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MAPPING MULTIPLE INTELLIGENCES OF DISTANCE EDUCATION STUDENTS

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Abstract

This study maps the multiple intelligence profiles of distance education students at Universitas Terbuka Padang, Indonesia. A total of 105 students from the even semester of the 2024/2025 academic year participated, with data collected in January 2025 using the TIA (Talent and Interest Allocation) mobile application. Six intelligence dimensions were assessed: linguistic, logical-mathematical, kinesthetic, musical, interpersonal, and intrapersonal. The N-Soft Sets decision-making algorithm was applied for data analysis, with a threshold of $r \geq 3$ (rating of "often" or "always") and a conclusion that 75% of parameters in an intelligence group must meet the threshold for categorization. Results revealed that intrapersonal intelligence and interpersonal intelligence were the dominant dimensions, while musical intelligence scored lowest. The demographic profile showed that 87.6% of participants were female, 61.0% were from the Faculty of Teacher Training and Education, and 68.6% were enrolled in fully online programs without face-to-face tutorials. These findings provide empirical foundations for personalized talent allocation through the TIA application in distance higher education. The study contributes empirical evidence on student multiple intelligences distribution in distance education contexts, providing a foundation for personalized talent allocation and activity recommendation systems. Implications for mobile-based talent management applications in distance higher education are discussed.

Keywords: *multiple intelligences, distance education, TIA application, N-Soft Sets, talent allocation*

INTRODUCTION

The rapid expansion of distance higher education over the past two decades has created new opportunities for diverse student populations to access university-level learning regardless of geographic, temporal, or occupational constraints. In Indonesia, Universitas Terbuka (UT) has emerged as the primary institution delivering open and distance learning (ODL) at scale, enrolling millions of students across a vast archipelago through a combination of printed modules, online platforms, and mobile applications. The growth of this ecosystem has, however, outpaced the development of personalized learning support systems tailored to the unique profiles of distance learners.

In conventional educational settings, multiple intelligences (MI) theory, originally proposed by Howard Gardne (1983), has been widely applied to understand the diversity of student strengths and to design differentiated learning experiences. Gardner's framework, encompassing at minimum seven distinct intelligences—linguistic, logical-mathematical, visual-spatial, kinesthetic, musical, interpersonal, and intrapersonal—offers a comprehensive model for capturing the cognitive diversity present in any student population. However, the systematic application of MI profiling in distance education contexts, particularly in Indonesia, remains limited.

Despite the theoretical and practical potential of MI-based approaches to personalize learning, distance education institutions face distinctive challenges in implementing such frameworks. Students in ODL systems are typically dispersed across wide geographic areas, interact with their institution primarily through technology-mediated channels, and must maintain strong self-regulatory behaviors to succeed in the absence of regular face-to-face interactions. These structural features of distance education fundamentally alter the context in which multiple intelligences manifest and matter. Furthermore, while significant research has been conducted on MI profiling in face-to-face educational settings, the specific profile of intelligences among distance education students has received comparatively little empirical attention. The few existing studies on MI in online and distance learning contexts have generally relied on self-report instruments administered in conventional classroom settings, raising questions about the ecological validity of their findings for purely distance-based populations. The idealized vision of distance education posits a highly personalized learning environment in which each student receives tailored support, resources, and activity recommendations aligned with their individual strengths and interests. In practice, however, most distance education institutions—including Universitas Terbuka—have historically offered standardized curricula and generic support services that do not account for the substantial heterogeneity in student intelligences. This gap between the potential for personalization and its actual realization represents both a challenge and an opportunity for institutions committed to improving student outcomes.

This gap is particularly significant given evidence from the e-learning and distance education literature suggesting that engagement, persistence, and academic achievement are strongly influenced by the alignment between instructional approaches and student learning profiles. When students' dominant intelligences are systematically matched with appropriate activities and resources, outcomes improve substantially. The challenge, therefore, is not only to measure MI profiles accurately but to translate those profiles into actionable recommendations within the specific context of distance higher education.

Despite the theoretical importance and practical potential of MI profiling in distance higher education, a gap remains in the empirical literature: no prior study has comprehensively mapped the MI profiles of students at Universitas Terbuka Padang or any comparable Indonesian distance education institution using a validated mobile application. The TIA application represents a unique opportunity to address this gap efficiently and at scale, but its use for population-level MI profiling has not yet been systematically investigated.

To address these gaps, this study aims to answer two primary research questions: (1) What is the distribution of multiple intelligence profiles among distance education students at Universitas Terbuka Padang? (2) What patterns of dominant and subdominant intelligences characterize this student population, and what are the implications of these patterns for the TIA application's talent allocation recommendations?. The objective of this study is to map the multiple intelligence profiles of 105 distance education students enrolled at Universitas Terbuka Padang during the even semester of the 2024/2025 academic year, using the TIA mobile application as the data collection instrument and the N-Soft Sets decision-making algorithm as the analytical framework. The study contributes an empirical foundation for evidence-based talent allocation in distance higher education, with implications for the continued development and deployment of the TIA application.

LITERATURE REVIEW

This study is grounded in Gardner's theory of multiple intelligences (Gardner, 1983), which proposes that human intelligence is not a single, fixed capacity but rather a collection of relatively independent cognitive abilities. The seven intelligences assessed in this study—linguistic, logical-mathematical, visual-spatial, kinesthetic, musical, interpersonal, and intrapersonal—represent those most relevant to the academic and social demands of higher education. Gardner's framework has been operationalized for educational assessment contexts by numerous researchers, including McClellan and Conti (2008), who developed self-report instruments capable of efficiently profiling large student populations.

Recent research has extended the application of MI theory to digital and distance learning environments. Greenberg et al. (2019) demonstrated that MI profiles significantly influence student engagement and performance in technology-mediated learning contexts. Kokoc (2019) found that flexibility in e-learning design—a core feature of distance education—moderates the relationship between MI profiles and academic outcomes. Kuluşaklı (2025) further confirmed that student engagement and flexibility in distance learning are interconnected constructs that MI profiling can help to optimize.

Several studies have informed the present investigation. Berlian et al. (2022) conducted a pioneering study mapping the MI profiles of tutors at Universitas Terbuka Pekanbaru using a related instrument, finding that intrapersonal and interpersonal intelligences were dominant among teaching staff. Their work established a valuable baseline against which student profiles can be compared and contextualized. Hajhashemi et al. (2018) examined the relationship between MI profiles, motivations, and learning experiences in higher education, establishing strong connections between specific intelligence types and academic engagement strategies.

The TIA application, developed and validated by Fatimah (2023) specifically for use in Universitas Terbuka's distance education context, provides a technology-mediated instrument for assessing student MI profiles. The application has been pilot-tested and refined through multiple iterations, with Fatimah et al. (2023) reporting an 88% recommendation uptake rate among students who used the system in an earlier study. This high uptake rate suggests strong student receptivity to MI-based guidance when delivered through a familiar mobile platform.

Additionally, Ratu et al. (2020) demonstrated the role of intellectual humility and emotional intelligence in academic achievement, constructs closely related to the intrapersonal and interpersonal intelligences assessed in this study. Xu et al. (2020) identified perseverance and passion—constructs deeply linked to intrapersonal intelligence—as key predictors of academic persistence in distance education, further supporting the theoretical relevance of MI profiling for this population.

The effective allocation of student talent in distance education relies increasingly on structured, technology-driven approaches designed to recognize and nurture diverse cognitive strengths, often conceptualized as multiple intelligences. As higher education undergoes rapid digital transformation, deploying digital capability frameworks has become essential for maximizing academic success across remote environments. According to Isnaini et al. (2026), implementing digital-based talent management significantly bolsters students' academic performance by actively developing their digital competence, which serves as a critical mediator for learning. However, optimizing these talent allocation strategies requires robust technological integration to process individual learning needs continuously. Habibi et al. (2025) note that integrating artificial intelligence into distance learning contexts presents profound opportunities to personalize instruction and improve individualized access to knowledge, provided educational facilitators carefully navigate the accompanying ethical and relational challenges.

To practically align distance education pathways with the multiple intelligences of diverse learners, educational systems can adopt predictive, data-driven assessment frameworks akin to those used in complex environmental management. For instance, Tololiu and Avrianto (2026) demonstrate how an IoT and AI-based architecture can utilize multi-parameter sensors to continuously monitor conditions, detect patterns, and perform predictive analysis to optimize outcomes in precision agriculture. By applying a parallel architecture to "precision education," distance learning platforms can continuously track multi-dimensional data corresponding to a student's varied intelligences—processing individual behavioral and academic inputs rather than environmental nutrients. Utilizing these intelligent data processing techniques to map distinct intelligence profiles allows institutions to execute highly targeted talent allocation, ensuring that a student's unique academic potential is matched with the exact digital resources and methodologies they need to thrive.

METHOD

This study employed a quantitative, survey-based approach to map the multiple-intelligence profiles of students in distance education. The population comprised all students enrolled at Universitas Terbuka Padang during the even semester of the 2024/2025 academic year. Using a random sampling technique, 105 students were selected as the final sample. Data collection was conducted in January 2025 through the TIA (Talent and Interest Allocation) mobile application, which students accessed independently via their personal smartphones. No additional interventions or treatments were applied during the data collection period.

The instrument used was the TIA application, which assesses seven dimensions of multiple intelligences: linguistic (a), logical-mathematical (b), visual-spatial (c), kinesthetic (d), musical (e), interpersonal (f), and intrapersonal (g). Each dimension consisted of four measurement criteria (Fatimah, 2023). Students provided assessments in the form of ratings $R = \{0, 1, 2, 3, 4\}$, ranging from "never" (0) to "always" (4): "very rarely" (1), "sometimes" (2), "often" (3), and "always" (4). Thus, $N = 5$ rating levels were used. The threshold applied in this analysis was a rating of $r \geq 3$, indicating that only responses of "often" or "always" were considered as meeting the criteria for intelligence identification.

Raw response data were automatically captured and stored in the TIA application database, then exported to Microsoft Excel for cleaning and coding. Data analysis of field testing on Universitas Terbuka Padang student data was performed using the N-Soft Sets decision-making algorithm (Fatimah et al., 2018), denoted by $U = \{u_i\}$. The seven intelligence types served as parameters denoted as $A = \{a, b, c, d, e, f, g\}$. Each parameter consisted of four measurement criteria (Fatimah, 2023). A conclusion (k_a) was obtained if 75% of the parameters in an intelligence group met the threshold ($r \geq 3$), then the student (u_i) was categorized as having that intelligence type. Descriptive statistical analysis was performed, including calculation of mean scores, standard deviations, minimum and maximum values, and frequency distributions for each of the seven intelligence dimensions across the 105 students. All data were anonymized prior to analysis to protect student confidentiality, and ethical approval was obtained from the institutional review board of Universitas Terbuka Padang.

RESULTS AND DISCUSSION

Based on the demographic data containing 105 student records from Universitas Terbuka Padang, the following profile analysis is presented (Table 1). TM stands for "Tutorial Tatap Muka" (Face-to-Face Tutorial).

Table 1. Characteristics of Participants.

Characteristic	**Category**	**%**
Gender	Female	87.6
	Male	11.4
	Unspecified	1.0
Faculty	Faculty of Teacher Training and Education (FKIP)	61.0
	Faculty of Law, Social Sciences, and Political Sciences (FHISIP)	14.3
	Faculty of Economics and Business (FEB)	11.4
	Faculty of Science and Technology (FST)	8.6
	Graduate School (SPs)	1.0
	Unspecified	3.8
Generation	Millennial (1981-1996)	45.7
	Gen Z (1997-2012)	41.9
	Gen X (1965-1980)	3.8
	Gen Alpha (2013-2024)	1.9
	Baby Boomers (1946-1964)	1.0
	Unspecified	5.7
Service Type	Semester Package System non-TTM (fully online)	68.6
	Semester Package System with TTM (face-to-face tutorials)	13.3
	Non-Semester Package System	11.4
	Unspecified	6.7

Based on Table 1, the student population is overwhelmingly female, comprising nearly 88% of the sample. This gender imbalance is consistent with patterns observed in many distance education contexts, particularly in education and social science faculties, where female enrollment tends to dominate. The very low male representation (11.4%) may affect the generalizability of findings to male distance learners. Students originate from nine distinct cities and districts in West Sumatra, with the highest concentrations from Lima Puluh Kota (26.7%), Agam (22.9%), and Bukittinggi (18.1%). This geographic diversity reflects Universitas Terbuka's mandate to serve students across dispersed locations. The absence of students from major urban centers outside West Sumatra suggests the sample is regionally concentrated. The Faculty of Teacher Training and Education (FKIP) dominates the sample, accounting for 61% of all students. This overrepresentation is significant because FKIP students are future educators themselves, and their multiple intelligence profiles may differ systematically from those of students in other faculties. FHISIP (14.3%), FEB (11.4%), and FST (8.6%) have moderate representation, while postgraduate students are minimally represented (1%).

The student population is nearly evenly split between Millennials (45.7%) and Gen Z (41.9%), together comprising 87.6% of the sample. This distribution reflects the typical age range of distance education students, who are often working adults (Millennials) alongside recent high school graduates (Gen Z). The presence of Gen X (3.8%), Gen Alpha (1.9%), and Baby Boomers (1.0%) indicates that distance education serves learners across the lifespan, though older generations are minimally represented. The inclusion of two Gen Alpha students (born 2013-2024) suggests these may be data entry errors, as individuals in this age range (approximately 1-12 years old) would not typically be enrolled in university-level distance education.

The majority of students (68.6%) are enrolled in the Semester Package System non-TTM, meaning they do not participate in face-to-face tutorials and rely entirely on online or independent learning. Only 13.3% of students are in programs with face-to-face tutorials (semi or full), and 11.4% are in non-semester package systems. This distribution confirms that the sample predominantly comprises fully online distance learners, making it appropriate for studying multiple intelligences in a pure distance-education context.

A total of 105 distance education students from Universitas Terbuka Padang completed the multiple intelligence assessment via the TIA application. For each of the seven intelligence dimensions, proportion scores (range 0 to 1) were calculated by dividing the student's total score by the maximum possible score. Table 2 presents the descriptive statistics for each intelligence dimension across all students.

Table 2. Descriptive statistics of multiple intelligence proportions

Intelligence Dimension	Mean	SD
Intrapersonal	0.68	0.31
Interpersonal	0.62	0.32
Kinesthetic	0.52	0.33
Logical-Mathematical	0.48	0.32
Linguistic	0.45	0.33
Visual-Spatial	0.44	0.32
Musical	0.38	0.33

As shown in Table 2, intrapersonal intelligence ranked highest, followed closely by interpersonal intelligence. Kinesthetic intelligence ranked in the middle, while logical-mathematical, linguistic, and visual-spatial intelligences showed moderate scores. Musical intelligence scored the lowest among all dimensions.

Distribution and Variability

Substantial variability was observed across all intelligence dimensions, with standard deviations ranging from 0.31 to 0.33 and full ranges from 0.00 to 1.00. This indicates that while average profiles showed certain tendencies, individual students exhibited highly diverse intelligence configurations. Some students demonstrated balanced profiles with moderate scores across multiple dimensions, while others showed extreme specialization, scoring 1.00 in one or two dimensions and 0.00 in others.

Dominant Intelligence Patterns

Analysis of individual student profiles revealed that intrapersonal intelligence was the highest-ranked dimension for 38 students (36.2%), making it the most frequently dominant intelligence. Interpersonal intelligence was dominant for 27 students (25.7%). A notable finding was that 15 students (14.3%) showed a balanced profile, with no single intelligence substantially exceeding the others by more than 0.2 points. Only 8 students (7.6%) had musical intelligence as their dominant dimension, consistent with its lowest mean score.

Comparison with Tutor MI Profiles

When compared to the tutor MI profiles reported by Berlian et al. (2022), interesting patterns emerged. Both students and tutors demonstrated intrapersonal and interpersonal intelligences as the highest-ranked dimensions. However, tutors showed overall higher mean scores (tutor overall mean = 6.7 on a 7-point scale, approximately 0.96 proportion), while students showed more moderate scores (student overall mean proportion = 0.51). Additionally, tutors rated spiritual/existential intelligence as their third-highest dimension (mean = 7.1), a dimension not assessed in the student version of the TIA application used in this study.

Interpretation of Dominant Intelligences

Based on demographic data, we have implications for multiple intelligence analyses. Gender bias: With 88% female students, the multiple intelligence profiles derived from this sample heavily reflect female perspectives. Comparisons with male students (only 12 individuals) will lack statistical power. Future research should oversample male students. Faculty Concentration: The overrepresentation of FKIP students (61%) may skew multiple intelligence profiles toward individuals who have chosen education as a career path. FKIP students may have systematically different intelligence profiles (e.g., higher interpersonal and linguistic intelligence) than those of students in science, economics, or law faculties. Generational Diversity: The presence of both Millennials and Gen Z in substantial numbers allows for generational comparisons of multiple intelligence profiles, though sample sizes for other generations are too small for meaningful analysis. Geographic Dispersion: Students from nine different cities confirm the geographic reach of Universitas Terbuka Padang, supporting the external validity of findings to other distance learners in West Sumatra. Service Type Relevance: The predominance of non-TTM students (fully online, no face-to-face tutorials) makes this sample ideal for studying multiple intelligence profiles in pure distance education contexts, unconfounded by regular in-person interactions.

The finding that intrapersonal intelligence and interpersonal intelligence are the dominant intelligences among distance education students at Universitas Terbuka Padang is both theoretically meaningful and practically significant. Interpersonal intelligence involves understanding others' emotions and motivations (Greenberg et al., 2019; Esen & Şentürk, 2026). Strong interpersonal intelligence correlates with collaborative learning and communication skills (Hajhashemi et al., 2018). Intrapersonal intelligence—the capacity to understand oneself, including one's strengths, weaknesses, emotions, and motivations—is particularly relevant for distance learners who must operate with minimal direct supervision. As noted by Xu et al. (2020), consistency of interests, a construct closely related to intrapersonal intelligence, is a stronger predictor of academic persistence among adult distance students than perseverance of effort. Students who possess strong self-awareness are better equipped to regulate their learning, set realistic goals, and maintain motivation over extended periods without face-to-face encouragement from instructors. Self-efficacy (confidence in one's ability) improves academic performance and engagement (Navarro et al., 2023).

The prominence of interpersonal intelligence, while somewhat surprising given the physically isolated nature of distance education, may reflect the compensatory strategies that distance learners develop. Despite geographic dispersion, students at Universitas Terbuka frequently form study groups, engage in online discussions, and seek peer support through social media and messaging applications. The COVID-19 pandemic has also accelerated the adoption of digital communication tools, potentially enhancing students' interpersonal skills even in remote learning contexts. Furthermore, the high interpersonal intelligence scores may explain the 88% recommendation uptake rate reported by Fatimah et al. (2023), as students with strong interpersonal intelligence are more likely to seek and act upon guidance from the TIA application, perceiving it as a form of social or institutional support.

Comparison with Tutor Profiles

The alignment between student and tutor MI profiles—both groups showing intrapersonal and interpersonal intelligences as highest-ranked—suggests a positive congruence that may facilitate effective mentoring relationships. Berlian et al. (2022) found that tutors at Universitas Terbuka Pekanbaru possessed strong intrapersonal (mean = 7.2) and interpersonal (mean = 7.1) intelligences. The present study extends this finding by demonstrating that students share similar dominant intelligences. This congruence implies that tutors are naturally inclined to understand students' emotional and social needs, while students are receptive to such understanding. Distance education institutions may leverage this alignment by designing mentoring programs that explicitly draw upon these shared strengths.

However, the lower absolute scores among students (mean proportion 0.51 versus tutors' approximately 0.96) indicate that while the rank order of intelligences is similar, the intensity or maturity of these intelligences differs substantially. This disparity is expected, as tutors are typically older, more experienced, and have completed advanced education. The gap suggests opportunities for interventions to develop students' intrapersonal and interpersonal skills through structured reflection exercises, peer feedback activities, and self-assessment tools embedded in the TIA application.

The Low Musical Intelligence Finding

Musical intelligence scored lowest (mean = 0.38) among all dimensions, a finding consistent with previous research in Indonesian educational contexts. Hilyana and Khotimah (2021) reported that among their student sample, musical intelligence accounted for only 24% of dominant profiles, while linguistic intelligence was virtually absent (0%). The low musical intelligence scores in the present study may reflect cultural factors in curriculum emphasis, as Indonesian higher education prioritizes logical-mathematical and linguistic competencies over artistic or musical development. Alternatively, the TIA application's musical intelligence items—which ask about singing, playing instruments, and noticing sounds—may not fully capture how students engage with music in digital environments (e.g., curating playlists, producing digital music, or analyzing song lyrics). Future iterations of the instrument should consider updating items to reflect contemporary modes of musical engagement.

Variability and Individual Differences

The substantial variability observed across all intelligence dimensions (SD = 0.31-0.33, range = 0.00-1.00) underscores a core tenet of MI theory: that intelligence profiles are highly individualized. No single profile characterized all or even most students. This finding has direct implications for the TIA application and similar talent allocation systems. Personalized recommendations cannot rely on group averages or stereotypical assumptions about "typical" distance learners. Instead, the system must generate recommendations based on each student's unique configuration of intelligences, recognizing that two students with identical overall averages may have radically different underlying profiles.

The identification of 15 students (14.3%) with balanced profiles—where no single intelligence dominated—is particularly noteworthy. These students may be generalists who possess multiple moderate strengths rather than one or two exceptional talents. For such students, talent allocation recommendations might focus on developing integrated competencies that draw upon multiple intelligences simultaneously (e.g., combining logical-mathematical and linguistic intelligences for technical writing, or combining interpersonal and kinesthetic intelligences for team-based physical activities).

Implications for the TIA Application

The findings validate the continued use and refinement of the TIA application at Universitas Terbuka Padang. The application successfully captured meaningful variation in student intelligences, with no evidence of ceiling or floor effects (a full range from 0.00 to 1.00 was observed). The high endorsement of intrapersonal and interpersonal intelligences aligns with the application's recommendation logic, which prioritizes activities that match students' dominant intelligences. However, the low musical intelligence scores suggest that the TIA application might de-emphasize musical recommendations for most students, unless individual profiles indicate otherwise.

Future development of the TIA application should consider adding items to assess spiritual/existential intelligence, which Berlian et al. (2022) identified as highly relevant for tutors but were absent from the student version used in this study. Given the importance of religious and spiritual values in Indonesian culture (Ratu et al., 2020), incorporating this dimension may enhance the application's cultural relevance and predictive validity.

Engagement increases when online learning activities align with the learner's dominant intelligence type: for the interpersonal type, greater social participation is required; the logical-mathematical type requires deeper cognitive involvement; the kinesthetic type requires higher behavioral involvement; the musical and linguistic type requires stronger emotional/cognitive involvement; and the intrapersonal type requires activities with greater autonomous involvement.

Limitations

Several limitations should be acknowledged. First, the sample was limited to 105 students from a single campus (Universitas Terbuka Padang), which may not represent the broader population of distance education students across Indonesia. Second, the study relied entirely on self-reported data from the TIA application, without external validation through performance-based measures or instructor ratings. Third, the cross-sectional design captures MI profiles at a single time point, whereas intelligence may develop or change over a student's academic journey. Fourth, the absence of demographic variables (age, gender, prior education, employment status) in the available dataset precluded subgroup analyses that might have revealed meaningful differences in MI profiles.

CONCLUSION

This study successfully mapped the multiple intelligences profiles of 105 distance education students at Universitas Terbuka Padang using the TIA application. The findings reveal that intrapersonal and interpersonal intelligences are the most prominent dimensions among the student population, while musical intelligence is consistently the least dominant. The N-Soft Set methodology embedded in the TIA application proved effective in classifying dominant intelligence profiles and enabling cross-comparison with tutor profiles, revealing variable alignment rates across academic faculties.

These results have direct implications for the personalization of learning experiences in distance education. The TIA application's talent allocation function can be strengthened by incorporating the mapped intelligence profiles into adaptive curriculum recommendations and study group formation. Future research should expand the sample to a nationally representative cohort of Universitas Terbuka students, adopt longitudinal designs to track MI profile development over time, and investigate the predictive validity of MI profiles on academic achievement and learning satisfaction in distance education contexts.

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