelligence	Social Intelligence	Statistical Research Process	In the learning outcomes covered under the theme of Statistical Research Process, the student will give a presentation discussing the societal contribution of statistical research.
7	Participant7		Musical Intelligence	Statistical Research Process	In the learning outcomes covered under the theme of Statistical Research Process, students will compose a song or rhythmic piece illustrating the steps of statistical research using the scientific method.
8	Participant8		Bodily-Kinesthetic Intelligence	Statistical Research Process	In the learning outcomes covered under the theme of Statistical Research Process, students prepare a drama that simulates the statistical research process.
9	Participant9		Existential Intelligence	Statistical Research Process	In the learning outcomes covered under the theme of Statistical Research Process, the student will give a presentation discussing the societal contribution of statistical research.
10	Participant10	Visual Intelligence	Verbal Intelligence	Statistical Research Process	In the topic of Statistical Research Process, the learning outcomes covered include preparing a poster and visual representation of the statistical research process using the scientific method.

Figure 3. Example of assignment distribution and reporting in the web-based system

The system also enabled teachers and administrators to access relevant student, assignment, and evaluation records through reporting interfaces. This functionality supported the documentation and monitoring of the assignment process throughout the implementation period. The overall system flow is presented in Figure 4, while the combined student, teacher, and administrator workflows are presented in Figure 5.

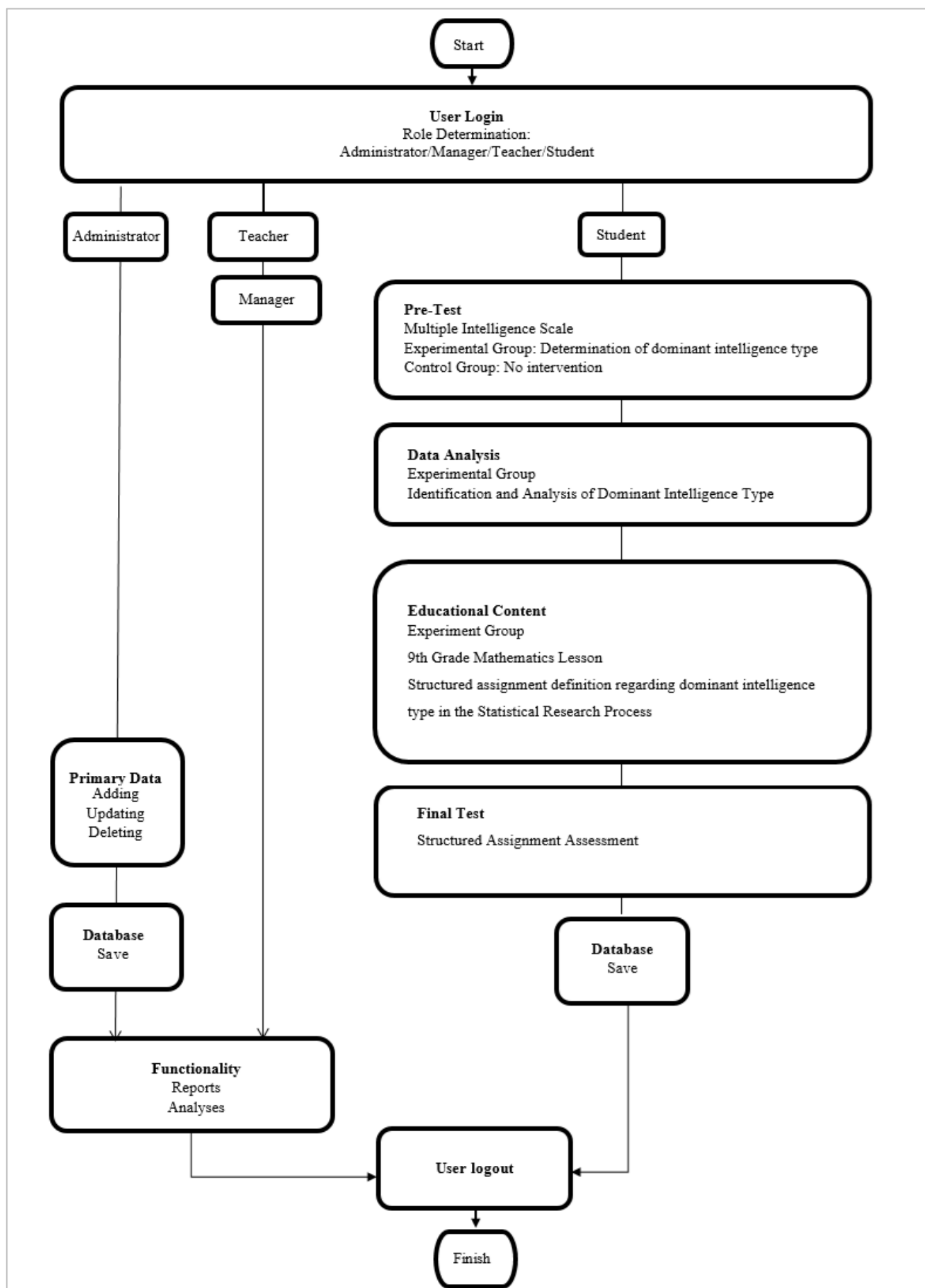


Figure 4. Flowchart of the Web-Based Talent Tracking System

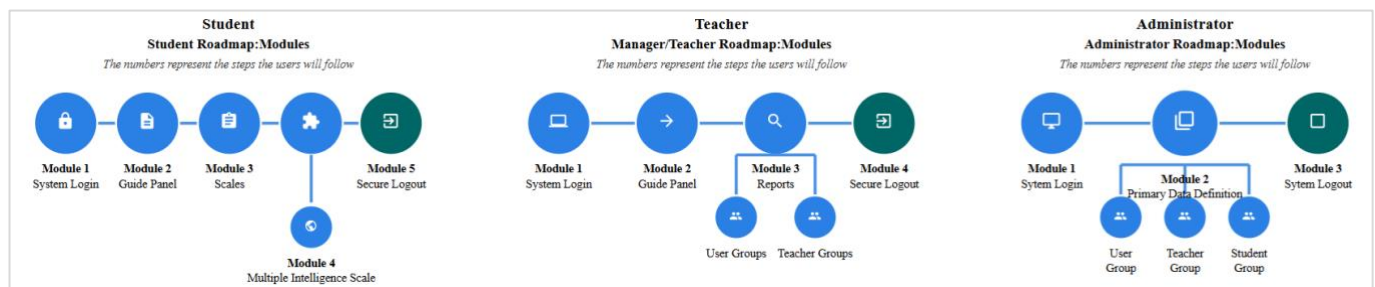


Figure 5. User Role Roadmaps of the Web-Based Talent Tracking System

The combined workflows illustrate the main interactions of the three user roles within the platform. Students access the assessment and assignment functions assigned to them, teachers can review student and assessment information, and administrators can manage relevant users and system records. These role-based interfaces support the operation of the assessment, student profiling, differentiated assignment, monitoring, and reporting processes within the web-based platform.

The main functional workflow of the platform consisted of student authentication, completion of the Multiple Intelligence Survey, automated processing of responses, identification of dominant intelligence types, assignment of mathematics tasks according to the identified profiles, recording and evaluation of assignments, and reporting of student- and assignment-related information.

2.6. Development of Multiple-Intelligence-Based Assignments

Following the identification of students' dominant intelligence types through the web-based Multiple Intelligence Survey, a set of mathematics assignments was developed for the experimental group. The assignment development focused on the ninth-grade mathematics topic "Statistical Research Process." The topic was selected because it allows the content to be addressed through different forms of reasoning, representation, visualization, communication, and practical activity. An assignment pool was prepared by an experienced mathematics teacher, with each task designed to correspond to a specific intelligence area. The aim was not to change the mathematical learning objectives of the topic, but to differentiate the form in which students engaged with and demonstrated their learning. After students' dominant intelligence types had been identified by the web-based system, the corresponding assignment type was associated with each student and recorded in the platform. For students identified with an intrapersonal intelligence profile, the task involved preparing an individual statistical research report based on a topic of personal interest. The assignment distribution among the 30 experimental-group students is presented in Table 2.

Table 2.

Distribution of Differentiated Performance Tasks According to Dominant Intelligence Types

Number of Participants	Dominant Intelligence Type	Topic	Performance Task	Presentation Format
6	Intrapersonal Intelligence	Statistical Research Process	Preparing an individual statistical research report based on the student's own area of interest	Written report
1	Logical Intelligence	Statistical Research Process	Preparing a table that performs statistical calculations and analyses on a dataset showing temperature changes across given years	Table/Graph
6	Bodily Intelligence	Statistical Research Process	Preparing a drama performance that represents the statistical research process	In-class group performance
4	Visual Intelligence	Statistical Research Process	Designing a visual poster that presents the statistical research process using the scientific method	Poster /digital slide
5	Musical Intelligence	Statistical Research Process	Presenting the stages of statistical research using a song or rhythmic composition based on the scientific method	Group performance or video presentation
8	Existential Intelligence	Statistical Research Process	Giving a presentation discussing the societal contributions of statistical research	In-class discussion

A total of 30 students participated in the differentiated assignment process. Although the assignment format varied according to the students' identified dominant intelligence types, all tasks addressed the same mathematics topic and curricular focus. Thus, the intervention differentiated the format and mode of engagement rather than the underlying mathematical content or learning objectives.

The assignments were evaluated by the mathematics teacher using the assessment criteria applied at the school and aligned with the relevant Ministry of National Education (MoNE) performance-assessment criteria. The evaluation criteria were integrated into the web-based platform so that assignment evaluation could be recorded and monitored digitally. An example of these criteria as integrated into the system is presented in Figure 6.

Participants	Group	Mathematics Class Performance Assignment Evaluation Criteria																																				
		"Making a suitable plan for the assignment and implementing that plan" gerekleştirme				Gathering information from different sources				The accuracy and originality of the information in the assignment.				Demonstrate critical thinking skills in homework.				Original thinking				The report does not adequately reflect the research. kadar bilgisi yer vermemiş				Support the report with sufficient material.				Writing the report clearly, spelling. ve dil bilgisi kurallarına uyuma				Submit the report on time.				TOTAL SCORE
		It needs improvement 1	Acceptable 2	Sufficient 3	Very good 4	It needs improvement 1	Acceptable 2	Sufficient 3	Very good 4	It needs improvement 1	Acceptable 2	Sufficient 3	Very good 4	It needs improvement 1	Acceptable 2	Sufficient 3	Very good 4	It needs improvement 1	Acceptable 2	Sufficient 3	Very good 4	It needs improvement 1	Acceptable 2	Sufficient 3	Very good 4	It needs improvement 1	Acceptable 2	Sufficient 3	Very good 4	It needs improvement 1	Acceptable 2	Sufficient 3	Very good 4	100				
PARTICIPANT1	EXPERIMENT																																	0				
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PARTICIPANT9	EXPERIMENT																																	0				
PARTICIPANT10	EXPERIMENT																																	0				
Evaluation System																																						
This scale has 9 criteria and 4 achievement levels. A student can receive a maximum of $9 \times 4 = 36$ points and a minimum of $9 \times 1 = 9$ points on this scale.																																						
The total score obtained from the scale is divided by the highest possible score the student can receive and multiplied by 100. For example, if a student receives a total of 27 points on this scale, the student's score is calculated as $(27/36) \times 100 = 75\%$. In this case, the student will receive 75 points.																																						

Figure 6. Example of MoNE Performance-Assessment Criteria Integrated into the Web-Based System

2.7. Implementation Procedure

The implementation was conducted during the spring semester of the 2024–2025 academic year in a ninth-grade mathematics course at the participating science high school. The intervention focused on the Statistical Research Process topic and lasted approximately two months, from early April to early June 2025. Before the intervention, mathematics performance scores for both groups were obtained from official school records with the necessary institutional permission and used as pretest scores. At the beginning of April 2025, students in the experimental group completed the Multiple Intelligence Survey through the web-based platform. Following completion, the responses were processed by the researcher-developed algorithm, and the intelligence area with the lowest total ranking score was identified as the student's dominant intelligence area. Students were then assigned mathematics tasks from the prepared assignment pool according to their identified dominant intelligence types. Although the assignment formats differed, all tasks addressed the same Statistical Research Process topic and curricular focus. The control group continued its regular instructional and assessment practices without receiving these differentiated assignments. During the implementation period, the experimental-group assignments were monitored through the web-based platform and evaluated by the mathematics teacher using the assessment criteria applied at the school and aligned with the relevant Ministry of National Education (MoNE) performance-assessment criteria. Assignment evaluation scores were recorded for monitoring and reporting purposes and were not used as the academic performance outcome measure. At the beginning of June 2025, mathematics performance scores for both groups were obtained again from official school records and used as posttest scores. The pretest and posttest scores were subsequently analyzed using SPSS Statistics to examine within-group changes and differences in change scores between the experimental and control groups.

2.8. Data Analysis

The data were analyzed using SPSS Statistics. Descriptive and inferential analyses were conducted to examine changes in mathematics performance between the pretest and posttest measurements. Before the inferential analyses, the distributional characteristics of the pretest and posttest scores were examined separately for the experimental and control groups using the Shapiro–Wilk test (Shapiro & Wilk, 1965) and skewness and kurtosis coefficients. These results were used to determine the appropriate procedure for within-group comparisons.

A paired-samples t-test was used for the experimental group because the distributional assumptions were considered satisfactory. For the control group, where the normality assumption was not satisfied, the Wilcoxon signed-rank test was used. The selection of parametric and non-parametric procedures was based on the distributional characteristics of the data (Büyüköztürk, 2018; Pallant, 2020). To compare the amount of change between the experimental and control groups, a change score was calculated for each participant as posttest minus pretest. The resulting change scores were compared using the Mann–Whitney U test (Field, 2024). The statistical significance level was set at $\alpha = .05$. Statistical results were interpreted in relation to both the direction and magnitude of the observed changes rather than statistical significance alone.

3. Results

3.1. Distribution of Dominant Intelligence Types

The distribution of the experimental-group students according to their identified dominant intelligence types is presented in Figure 7. Among the 30 students, existential intelligence was identified as the dominant area for 8 students, intrapersonal and bodily-kinesthetic intelligence for 6 students each, musical intelligence for 5 students, visual-spatial intelligence for 4 students, and logical-mathematical intelligence for 1 student.

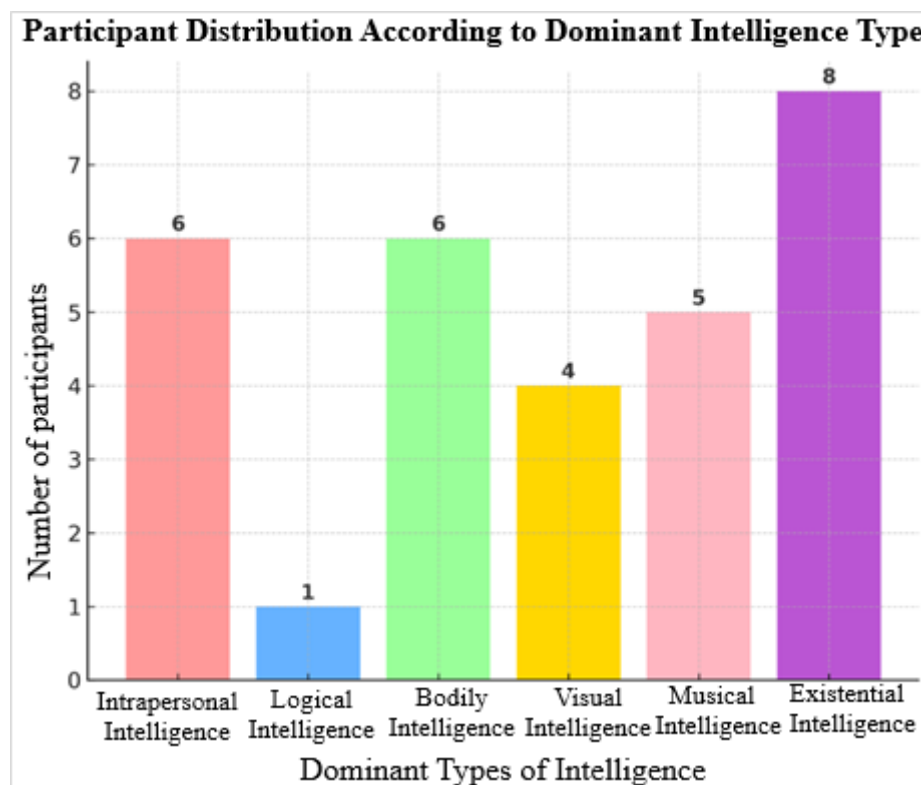


Figure 7. Distribution of Participants According to Dominant Intelligence Types

The distribution shows variation in the dominant intelligence types identified among the experimental-group students. These profiles were subsequently used by the web-based system to determine the corresponding differentiated mathematics assignment types.

3.2. Normality Analysis

The distributional characteristics of the before assignment(pretest) and after assignment(posttest) mathematics performance scores were examined separately for the experimental and control groups using the Shapiro–Wilk test and skewness and kurtosis coefficients. The results for the experimental group are presented in Tables 3 and 4.

Table 3.

Normality Indicators for the Experimental Group

		Statistics	Standart Error
Before assignment	Mean	87.00	1.90
	Std. Deviation	10.39	
	Skewness	-1.06	0.43
	Kurtosis	0.56	0.83
After assignment	Mean	88.67	2.05
	Std. Deviation	11.21	
	Skewness	-0.70	0.43
	Kurtosis	-0.34	0.83

The skewness values for the experimental group were -1.06 before assignment and -0.70 after assignment, while the corresponding kurtosis values were 0.56 and -0.34, respectively. These values show relatively similar distribution characteristics between the two measurements.

Table 4.

Shapiro–Wilk normality test results for the performance scores of the experimental group

Measurement	W	df	p
Before assignment	.94	30	.086
After assignment	.96	30	.214

The Shapiro–Wilk test was non-significant for both the pretest ($W = .94$, $p = .086$) and posttest ($W = .96$, $p = .214$). Taken together with the skewness and kurtosis results, these findings were considered consistent with the use of a parametric within-group comparison for the experimental group.

On the other hand, the distributional characteristics of the control group are presented in Tables 5 and 6.

Table 5.

Normality indicators for the performance scores of the control group

		Statistics	Standart Error
Before assignment	Mean	90.50	1.79
	Std. Deviation	9.82	
	Skewness	-1.93	0.43
	Kurtosis	6.02	0.83
After assignment	Mean	87.30	1.86
	Std. Deviation	10.18	
	Skewness	-1.97	0.43
	Kurtosis	5.38	0.83

The control group's skewness values were -1.93 for the before assignment-pretest and -1.97 for the after assignment-posttest, while the corresponding kurtosis values were 6.02 and 5.38, respectively. These values indicate greater departures from a normal distribution than those observed in the experimental group.

Table 6.

Shapiro–Wilk normality test results for the performance scores of the control group

Measurement	W	df	p
Before assignment	.81	30	$p < .001$
After assignment	.83	30	$p < .001$

The Shapiro–Wilk test was significant for both the pretest ($W = .81, p < .001$) and posttest ($W = .83, p < .001$), indicating substantial departures from normality. Accordingly, a non-parametric within-group comparison was used for the control group.

Based on these distributional characteristics, a paired-samples t-test was used for the experimental group, whereas the Wilcoxon signed-rank test was used for the control group.

3.3. Within-Group Academic Performance Results

3.3.1. Experimental Group

The experimental group's mean mathematics performance score increased from 87.00 at pretest to 88.67 at posttest. The paired-samples t-test results are presented in Table 7.

Table 7.

Paired-Samples t-Test Results for the Experimental Group

Group	Pretest (SD)	Posttest (SD)	Mean Difference	SD Difference	95% CI	t	df	p
Experimental	87.00 (10.39)	88.67 (11.21)	1.67	7.91	−4.62 to 1.29	1.15	29	.258

The mean difference was 1.67 because the paired difference was calculated as pretest minus posttest. The 95% confidence interval for the mean difference ranged from −4.62 to 1.29. The paired-samples t-test did not indicate a statistically significant difference between the pretest and posttest scores, $t(29) = 1.15, p = .258$. Thus, although the experimental group showed a descriptive increase in mean performance, the within-group change was not statistically significant.

3.3.2. Control Group

The control group's mean mathematics performance score decreased from 90.50 at pretest to 87.30 at posttest. The Wilcoxon signed-rank test results are presented in Table 8.

Table 8.

Wilcoxon Signed-Rank Test Results for the Control Group

Measurement	N	Z	p	r
Before assignment	30	-2.48	.013	.45
After assignment				

The Wilcoxon signed-rank test indicated a statistically significant within-group difference, $Z = -2.48, p = .013$, with an effect size of $r = .45$. The direction of the descriptive change indicates a decrease in the control group's mean mathematics performance score during the study period.

3.4. Between-Group Comparison of Change Scores

To examine whether the amount of academic performance change differed between the experimental and control groups, a change score was calculated for each participant as posttest minus pretest. The resulting change scores were compared using the Mann–Whitney U test. The results are presented in Table 9.

Table 9.

Mann–Whitney U Test Results for Change Scores Between the Experimental and Control Groups

Group	N	U	p	Z	r
Experimental Group	30	627.50	.007	-2.70	.35
Control Group	30				

The Mann–Whitney U test indicated a statistically significant difference between the experimental and control groups in terms of change scores, $U = 627.50, p = .007, Z = -2.70, r = .35$. Descriptively, the

experimental group showed an increase in mean performance, whereas the control group showed a decrease. Thus, the statistically significant between-group difference occurred in the context of different directions of change across the two groups.

4. Discussion

4.1. Academic Performance Findings

The academic performance results indicate different patterns of change in the experimental and control groups. The experimental group's mean performance score increased from pretest to posttest; however, the paired-samples t-test showed that this within-group change was not statistically significant. In contrast, the control group showed a decrease in mean performance, and the Wilcoxon signed-rank test indicated a statistically significant within-group change. The Mann–Whitney U test of individual change scores also indicated a statistically significant difference between the experimental and control groups. This result should be interpreted in the context of the descriptive increase in the experimental group and the decrease in the control group. Therefore, the findings indicate different patterns of change between the groups but do not provide sufficient evidence to conclude that the differentiated assignment process significantly improved academic performance within the experimental group. These findings differ from some previous studies that reported positive effects of Multiple Intelligences Theory-based instructional approaches on mathematics achievement. Yıldırım and Tarım (2008) reported positive effects on mathematics achievement and retention, while Yıldırım et al. (2006) reported positive effects of a Multiple Intelligences Theory-supported cooperative learning approach on mathematics achievement. Kaplan et al. (2015) likewise examined the effects of Multiple Intelligences Theory-based instruction on mathematics achievement. The difference between those findings and the present results may be related to differences in intervention design, duration, sample characteristics, instructional context, and outcome measures. Unlike the broader instructional approaches examined in some previous studies, the present study used students' identified intelligence profiles to differentiate the format of mathematics assignments within a web-based environment. The intervention also lasted approximately two months and focused on a single mathematics topic, while academic performance was assessed using teacher-assigned school performance scores. These contextual differences should be considered when interpreting the findings.

4.2. Contribution of the Web-Based System

A central contribution of the study is the integration of assessment, student profiling, differentiated assignment, monitoring, and reporting within a common web-based environment. The platform administered the Multiple Intelligence Survey, processed student responses through the researcher-developed algorithm, identified dominant intelligence types, and associated the resulting profiles with mathematics assignments. This structure connected assessment information with subsequent instructional action within a single workflow. The technological contribution should be distinguished from the academic performance findings. The present study does not demonstrate that the web-based platform itself significantly improved academic achievement. Rather, it demonstrates how a digital environment can be used to transform student assessment information into differentiated instructional activities and to record the subsequent assignment and evaluation processes. This applied structure is consistent with the broader emphasis on data-informed educational processes and learning analytics for educational decision-making (Ifenthaler et al., 2019; Schildkamp, 2019).

4.3. Theoretical and Educational Implications

The study also illustrates how Multiple Intelligences Theory can be operationalized within a technology-supported learning process. In the present study, the theory was used as a pedagogical framework for recognizing differences in students' relative strengths and differentiating the format of mathematics assignments rather than as a psychometric model to be validated. This use is consistent with the educational application of Multiple Intelligences Theory described by Armstrong (2009).

An important implication is that assessment information becomes more instructionally useful when it can be translated into a concrete educational action. In this study, students' assessed profiles were used to

determine the format of subsequent mathematics assignments. At the same time, the non-significant within-group change in the experimental group indicates that the implementation of differentiated assignments should not automatically be equated with improved academic achievement. The study therefore highlights the importance of evaluating both the functionality of a technology-supported instructional process and its educational outcomes.

4.4. Practical Implications for Educational Technology

From an educational technology perspective, the developed platform demonstrates how web-based systems can connect assessment, student profiling, differentiated assignment, monitoring, and reporting within a common workflow. Such integration may reduce fragmentation between assessment and instructional planning and provide teachers with a more systematic means of managing student-level information.

The platform may also be adapted to other subject areas and grade levels. However, such adaptations should consider the characteristics of the curriculum, the suitability of the assessment instrument, the design of differentiated tasks, and the methods used to evaluate academic outcomes. The present study therefore provides an applied model for technology-supported differentiated learning rather than a definitive model that can be generalized across educational contexts.

5. Limitations

Several limitations should be considered when interpreting the findings of this study.

First, the study was conducted in a single science high school with a relatively small sample of 60 ninth-grade students. The participants were drawn from the two ninth-grade classes available at the school. Therefore, the findings may not be directly generalizable to students from different school types, grade levels, or educational contexts.

Second, the study employed a quasi-experimental rather than a randomized experimental design. Students were ordered according to their LGS placement scores and assigned sequentially to the experimental and control groups. Although this procedure was intended to establish groups with relatively comparable prior academic characteristics, individual random assignment was not performed and the possibility of selection bias cannot be excluded. The findings should therefore be interpreted within the limits of the quasi-experimental design.

Third, the intervention lasted approximately two months, from early April to early June 2025, and focused on a single ninth-grade mathematics topic, "Statistical Research Process." The relatively short implementation period and the focus on a single topic limit the extent to which longer-term or broader effects of the differentiated assignment approach can be inferred.

Fourth, academic performance was measured using mathematics performance scores assigned through the school's regular assessment process rather than through a researcher-developed standardized achievement measure. Although the same assessment framework was used for both groups, teacher-assigned performance scores may be influenced by contextual and assessment-related factors. Future studies could therefore combine school-based performance scores with standardized achievement measures or other common outcome measures.

Fifth, the study used the Turkish adaptation of the Multiple Intelligence Survey to identify students' relative intelligence profiles. Although the adaptation study reported evidence of validity and reliability, no new psychometric validation of the instrument was conducted with the present sample. The findings should therefore not be interpreted as providing new evidence concerning the psychometric validity of the instrument or of Multiple Intelligences Theory.

Sixth, the dominant intelligence identification procedure was implemented computationally within the web-based platform using the researcher-developed algorithm. Although the algorithm operationalized the ranking-based scoring procedure used in the study, the resulting classification depends on the measurement

characteristics of the underlying instrument. Further research with larger samples could examine the robustness of this classification procedure using additional validation approaches.

6. Conclusion and Implications

This study developed and implemented a web-based system that integrates multiple intelligence assessment, student profiling, differentiated mathematics assignments, monitoring, and reporting within a single educational workflow. The system enabled students' intelligence profiles to be identified through a web-based assessment process and used the resulting profiles to organize differentiated mathematics assignments for a common curricular topic. The academic performance findings should be interpreted cautiously. The experimental group showed a descriptive increase in performance from pretest to posttest, but the within-group change was not statistically significant. The control group showed a decrease in performance, and the comparison of change scores indicated a statistically significant difference between the two groups. Thus, the findings indicate different patterns of change across the groups, but they do not provide sufficient evidence to conclude that the differentiated assignment process significantly improved academic performance within the experimental group. The primary contribution of the study is the integration of assessment, student profiling, differentiated assignment, and digital monitoring within a web-based environment. Rather than treating digital assessment as an end in itself, the developed platform connects assessment information to subsequent instructional action and provides a mechanism for recording and monitoring the resulting process. Such technology-supported approaches are consistent with the broader use of digital tools for supporting data-informed educational practices and technology-enhanced learning environments (Redecker, 2017). The study also demonstrates a practical way of using students' identified dominant intelligence types to vary the format of mathematics assignments while maintaining the same curricular topic and learning objectives. However, the findings should not be interpreted as evidence for the effectiveness of Multiple Intelligences Theory itself or as new psychometric evidence concerning the measurement instrument. From an educational technology perspective, the modular structure of the platform provides a basis for adapting the system to other subject areas, grade levels, and assessment processes. Such adaptations should be accompanied by further empirical evaluation using larger and more diverse samples, longer implementation periods, multiple curricular topics, and robust academic performance measures. The use of digital technologies to support differentiated and data-informed educational practices may provide opportunities for systematic monitoring and instructional planning (Holmes et al., 2019; Redecker, 2017). Future studies may also examine how assessment-based differentiation interacts with factors such as student engagement, assignment completion, and learning outcomes. Comparing different assignment formats and implementation contexts may further clarify the conditions under which technology-supported differentiated learning processes are associated with student achievement. Overall, the study provides an applied technological framework for connecting student assessment with differentiated instructional planning and digital monitoring. The findings support the feasibility of this integrated approach while indicating the need for further research before stronger claims can be made regarding its effects on academic achievement.

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