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Digital Managerial Readiness of University Teachers: A Formative Index and Evidence of Competence-Effect Imbalance from Uzbekistan

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Abstract: This article develops a formative index of digital managerial readiness (DMR) for university teachers and applies it to an anonymous survey of 110 teachers in Uzbekistan conducted in September-October 2025. The index combines eight indicators in four blocks – use, competence, organisational support and perceived managerial effect with equal weights, and a variant (DMR3) excludes the effect block to avoid tautology when readiness is related to its perceived outcome. Estimates use Wilson and bootstrap confidence intervals, Spearman correlations with Holm correction, and robustness checks over five alternative codings and 5,000 random weighting schemes. The mean DMR is 68.7 (95% CI 66.5–70.9) and DMR3 is 63.4 (60.9–65.9), but the profile is markedly unbalanced: perceived effect (84.4) exceeds competence (53.4) by 31 points on average, and 59.1% of respondents show a gap of 20 points or more. Blocks are weakly correlated (Spearman ρ between 0.01 and 0.16, except use-effect at 0.40), which supports interpreting readiness as a profile rather than a single score. Rankings of respondents are moderately robust to weights (median $\rho = 0.85$), whereas absolute levels are not. Open-ended answers name equipment and internet quality as the main obstacles, and this is consistent with closed-question data. The study offers a reproducible diagnostic instrument and a pilot-control design for evaluating managerial measures, and it states clearly what a self-selected single survey can and cannot support.

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1. Introduction

Digital tools now carry a large share of the operations through which universities plan, organise, coordinate and control teaching: course materials are distributed, assignments are collected, feedback is given and records are kept through learning platforms, messengers and cloud services. In Uzbekistan this shift is supported by national policy that places digital technologies among the priorities of higher-education modernisation [1], [2]. Yet policy documents set goals and conditions; they do not show how an individual teacher's use of digital tools translates into managerial capacity at the level of a course, a department or a university.

From the management perspective, the functional view of administration – planning, organisation, coordination and control [3] and the theory of transaction costs [4] suggest that digital tools lower coordination costs only when they are embedded in organisational procedures. The resource-based view adds that technology alone is rarely a source of advantage; it matters in combination with competences and routines that are hard to

replicate [5]. Technology-acceptance research stresses perceived usefulness and facilitating conditions [6], [7], teacher-knowledge frameworks stress the interplay of technology, pedagogy and content [8], [9], and the information-systems success model emphasises the quality of the system, the information and the service [10]. Together these streams imply that readiness for digital management has several distinct components that need not move together.

Most empirical studies, however, either evaluate the pedagogical effectiveness of tools or the acceptance of technology by individual users. Reproducible diagnostics at the level of teachers that combine practice, competence, organisational support and perceived managerial effect in one instrument are rare, and they are particularly scarce for transition economies. A second difficulty concerns measurement. Readiness components are not interchangeable indicators of a single latent trait, so reflective scale logic is inappropriate, and a formative index is the natural choice [11], [12]. Such an index, however, is only useful if its construction rules are explicit and its sensitivity to those rules is reported.

The purpose of this article is to develop and test a formative index of digital managerial readiness for university teachers, and to establish what it reveals in an anonymous survey of 110 teachers in Uzbekistan. The contribution is threefold. First, the article specifies the index and a variant that separates readiness from perceived effect. Second, it documents a systematic imbalance between perceived effect and competence and shows that the blocks are only weakly related, so that a single score hides the managerially relevant information. Third, it reports sensitivity to coding and weights and derives, from the data, a design for evaluating managerial measures on pilot and control groups.

2. Materials and methods

The data come from an anonymous bilingual (Uzbek and Russian) online questionnaire administered with Google Forms between 23 September and 15 October 2025. It contains 15 substantive questions: twelve closed single-answer items, one multiple-choice item on platforms and two open-ended items. The dataset has 110 responses with no missing values in the substantive fields and no fully identical questionnaires. The survey did not record institution, position, tenure, age or region, and participation was voluntary: 69.1% of the responses arrived on a single day (4 October 2025), which points to one main distribution wave. The sample is therefore an accessible, self-selected group [13]; results describe this group, confidence intervals treat it as a simple random sample and should be read as technical descriptions, and no extrapolation to all Uzbek teachers is attempted. Participants gave their answers anonymously and no personal data were collected.

Eight indicators represent four blocks (Table 1). B_1 (use) combines frequency of use and breadth of platforms; B_2 (competence) combines completed training and self-assessed proficiency in media technologies; B_3 (support) combines knowledge of a media or coordination centre and perceived internet stability; B_4 (perceived effect) combines the perceived contribution of platforms to management efficiency and the perceived impact of digital tools on managing the educational system. Each indicator is rescaled to [0, 1]. Frequency of use is coded 1 (regular) or 0.5 (sometimes); breadth is the number of platforms ticked divided by 10 and capped at 1; training is 1 (yes), 0.5 (planning) or 0 (no); the four-category ordinal items are coded 0, 1/3, 2/3, 1; the existence of a centre is coded 1 (yes), 0.5 (do not know; 0 in the conservative scenario) or 0 (no).

Table 1. Indicator system and coding of the DMR index

Block	Indicators (questionnaire item)	Coding (0-1)
B ₁ Use	Frequency of use (Q1); breadth of platforms (Q3)	regular = 1, sometimes = 0.5; platforms ticked / 10, capped at 1
B ₂ Competence	Training completed (Q5); self-assessed proficiency (Q7)	yes = 1, planning = 0.5, no = 0; four ordinal categories 0, 1/3, 2/3, 1
B ₃ Support	Media/coordination centre exists (Q8); internet stability (Q10)	yes = 1, do not know = 0.5 (0 in conservative scenario), no = 0; four ordinal categories
B ₄ Perceived effect	Contribution of platforms to management efficiency (Q4); impact of digital tools on managing the educational system (Q13)	four ordinal categories 0, 1/3, 2/3, 1

Note: Q2, Q6, Q9, Q14 and Q15 are analysed as context and are not part of the index. DMR = mean of B₁–B₄; DMR₃ = mean of B₁–B₃.

For respondent *i*, the block score is the mean of its indicators, and the indices are

$$B_{k,i} = 100 \cdot (1/|I_k|) \sum_{j \in I_k} x_{ij}, \quad k = 1, \dots, 4 \quad (1)$$

$$DMR_i = (1/4) \sum_{k=1}^4 B_{k,i} \quad (2)$$

$$DMR_{3i} = (1/3) \sum_{k=1}^3 B_{k,i} \quad (3)$$

$$G_i = B_{4,i} - B_{2,i} \quad (4)$$

where x_{ij} is the coded indicator *j* of respondent *i*, I_k is the set of indicators of block *k* and G_i is the effect–competence gap. DMR₃ excludes B₄ because a perceived result cannot be part of the readiness that is supposed to explain it. Following the formative logic, Cronbach's alpha is not used to judge the index [11]; it is reported only as an illustration. Interpretation bands (below 40 – low; 40–59.99 – emerging; 60–79.99 – established; 80 and above – high) are an author-defined segmentation without external calibration.

Proportions are reported with Wilson intervals [14]; means with 95% bootstrap intervals (5,000 resamples, fixed seed 20250923) [15]. Associations between ordinal indicators use Spearman's ρ with bootstrap intervals; the 12 correlations between readiness indicators and perceived effect are adjusted by the Holm procedure [16]. Group differences use the Kruskal–Wallis and Mann–Whitney tests with Cliff's δ [17], and categorical pairs use χ^2 with Cramér's *V* supplemented by exact and permutation tests because most tables are sparse. Robustness is examined through five alternative codings and through changes of block weights, including 5,000 random weight vectors from a flat Dirichlet distribution. Open-ended answers are coded manually into multi-label themes. Calculations were carried out in Python (NumPy, SciPy, pandas).

3. Results and discussion

Regular use of digital tools in teaching is reported by 78 respondents (70.9%, 95% CI 61.8–78.6); the rest use them sometimes (the questionnaire offered no "do not use" option, so this is not a share of users among all teachers). The platform profile is hybrid: Telegram is used by 86.4%, ChatGPT and YouTube by 67.3% each, whereas LMS-type platforms (Moodle, Google Classroom, Bilim) are used by 36.4% of respondents, and 53.6% use Telegram without any of them. On average 4.12 platforms are ticked (median 4). Training in digital technologies has been completed by 38.2% (29.6–47.5), although 93.6% regard such courses as important; 72.7% rate their media-technology proficiency as advanced or expert, and this rating does not differ by training status (71%, 76% and 73% among those trained, planning and not trained; $\rho = -0.02$). A centre for digital technologies is reported by 55.5%, while 26.4% do not know whether one exists, and 48.2% report at least occasional

internet interruptions. Perceived impact of digital tools on management is positive for 81.8% (73.6–87.9).

Table 2. Block scores and indices (0–100), n = 110

Measure	Mean	95% CI	Median	SD
B ₁ Use	63.32	60.36–66.18	67.50	15.83
B ₂ Competence	53.41	48.71–58.11	50.00	25.17
B ₃ Support	73.56	69.09–78.03	75.00	24.34
B ₄ Perceived effect	84.39	81.36–87.27	83.33	16.01
DMR	68.67	66.51–70.86	68.33	11.71
DMR ₃	63.43	60.94–65.89	63.89	13.37

Source: author's calculation. CI – bootstrap, 5,000 resamples.

The mean DMR is 68.7 (95% CI 66.5–70.9; SD 11.7), and DMR₃ is 63.4 (60.9–65.9; SD 13.4), which places the group in the "established" band (Table 2). The difference of 5.2 points is the contribution of the effect block. The share of respondents below 60 points is 20.0% by DMR but 39.1% by DMR₃. Block means differ markedly: perceived effect B₄ is highest (84.4), followed by support B₃ (73.6), use B₁ (63.3) and competence B₂ (53.4); the intervals of B₂ and B₄ do not overlap.

The central result is not the level but the structure. Perceived effect exceeds competence in 90 of 110 cases (81.8%), the mean gap G is 31.0 points, and the gap reaches 20 points in 65 cases (59.1%). Defining high effect as B₄ ≥ 80 and low competence as B₂ < 50, 51 respondents (46.4%) combine high perceived effect with low competence, 35 (31.8%) high effect with adequate competence, 14 (12.7%) moderate effect with low competence and 10 (9.1%) moderate effect with adequate competence. B₂ is the weakest block for 57 respondents, B₁ for 32, B₃ for 19 and B₄ for 2 (ties assigned to the first block). In terms of the technology-acceptance logic, perceived usefulness is high but the organisational and individual ability to realise it lags behind [6], [7].

Block correlations are low (Spearman ρ of 0.084, 0.029 and 0.041 among B₁–B₃, 0.156 for B₂–B₄ and 0.006 for B₃–B₄), with the exception of use and effect ($\rho = 0.399$, $p < 0.001$). Cronbach's alpha of the eight indicators is 0.32 (mean inter-item correlation 0.08). For a reflective scale this would signal poor reliability; for a formative index it confirms that use, competence and support vary largely independently, so that the same total score may hide very different profiles. The correlation between DMR and B₄ ($\rho = 0.51$) is partly mechanical because B₄ is a component of DMR; the correlation between DMR₃ and B₄ is 0.245 (95% CI 0.056–0.420, $p = 0.010$).

Table 3. Spearman correlations between readiness indicators and perceived effect

Pair of indicators	ρ	95% CI	p	Holm-adjusted p
Frequency of use (Q1) – Perceived contribution of platforms (Q4)	0.320	0.150 to 0.475	<0.001	0.0073
Frequency of use (Q1) – Perceived impact on management (Q13)	0.156	-0.041 to 0.356	0.1029	0.8230
Breadth of platforms (Q3) – Perceived contribution of platforms (Q4)	0.253	0.069 to 0.439	0.0077	0.0773
Breadth of platforms (Q3) – Perceived impact on management (Q13)	0.359	0.207 to 0.499	<0.001	0.0014
Training (Q5) – Perceived contribution of platforms (Q4)	0.177	-0.016 to 0.350	0.0646	0.5815

Pair of indicators	ρ	95% CI	p	Holm-adjusted p
Training (Q5) – Perceived impact on management (Q13)	0.144	-0.041 to 0.311	0.1336	0.8998
Self-assessed proficiency (Q7) – Perceived contribution of platforms (Q4)	0.004	-0.185 to 0.199	0.9682	1.0000
Self-assessed proficiency (Q7) – Perceived impact on management (Q13)	-0.046	-0.282 to 0.200	0.6302	1.0000
Support centre (Q8) – Perceived contribution of platforms (Q4)	-0.140	-0.328 to 0.043	0.1442	0.8998
Support centre (Q8) – Perceived impact on management (Q13)	0.010	-0.177 to 0.192	0.9207	1.0000
Internet stability (Q10) – Perceived contribution of platforms (Q4)	0.091	-0.080 to 0.262	0.3468	1.0000
Internet stability (Q10) – Perceived impact on management (Q13)	0.146	-0.051 to 0.343	0.1285	0.8998

Source: author's calculation. 12 correlations; Holm correction applied to the whole set.

Of the 12 correlations between readiness indicators and perceived effect only two remain significant after the Holm correction (Table 3): breadth of platforms with perceived impact on management ($\rho = 0.359$, adjusted $p = 0.0014$) and frequency of use with the perceived contribution of platforms ($\rho = 0.320$, adjusted $p = 0.0073$). Training, self-assessed proficiency, the presence of a centre and internet stability are unrelated to perceived effect, and χ^2 and exact tests for the corresponding categorical pairs also show no association. Perceived effect differs by training status ($B_4 = 89.7$ for trained, 79.4 for those planning and 81.7 for those not trained; Kruskal–Wallis $p = 0.013$; trained versus untrained Mann–Whitney $p = 0.043$, $\delta = 0.229$) and between users and non-users of LMS-type platforms (90.0 versus 81.2, $p = 0.011$); these differences are exploratory and not corrected for multiplicity. Thus the hypothesis that perceived effect rises with breadth and regularity of use is partly supported, whereas the expectation that a support centre and a stable network are associated with perceived effect is not, and training is related to perceived usefulness but not to self-rated proficiency. The pattern suggests that in this group perceived usefulness is shaped by individual experience of using tools more than by institutional conditions, while competence is not captured by self-rating.

The absolute value of the index depends on coding rules (Table 4). Alternative codings move DMR within 67.0–71.8; the rank correlation of respondents with the base index stays at 0.975–0.994. Doubling the weight of one block gives rank correlations of 0.946–0.959 but changes the band of 6 to 21 respondents; across 5,000 random weight vectors the mean index lies between 58.9 and 78.6 (95% interval), the median rank correlation with the base index is 0.85 (0.66–0.98), and a median of 35 of 110 respondents change band. Rankings are therefore moderately stable while absolute levels and classification are not, and the index is best used as a profile and for tracking changes under fixed rules. A principal-component analysis of the blocks did not produce a dominant component (37.1% of variance for the first), which again argues against a statistically derived single weighting on this sample size.

Table 4. Sensitivity of the mean DMR to coding rules and block weights

Scenario	Mean index	Change vs. base
Base coding	68.67	—
“Do not know” (Q8) = 0	67.02	−1.65
Breadth normalised by 6 platforms	71.84	+3.17
Q4 coded by interval midpoints	67.47	−1.20
Without B ₄ (DMR ₃)	63.43	−5.24
“Do not know” (Q8) excluded	69.52	+0.85
Custom platform entries split by commas	68.81	+0.14
Weight of B ₁ doubled	67.60	−1.07
Weight of B ₂ doubled	65.62	−3.05
Weight of B ₃ doubled	69.65	+0.98
Weight of B ₄ halved	66.42	−2.25

Source: author's calculation. Rank correlation with the base index: 0.994 (breadth/6), 0.975 (conservative), 0.946–0.959 (doubled weights), 0.99 (B₄ halved); 5,000 random weight vectors: median 0.85.

Of 110 respondents, 47 (42.7%) named no problem and 12 (10.9%) gave uninformative answers; 51 (46.4%) described concrete obstacles, mainly equipment and infrastructure (22.7%) and internet quality (18.2%). Competence was named in only two answers although B₂ is the weakest block. The closed and open items agree on infrastructure: among the 53 respondents reporting interruptions in the closed item, 17 (32.1%) mention the internet in the open question, against 3 of 57 (5.3%) among those with a stable connection (Fisher $p = 0.0003$, odds ratio 8.5). Conversely, 74 respondents use ChatGPT, yet only 13 of them mention artificial intelligence when listing technologies, which suggests that widely used generative tools are not recognised as a managerial object, a point relevant for institutional guidance on their use [18].

Four implications follow. First, because perceived effect is already high, communication campaigns about the benefits of digitalisation address a need that is largely met; the binding constraints are competence and conditions. Second, competence should be assessed by tasks rather than by self-rating, since self-assessed proficiency is high and independent of training. Third, practice is fragmented around general-purpose services, so a mandatory core of functions, data-handling rules and a visible service centre are more realistic than a ban on informal channels. Fourth, indicators should be introduced at the level of processes and units rather than individual teachers, because rating individuals on imperfect indicators invites gaming [19]. To evaluate any package of measures, the index and process indicators should be measured before and after implementation in pilot and control units and the effect estimated as a difference in differences [20]:

$$\Delta^* = (\bar{Y}_{post} - \bar{Y}_{pre})_{pilot} - (\bar{Y}_{post} - \bar{Y}_{pre})_{control} \quad (5)$$

With the observed SD of DMR₃ (13.4) and an assumed correlation of 0.5 between repeated measurements, the minimum detectable effect ($\alpha = 0.05$, power 0.8) is about 9.7 points with 30 respondents per group and 5.9 points with 80, so a pilot of the first size can reveal only large changes.

The sample is accessible and self-selected, without institution, position or tenure, so between-institution comparisons and population estimates are not possible; all indicators are self-reports from one instrument and are exposed to common-method bias [21]; several

response scales are asymmetric or lack a "do not use" category; open answers were coded by one researcher; and block weights are equal by convention. Content validity of the indicators was checked by the author against the theoretical frameworks, not by an independent expert panel, and the robustness stage of validation is completed, while external and predictive validation remain for further work.

4. Conclusion

The study developed a formative index of digital managerial readiness for university teachers and applied it to a survey of 110 teachers in Uzbekistan. The group's readiness is at an established level (DMR 68.7; DMR₃ 63.4), but the main finding concerns structure: perceived managerial effect (84.4) exceeds competence (53.4) by 31 points, 59.1% of respondents show a gap of at least 20 points, and the blocks are only weakly related, so a single score is insufficient for managerial decisions.

Perceived effect is associated with breadth and regularity of use but not with training, support centres or internet stability, while rankings of respondents are moderately robust to coding and weights and absolute levels are not. Open-ended answers point to equipment and internet quality as the main perceived obstacles and agree with the closed items on infrastructure.

Practically, the index supports targeting competence development, increasing the visibility of service structures, defining a mandatory core of platform functions and regulating generative AI, and it can be re-measured on pilot and control groups to test managerial measures. Future research should add an independent expert evaluation of content validity, a larger sample with institution and position identifiers, process data from learning platforms for external validation, and a pilot-control evaluation with measured time savings.

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