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IMPROVING THE METHODOLOGY OF TEACHING DIGITAL TECHNOLOGIES BASED ON MULTITYPE DATA-PROCESSING ALGORITHMS

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ABOUT ARTICLE

Key words: multitype data fusion; digital technology education; pedagogical methodology; multimodal learning analytics; TPACK; higher education; instructional design; digital competency; Uzbekistan; quasi-experimental study.

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Abstract: Digital-technology courses now cover subject matter that resists plain-text explanation: cloud architecture, blockchain mechanics, algorithmic platforms, artificial intelligence. Teaching this material well usually means combining prose with statistics and visuals, yet most instruction still relies on text alone. The international literature on multimodal learning analytics has built solid frameworks for classifying and combining heterogeneous educational data (Mu, Cui, & Huang, 2020), and digital-competency instruments have been validated across several institutional settings (Moreira-Choez et al., 2024).

What has not been done is turning these ideas into a tested teaching method for digital-technology instruction specifically, or checking whether such a method holds up in a Central Asian university. This study builds and tests a multitype data-fusion teaching method grounded in TPACK (Mishra & Koehler, 2006), connectivism (Siemens, 2005), and the zone of proximal development (Vygotsky, 1978). Sixty-four students at a Uzbekistani technical university were split into a text-only control group and a multitype-fusion experimental group across eleven course topics. The experimental group scored 13.4 points higher on average (Cohen's $d = 1.54$, $p < .001$), needed 22% less time to master each topic, and showed a clear pattern: achievement rose with each added data type, from $r = 0.42$ for text plus table up to $r = 0.67$ for text, table, and visual combined.

Expert raters (Cronbach’s α = 0.89) and student feedback backed these numbers, though some students flagged sections as too dense, which points to a real limit on how much can be fused at once. Multitype fusion pedagogy works, in other words, but it needs calibration. The paper closes with concrete recommendations for curriculum designers and institutional policy. Expert raters (Cronbach’s α = 0.89) and student feedback backed these numbers, though some students flagged sections as too dense, which points to a real limit on how much can be fused at once. Multitype fusion pedagogy works, in other words, but it needs calibration. The paper closes with concrete recommendations for curriculum designers and institutional policy.

MULTI TIPLI MA’LUMOTLARNI QAYTA ISHLASH ALGORITMLARI ASOSIDA RAQAMLI TEXNOLOGIYALARNI O‘QITISH METODIKASINI TAKOMILLASHTIRISH

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MAQOLA HAQIDA

Kalit so‘zlar: multitipli ma’lumotlar birlashuvi; raqamli texnologiyalar ta’limi; pedagogik metodika; multimodal ta’lim tahlili; TPACK; oliy ta’lim; o‘quv dizayni; raqamli kompetentlik; O‘zbekiston; kvazi-eksperimental tadqiqot.

Annotatsiya: Bugungi raqamli texnologiyalar kursi shunday materiallarni o‘z ichiga oladiki, ularni faqat matn orqali tushuntirish qiyin: bulutli hisoblash arxitekturasi, blokcheyn mexanizmi, algoritmik platformalar, sun’iy intellekt. Bunday materialni sifatli o‘qitish odatda matnni statistika va vizual materiallar bilan birga qo‘llashni talab qiladi, biroq o‘qitishning katta qismi hamon faqat matnga tayanadi. Multimodal ta’lim tahlili bo‘yicha xalqaro adabiyot heterogen ta’lim ma’lumotlarini tasniflash va birlashtirish uchun ishonchli modellar yaratgan (Mu, Cui, & Huang, 2020), raqamli kompetensiyalarni baholash vositalari esa turli institutsional sharoitlarda tasdiqlangan (Moreira-Choez va boshq., 2024).

Biroq hech kim bu g‘oyalarni aynan raqamli texnologiyalarni o‘qitish uchun sinovdan o‘tkazilgan metodikaga aylantirmagan va bunday metodikaning Markaziy Osiyo universitetida ishlashini tekshirmagan edi. Ushbu tadqiqot TPACK (Mishra & Koehler, 2006), konnektivizm (Siemens, 2005) va yaqin rivojlanish zonasi (Vygotsky, 1978) nazariyalariga tayanib, multitipli ma'lumotlarni birlashtirish metodikasini ishlab chiqadi va sinovdan o'tkazadi. O'zbekiston texnika universitetidagi 64 nafar talaba nazorat guruhi (faqat matn) va tajriba guruhi (multitipli birlashtirilgan ma'lumotlar) ga bo'lindi, 11 ta kurs mavzusi bo'yicha solishtirildi. Tajriba guruhi o'rtacha 13,4 ballga ko'proq to'pladi (Koen d = 1,54, p < 0,001), har bir mavzuni o'zlashtirishga 22% kamroq vaqt sarfladi, natijalar esa aniq qonuniyatni ko'rsatdi: har bir qo'shimcha ma'lumot turi bilan o'zlashtirish darajasi oshib bordi - matn+jadval uchun r=0,42 dan to matn+jadval+vizual to'liq birikmasi uchun r=0,67 gacha.

Ekspertlar bahosi (Kronbax alfasi = 0,89) va talabalar fikri bu raqamlarni tasdiqladi, garchi ba'zi talabalar alohida bo'limlarni axborot bilan haddan tashqari to'yingan deb baholagan bo'lsa-da - bu bir vaqtning o'zida qancha ma'lumot turini birlashtirish mumkinligining real chegarasi borligini ko'rsatadi. Boshqacha aytganda, multitipli ma'lumotlarni birlashtirish pedagogikasi ishlaydi, lekin kalibrlashni talab qiladi. Maqola yakunida o'quv dastur ishlab chiquvchilar va institutsional siyosat uchun aniq tavsiyalar keltiriladi.

СОВЕРШЕНСТВОВАНИЕ МЕТОДИКИ ОБУЧЕНИЯ ЦИФРОВЫМ ТЕХНОЛОГИЯМ НА ОСНОВЕ АЛГОРИТМОВ ОБРАБОТКИ ДАННЫХ РАЗЛИЧНЫХ ТИПОВ

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О СТАТЬЕ

Ключевые слова: мультитипное слияние данных; обучение цифровым технологиям; педагогическая методика; мультимодальная аналитика обучения; TPACK; высшее образование; дизайн обучения; цифровая компетентность; Узбекистан; квазиэкспериментальное исследование.

Аннотация: Курсы по цифровым технологиям сегодня охватывают материал, который плохо поддаётся объяснению одним лишь текстом: архитектуру облачных вычислений, механику блокчейна, алгоритмические платформы, искусственный интеллект. Качественное преподавание такого материала обычно требует сочетания

текста со статистикой и визуальными материалами, однако большая часть обучения по-прежнему опирается только на текст. Международная литература по мультимодальной аналитике обучения выработала надёжные модели классификации и объединения разнородных образовательных данных (Mu, Cui, & Huang, 2020), а инструменты оценки цифровых компетенций прошли валидацию в различных институциональных условиях (Moreira-Choez et al., 2024).

Однако до сих пор никто не превратил эти идеи в проверенную методику именно для преподавания цифровых технологий и не проверил, работает ли такая методика в университете Центральной Азии. Данное исследование разрабатывает и проверяет методику слияния мультитипных данных, опираясь на TPACK (Mishra & Koehler, 2006), коннективизм (Siemens, 2005) и зону ближайшего развития (Vygotsky, 1978). 64 студента узбекистанского технического университета были разделены на контрольную группу (только текст) и экспериментальную группу (слияние мультитипных данных) по одиннадцати темам курса. Экспериментальная группа в среднем набрала на 13,4 балла больше (d Коэна = 1,54, $p < 0{,}001$), тратила на 22% меньше времени на освоение каждой темы, и результаты показали чёткую закономерность: успеваемость росла с добавлением каждого нового типа данных - от $r = 0{,}42$ для сочетания текст+таблица до $r = 0{,}67$ для полного сочетания текст+таблица+визуал.

Оценки экспертов (α Кронбаха = 0,89) и отзывы студентов подтвердили эти цифры, хотя часть студентов отметила отдельные разделы как перегруженные информацией, что указывает на реальный предел того, сколько типов данных можно объединять одновременно. Иными словами, педагогика слияния мультитипных данных работает, но требует калибровки. В заключение статьи приводятся конкретные рекомендации для разработчиков учебных программ и институциональной политики.

Introduction. Digital technologies have moved into university curricula faster than teaching methods have adapted to them. Cloud computing, cryptocurrencies and blockchain, artificial intelligence, the Internet of Things, and platform-based business models are now standard course content, and none of them explain well in plain prose alone. A lecture on cloud architecture needs a comparison table of service models, a diagram of how the pieces fit together, and a market chart showing who the major providers are; text by itself leaves gaps that students notice. This gap between what the content demands and how it tends to get taught is what motivated the research reported here.

Researchers working in multimodal learning analytics have spent the past several years building frameworks for classifying and combining different kinds of educational data, text, video, log files, physiological signals, and more (Mu, Cui, & Huang, 2020; Chango, Lara, Cerezo, & Romero, 2022). A parallel line of work has produced validated instruments for measuring digital competency among faculty and students (Moreira-Choez et al., 2024; UNESCO, 2018). Both bodies of work are mature. Neither has been turned into a concrete teaching method for a specific subject area such as digital technology instruction, and neither has been tested in Central Asia.

That gap matters in Uzbekistan specifically, where the "Digital Uzbekistan - 2030" strategy has made digital-technology education a matter of state policy. Technical universities are expected to produce graduates who understand cloud infrastructure, cryptographic systems, and AI well enough to work with them professionally. Existing local research on the topic, including work by Alimardonov, Abdullayev, and Rizayeva and several dissertations reviewed by the Higher Attestation Commission, has focused on digital infrastructure and institutional strategy rather than on the narrower question this paper takes up: how should text, tables, and visual material actually be combined when teaching a digital-technology course?

Three problems follow from this. First, the fusion models built by MMLA researchers were designed to interpret data collected about learners, not to guide how instructional materials themselves should be built; almost nobody has tried using them the other way around. Second, digital-competency instruments validated abroad have not been tested on Central Asian students. Third, and most practically, nobody has worked out how much text, table, and visual content to combine in a single lesson before it becomes too much rather than just right, a question this study's own data end up answering.

This study sets out to build and test a teaching method, grounded in multitype data-processing principles, for digital-technology courses, with five specific aims: reviewing the relevant international research and classical pedagogical theory; sorting out what kinds of instructional data are actually used in this subject area; designing a fusion method that instructors could realistically apply; testing it experimentally against conventional text-only teaching; and checking, through expert and student evaluation, whether the resulting materials hold up in practice. What is new here is putting MMLA fusion theory to work as a design principle for teaching materials rather than as an analytic tool, and doing so inside a real Uzbekistani classroom rather than a hypothetical one.

2. Literature Review

2.1. Multimodal Data Fusion Theory

Mu, Cui, and Huang (2020) reviewed 346 studies on multimodal learning analytics using a PRISMA-based method and sorted the data these studies used into five types: digital, physical, physiological, psychometric, and environmental. More useful for present purposes, they described three ways such data can be fused. Many-to-one fusion combines several data streams to pin down a single indicator more precisely. Many-to-many fusion widens the overall picture rather than sharpening one point in it. Cross-validation fusion uses one data type to check another. The many-to-one idea maps directly onto the hypothesis tested here: that explaining one concept through text, a table, and a visual at once should produce better understanding than any single format on its own.

Chango, Lara, Cerezo, and Romero (2022) broke fusion down further, into data-level, decision-level, and feature-level integration, which matters because it shows that "combining modalities" is not one move but several possible ones, each happening at a different point in the pipeline. The materials built for this study were fused at the feature level: each piece, text, table, visual, was worked out on its own first and only combined afterward. Luo (2023) makes a related point in passing, namely that digital-technology content is multimodal by nature, which means a text-only lecture on, say, blockchain is already a mismatch between the subject and how it is being taught. Later empirical work backs this up in classroom settings: Xu, Wu, and Ouyang (2023) found multimodal analysis picked up far more about how students collaborate during pair programming than text records alone would show, and Moon, Yeo, Banihashem, and Noroozi (2024) and Yan et al. (2024) report similar gains for formative assessment and reflective practice.

2.2. Digital Competency Models and Classical Pedagogical Foundations

Moreira-Choez et al. (2024) surveyed 279 faculty members at an Ecuadorian university and, using structural equation modeling, identified five competency factors: technological literacy, information access and use, communication and collaboration, digital citizenship, and creativity and innovation, with a reliability coefficient of $\alpha = 0.977$. UNESCO’s (2018) ICT Competency Framework for Teachers covers similar ground at a policy level, spelling out eighteen competencies across three stages of technology integration. Zhu and Sun (2023) and Molenaar, de Mooij, Azevedo, Bannert, Järvelä, and Gašević (2023) add evidence from the algorithmic side, showing that AI-driven personalization is now a normal part of how education gets delivered, not a novelty.

The theoretical grounding for this study draws on several older ideas as well. Shulman (1986) argued that good teaching requires a distinct kind of knowledge, neither pure subject expertise nor generic teaching skill, about how to make specific content understandable. Mishra and Koehler (2006) extended this into TPACK, framing effective technology-based teaching as the interaction of technological, pedagogical, and content knowledge. That framing fits this study's central question closely: deciding how to fuse multitype data with a teaching sequence is, at bottom, a TPACK problem applied to instructional-material design. Siemens (2005) argued, through connectivism, that learning in networked environments is less about memorizing isolated facts and more about building connections across scattered information, which supports the idea that materials linking text to tables and visuals mirror the kind of cognitive work students are already doing outside the classroom. Vygotsky (1978), through the zone of proximal development, suggested that learning improves when support is pitched between what a student can already do alone and what they can do with help, which is one way to read why visual and tabular entry points might make otherwise dense material workable for more students. Bourdieu (1986) and Cowen (2000) round this out: Bourdieu's work on capital has been extended by later scholars into the idea of "digital capital," relevant here because lowering the barrier to technical content has equity implications beyond test scores, and Cowen's insistence on context-sensitive comparative research is the reason this study was run in an actual Uzbekistani classroom rather than assumed to generalize from elsewhere.

2.3. Research Gap

Each of these three literatures, fusion theory, competency measurement, and classical pedagogy, is well developed on its own. What is missing is a study that combines them into a teaching method built specifically for digital-technology instruction and tests it somewhere other than North America, Europe, or Latin America, which is where nearly all of the empirical work cited above was actually conducted. That combination of a methodological gap and a geographic one is what this study addresses.

3. Methodology

3.1. Design, Participants, and Instruments

The study used a quasi-experimental, pretest–posttest design with a nonequivalent control group, run at the Department of Information Educational Technologies, Tashkent University of Information Technologies, with 64 students enrolled in "Digital Technologies and Innovations." Students were randomly split into a control group (n = 32, conventional text-only instruction) and an experimental group (n = 32, multitype fusion instruction). Table 1 shows the two groups were comparable at the outset.

Table 1. Demographic characteristics of participants (N = 64)

Characteristic	Control (n = 32)	Experimental (n = 32)
Mean age (years)	19.8 (SD = 0.9)	19.6 (SD = 1.0)
Gender (M / F)	19 / 13	18 / 14
Baseline achievement score	54.2 (SD = 8.1)	55.0 (SD = 7.6)

An eleven-topic course resource was built, covering cloud computing, cryptocurrencies, micromobility, ride-hailing, gig-economy platforms, on-demand services, short-term rentals, smart-home and IoT technology, AI and algorithmic systems, and digital inequality. The experimental version paired text with at least one comparison table and several relevant visuals per topic, following the many-to-one fusion logic from Mu et al. (2020); the control version presented the same content as continuous text with nothing added. Four instruments captured outcomes: a ten-item test given after each topic (summed to a 100-point score), a five-criterion expert rating scale (clarity, text-visual coherence, practical applicability, consistency, overall effectiveness) completed by five faculty members, and a student questionnaire adapted from the CDES approach used by Moreira-Choez et al. (2024).

3.2. Procedure and Data Analysis

The study ran in three stages: preparing the materials and reviewing the literature, delivering the eleven-topic course with instructional time and sequencing held constant across both groups, and analyzing the resulting data. Group comparisons used independent-samples t-tests ($\alpha = .05$) in SPSS; questionnaire reliability was checked with Cronbach's alpha; and Pearson correlation was used within the experimental group to see how achievement related to which combination of data types (text, text+table, text+visual, all three) each topic used.

3.3. Ethical Considerations

Participation was voluntary. Students were told the study compared two teaching approaches but not which specific outcomes were being measured, to avoid skewing their responses. Both groups received full, curriculum-aligned content that differed only in format, so nobody's grade was put at risk by group assignment. Data were anonymized before analysis, and the department approved the study before it began.

4. Results, Analysis and Discussion

4.1. Baseline Equivalence and Achievement Outcomes

A t-test found no meaningful difference between the two groups before instruction began ($t(62) = 0.41$, $p = .68$), so whatever showed up afterward could be attributed to the teaching method rather than a head start. Table 2 summarizes what happened after the intervention.

Table 2. Post-intervention achievement outcomes by group

Indicator	Control	Experimental	t	p
Mean achievement (0–100)	61.4 (SD=9.3)	74.8 (SD=7.9)	6.17	< .001
"Excellent" grade %	12.5%	40.6%	-	-
"Unsatisfactory" grade %	21.9%	3.1%	-	-
Time to mastery (min)	47.3	36.8	4.52	< .001
Effect size (Cohen's d)	-	1.54	-	-

The experimental group came out 13.4 points ahead on average ($p < .001$, Cohen's $d = 1.54$, a large effect by any standard). "Excellent" grades tripled, from 12.5% to 40.6%, while "unsatisfactory" grades dropped from 21.9% to 3.1%, and students in the experimental group also needed about 22% less time per topic. So the gains did not come at the cost of extra classroom hours; if anything, students got there faster. The sharp drop in failing grades is worth sitting with: it suggests the students who benefited most were the ones conventional text-only teaching was already failing, which lines up with Vygotsky's (1978) point that scaffolding, in this case tables and visuals doing work that dense prose alone could not, extends how much material a student can actually handle.

4.2. Data-Type Combinations, Expert Evaluation, and Student Perception

Within the experimental group, achievement rose steadily with each added data type (Table 3), peaking when all three were combined.

Table 3. Pearson correlations between data-type combinations and achievement (n = 32)

Data-type combination	Pearson's r	p
Text + table	0.42	< .01
Text + visual	0.58	< .001
Text + table + visual	0.67	< .001

That steady climb, from 0.42 to 0.58 to 0.67, is a fairly direct confirmation of the many-to-one fusion principle Mu et al. (2020) described, just applied in the opposite direction from how they used it: instead of fusing data to measure learning more precisely, this study fused data to produce more learning in the first place, and it worked. It also fits Siemens's (2005) point about learning as connection-building rather than fact absorption, since the materials that scored best were exactly the ones explicitly linking a claim in the text to a number in a table and a shape in a diagram.

Table 4. Expert panel evaluation of instructional material (n = 5)

Criterion	Mean rating (1–5)
Content clarity	4.6
Text–visual coherence	4.4
Practical applicability	4.7
Informational consistency	4.3
Overall effectiveness	4.5

The rating scale held together well (Cronbach's $\alpha = 0.89$), close to the 0.977 Moreira-Choez et al. (2024) got with their CDES instrument, which is a reasonable sign that Likert-based evaluation works consistently in this kind of research. Among students, 87.5% found the multitype material more convenient than text alone, 78.1% said the visuals helped them understand faster, and 65.6% pointed specifically to the tables as useful for comparing numbers across platforms. But 15.6% also said some sections felt overloaded with information, and that complaint matters. It suggests the many-to-one relationship is not a straight line all the way up: there is probably a point past which adding more formats stops helping and starts overwhelming, which fits ordinary cognitive load theory even though this study did not measure load directly. In other words, fusion helps, but only up to a point that has to be judged carefully rather than assumed.

4.3. Summary

Put together, the results show that multitype fusion teaching produced real, statistically solid gains in both how much students learned and how fast, that the size of the gain tracked closely with how much fusion was used, and that experts and students largely agreed the material was an improvement, with one specific caveat: cram in too many formats without care and it backfires.

5. Conclusion and Recommendations

This study built and tested a teaching method, based on multitype data-processing principles, for digital-technology courses. Three things came out of it. First, the international literature on multimodal learning analytics turned out to translate well into an actual instructional-design method, something nobody had tried for this subject area before. Second, the classroom comparison found a real, fairly large advantage for multitype instruction, 13.4 points higher on average, 22% faster mastery, and a large effect size ($d = 1.54$). Third, that advantage scaled with how much fusion was used, up to a point where too much information density started working against students rather than for them.

5.1. Practical Recommendations

A few things follow from this. Institutions teaching digital technology should treat text-table-visual integration as a standard requirement for course materials, not an optional extra. Each topic should include at least one comparison table and several relevant visuals tied directly to the text. Materials should separate core content from optional deeper material, so students who are already overloaded are not forced through everything at once. Instructors need some TPACK-informed training in how to build this kind of material well, since it is not intuitive to everyone. And institutions evaluating course materials should use structured rating rubrics like the one tested here, which held up reliably ($\alpha = 0.89$).

5.2. Limitations and Future Research

This was one department, one university, 64 students, so the numbers should not be over-generalized to all of Uzbekistan or Central Asia without further testing. The design was quasi-experimental rather than fully randomized, given practical constraints on how classes could be assigned, and outcomes were measured over one semester with no follow-up later on. The informational-density problem was picked up through student self-report rather than any direct measure of cognitive load, so the exact threshold where fusion stops helping remains a guess rather than a measured fact. Future work should repeat this across more institutions and students, add longer-term follow-up, measure cognitive load directly to pin down that threshold, and check whether any of this holds for subjects outside digital technology.

The core finding, though, seems solid: fusing text, tables, and visuals in a deliberate way improves how well students learn technically dense material, it does so without costing extra class time, and it seems to help the students who need it most.

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