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MOTIVATIONAL FACTORS AND PSYCHOLOGICAL BARRIERS AMONG FACULTY MEMBERS IN THE CONTEXT OF THE DIGITAL TRANSFORMATION OF HIGHER EDUCATION: AN EMPIRICAL STUDY

Abstract

The digital transformation of higher education requires faculty members to adopt new technologies, yet significant variability persists in adoption rates. This study examined the relationships among motivation factors, psychological barriers, and technology adoption among university faculty members. Drawing on Self-Determination Theory (SDT) and the Technology Acceptance Model (TAM), we investigated how different types of motivation relate to technology anxiety, resistance to change, and digital self-efficacy. A cross-sectional survey was conducted with 154 faculty members from public, private, and national research universities. Participants completed validated instruments measuring academic motivation, technology anxiety (CARS), resistance to change, digital self-efficacy, technology acceptance, digital competence, and burnout (MBI). Data were analyzed using correlation analysis, ANOVA, multiple regression, and k-means cluster analysis. Results revealed that age was the dominant predictor across all regression models, explaining substantial variance in intrinsic motivation ($\beta = -1.09$), technology anxiety ($\beta = 0.71$), digital self-efficacy ($\beta = -0.81$), and technology acceptance ($\beta = -0.80$). External negative motivation showed strong positive correlations with psychological barriers ($r = .39–.46$) and negative correlations with self-efficacy ($r = -.55$). The cluster analysis provided four types of faculty members: Digital Leaders, Digital Enthusiasts, Pragmatic Adapters and Resistant Sceptics, based on the age of the participants.

Keywords: digital transformation, higher education, faculty motivation, self-determination theory, technology anxiety, resistance to change, digital self-efficacy.

Introduction

The fast technology advancement has been dramatically impacted the sphere of higher education [1, 2]. Universities in Kazakhstan has increasingly integrate learning management systems, video conferencing platforms, artificial intelligence tools, and cloud-based services into their educational practices [3]. This digital transformation, accelerated by the COVID-19 pandemic, has placed unprecedented demands on faculty members to adopt and effectively utilize new technologies in their teaching practices [4, 5]. However, the success of institutional digitalization efforts ultimately depends on faculty members' willingness and ability to embrace these technological changes [6].

Despite substantial investments in educational technology infrastructure and training programs, significant variability persists in faculty technology adoption rates [7]. Research consistently demonstrates that many faculty members, particularly those in senior positions, exhibit reluctance or resistance to integrating digital tools into their pedagogical practices [8, 9]. Understanding the psychological factors that influence faculty technology adoption has therefore become a critical priority for higher education administrators and policymakers seeking to optimize digital transformation initiatives.

Self-Determination Theory (SDT) [10] provides a comprehensive framework for understanding human motivation that has been successfully applied to educational contexts. SDT distinguishes between intrinsic motivation–engaging in activities for their inherent satisfaction–and extrinsic motivation, which involves performing behaviors to obtain separable outcomes. Within extrinsic motivation, SDT further differentiates several regulatory styles along a continuum of autonomy: external regulation (behavior controlled by external rewards or punishments), introjected regulation (behavior motivated by internal pressures such as guilt or ego involvement), identified regulation (conscious valuing of a behavioral goal), and integrated regulation (full assimilation of identified regulations with one's values). Research applying SDT to technology adoption suggests that autonomous forms of motivation (intrinsic motivation and identified regulation) are associated with more sustained engagement with new technologies, greater persistence in overcoming technical challenges, and more innovative uses of digital tools [11]. Conversely, controlled forms of motivation (external and introjected regulation) have been linked to superficial technology use, compliance without genuine engagement, and higher rates of technology abandonment.

In the context of higher education digitalization, faculty members may be intrinsically motivated to explore new technologies due to intellectual curiosity or the satisfaction derived from innovative teaching. Alternatively, they may experience external pressure from institutional mandates, fear of negative evaluation, or concerns about being perceived as technologically incompetent. The quality of faculty motivation – not merely its quantity – may therefore be crucial in determining the success of digital transformation initiatives.

The Technology Acceptance Model (TAM) [12] has been the dominant theoretical framework for understanding technology adoption behavior. TAM posits that individuals' behavioral intentions to use technology are primarily determined by two cognitive factors: the usefulness and ease of use.

Extensive research has validated TAM across diverse populations and technological contexts [13]. In higher education settings, perceived usefulness has consistently emerged as a strong predictor of faculty technology adoption intentions, while perceived ease of use influences adoption primarily through its effect on perceived usefulness.

In addition, psychological barriers can be caused by technology anxiety. Technology anxiety can be seen among older adults and individuals with previous limited technology usage.

The CARS: The Computer Anxiety Rating Scale [14] examines three spheres of technology anxiety: interaction related anxiety, negative experience with technology and lack of confidence in usage. Oreg [15] conceptualized dispositional resistance to change as a stable personality trait comprising four dimensions: routine seeking (preference for stable, predictable environments), emotional reaction (tendency to experience negative emotions in response to change), short-term focus (preoccupation with immediate inconveniences of change), and cognitive rigidity (reluctance to consider alternative perspectives). Research has demonstrated that dispositional resistance to change negatively predicts technology adoption intentions and behaviors across various organizational contexts.

Digital self-efficacy – individuals' beliefs about their capability to successfully use digital technologies – may serve as either a facilitator or barrier to technology adoption depending on its level.

Given the aging demographic profile of faculty in many countries and consistent findings of age-related differences in technology attitudes and skills, understanding how age influences these relationships has important practical implications for designing targeted intervention strategies.

Third, few studies have attempted to identify distinct faculty profiles or typologies based on patterns of motivation and psychological barriers. Such typologies could inform the development of differentiated support strategies tailored to the specific needs of different faculty subgroups.

Fourth, while research has examined the consequences of technology adoption for student outcomes, less attention has been paid to the implications for faculty wellbeing. The potential links between technology-related stress, psychological barriers, and faculty burnout warrant investigation, particularly given concerns about increasing rates of burnout in academia.

The present study addresses these gaps by examining the relationships among motivation factors, psychological barriers, and technology adoption among university faculty members. Drawing on Self-Determination Theory, the Technology Acceptance Model, and research on psychological barriers, we investigate how different types of motivation relate to technology anxiety, resistance to change, and digital self-efficacy.

Materials and methods

The sample consisted of 154 university faculty members from various higher education institutions. Participants were recruited through purposive sampling from public universities (47.4%, n = 73), private universities (27.9%, n = 43), and national research universities (24.7%, n = 38). The sample included faculty from diverse academic disciplines: STEM fields (31.2%, n = 48), humanities (22.7%, n = 35), social sciences (19.5%, n = 30), medicine and health sciences (12.3%, n = 19), business and economics (11.0%, n = 17), and arts (3.2%, n = 5).

Most participants were female (60.4%, n = 93), with males comprising 39.6% (n = 61) of the sample. Participants ranged in age from 25 to over 65 years, distributed across five age groups: 25–34 years (17.5%, n = 27), 35–44 years (32.5%, n = 50), 45–54 years (24.7%, n = 38), 55–64 years (18.8%, n = 29), and 65 years and older (6.5%, n = 10).

Academic positions included lecturers (11.7%, n = 18), senior lecturers (28.6%, n = 44), associate professors (33.8%, n = 52), and full professors (26.0%, n = 40). Regarding academic qualifications, 40.3% (n = 62) held master's degrees, 14.9% (n = 23) held candidate of sciences degrees, 21.4% (n = 33) held PhD degrees, and 23.4% (n = 36) held doctoral degrees (Doctor of Sciences). The instruments used are: Academic Motivation Scale of Vallerand et al., intrinsic motivation questionnaire, Zamfir-Rean methodology, Computer Anxiety Rating Scale, Oreg's Resistance to Change Scale, digital-self-efficacy questionnaire, Technology Acceptance Model, Digital Competency Framework for Educators and Maslach Burnout Inventory (MBI).

Research participants were invited to the study via e-mail and WhatsApp invitations. The questionnaire was anonymous and took approximately 20–25 minutes.

The statistical analyses were conducted using R. Means, standard deviations, and ranges were calculated for all continuous variables. Frequency distributions were computed for categorical demographic variables. Pearson product-moment correlation coefficients were computed to examine bivariate relationships between motivation factors and psychological barrier variables. Given the number of correlations examined, a more conservative alpha level of .01 was adopted for interpretation, although coefficients significant at the .05 level are also reported. One-way analyses of variance (ANOVAs) were conducted to examine differences in motivation and psychological barrier variables across age groups (25–34, 35–44, 45–54, 55–64, and 65+ years), academic positions, and university types. Effect sizes were calculated using eta-squared (η^2), with values of .01, .06, and .14 interpreted as small, medium, and large effects, respectively (Cohen, 1988). Independent samples t-tests were conducted to examine gender differences. Effect sizes were calculated using Cohen's d.

Multiple linear regression analyses were conducted to identify predictors of key outcome variables: intrinsic motivation, technology anxiety, digital self-efficacy, technology acceptance, and emotional exhaustion. Predictor variables were selected based on theoretical relevance and preliminary correlation analyses. Age was included as a continuous predictor (coded as the midpoint of each age category: 30, 40, 50, 60, and 70 years). Standardized regression coefficients (β) were computed to allow comparison of predictor effect sizes. Multicollinearity was assessed using variance inflation factors (VIF), with values below 5.0 considered acceptable.

K-means cluster analysis was conducted to identify distinct faculty profiles based on motivation and psychological barrier variables. Six variables were included in the clustering solution: intrinsic motivation (total), external negative motivation, technology anxiety, digital self-efficacy, resistance to change, and digital competence. All variables were standardized (z-scores) prior to analysis to ensure equal weighting.

The optimal number of clusters was determined by examining the within-cluster sum of squares (elbow method) and the ratio of between-cluster to total variance. Solutions with 2 to 6 clusters were evaluated, and the final solution was selected based on interpretability and statistical criteria. The k-means algorithm was initialized with 25 random starts to ensure stable cluster assignments. Cluster profiles were characterized by examining mean scores on clustering variables and demographic composition.

Statistical significance was set at $\alpha = .05$ for all analyses unless otherwise specified. For multiple comparisons, appropriate corrections were applied, and effect sizes are reported alongside significance tests to facilitate interpretation of practical significance.

Results

Table 1 presents descriptive statistics for all key variables. Regarding motivation factors, intrinsic motivation scores were below the scale midpoint (M = 3.22, SD = 0.76, on a 1–7 scale), while external negative motivation was elevated (M = 4.91, SD = 0.73). Professional internal motivation was relatively low (M = 2.52, SD = 0.68, on a 1–5 scale), whereas external negative professional motivation was above average (M = 3.62, SD = 0.69). Concerning psychological barriers, technology anxiety was moderately high (M = 3.58, SD = 0.57, on a 1–5 scale), and resistance to change was elevated (M = 4.15, SD = 0.61, on a 1–6 scale). Digital self-efficacy was below the scale midpoint (M = 4.18, SD = 1.14, on a 1–10 scale). Digital competence was also relatively low (M = 2.41, SD = 0.46, on a 1–5 scale), and technology acceptance (TAM) scores were below average (M = 3.22, SD = 0.75, on a 1–7 scale).

Table 1 – Descriptive Statistics for Key Variables (N = 154)

Variable	M	SD	Min	Max	Scale
Motivation Factors					
Intrinsic motivation (total)	3.22	0.76	1.50	5.08	1–7
IM – Cognition	3.12	1.06	1.00	5.75	1–7
IM – Achievement	3.25	1.04	1.00	6.00	1–7
IM – Self-development	3.31	0.94	1.00	5.75	1–7
Identified regulation	4.52	0.55	3.50	6.00	1–7
Introjected regulation	4.94	0.94	2.50	7.00	1–7
External regulation	4.87	0.91	2.50	7.00	1–7
Amotivation	4.73	1.01	1.75	7.00	1–7
Internal professional motivation	2.52	0.68	1.00	4.25	1–5
External positive motivation	3.01	0.38	2.25	4.00	1–5
External negative motivation	3.62	0.69	1.50	5.00	1–5
Psychological Barriers					
Technology anxiety	3.58	0.57	2.25	4.75	1–5
Negative attitude toward technology	3.50	0.75	1.50	5.00	1–5
Confidence in technology use	2.45	0.68	1.00	4.00	1–5
Routine seeking	4.17	0.83	2.00	6.00	1–6
Emotional reaction to change	4.16	0.90	1.50	6.00	1–6
Short-term focus	4.25	0.79	2.25	5.75	1–6
Cognitive rigidity	4.04	0.91	1.00	6.00	1–6
Resistance to change (total)	4.15	0.61	2.56	5.56	1–6
Digital self-efficacy	4.18	1.14	1.50	6.80	1–10
Other Variables					
Digital competence	2.41	0.46	1.29	3.81	1–5
Technology acceptance (TAM)	3.22	0.75	1.58	5.00	1–7
Emotional exhaustion	3.77	0.78	1.78	5.56	0–6
Note: Compiled by the authors.					

Pearson correlation coefficients were computed to examine the relationships between motivation factors and psychological barriers. Table 2 presents the correlation matrix. The analysis revealed several significant associations.

Intrinsic motivation components showed consistent negative correlations with psychological barriers. Specifically, intrinsic motivation for cognition was negatively correlated with technology anxiety ($r = -.37$, $p < .001$), negative attitude ($r = -.30$, $p < .001$), and resistance to change ($r = -.39$, $p < .001$), while positively correlated with confidence ($r = .33$, $p < .001$) and digital self-efficacy ($r = .43$, $p < .001$). Similar patterns emerged for intrinsic motivation for achievement and self-development.

External negative motivation demonstrated strong positive associations with all barrier variables. The correlation between external negative motivation (SDT) and technology anxiety was $r = .46$ ($p < .001$), and its correlation with digital self-efficacy was $r = -.55$ ($p < .001$), representing the strongest association in the matrix. External negative professional motivation showed a comparable pattern, correlating positively with anxiety ($r = .39$, $p < .001$) and resistance ($r = .45$, $p < .001$), and negatively with self-efficacy ($r = -.49$, $p < .001$).

Internal professional motivation exhibited the opposite pattern, showing negative correlations with technology anxiety ($r = -.46$, $p < .001$) and resistance ($r = -.38$, $p < .001$), and a positive correlation with digital self-efficacy ($r = .48$, $p < .001$).

Notably, identified regulation showed no significant correlations with any psychological barrier variables (all rs < .15, all ps > .05), suggesting that internalized acceptance of digitalization's value is independent of psychological barriers.

Table 2 – Correlation Matrix: Motivation Factors and Psychological Barriers (N = 154)

Variable	1	2	3	4	5
Motivation Factors	Anxiety	Neg. Attitude	Confidence	Resistance	Self-efficacy
1. IM – Cognition	−.37***	−.30***	.33***	−.39***	.43***
2. IM – Achievement	−.35***	−.42***	.34***	−.48***	.43***
3. IM – Self-development	−.34***	−.22**	.34***	−.40***	.34***
4. Identified regulation	.03	−.03	−.04	−.12	.09
5. Introjected regulation	.28***	.28***	−.27***	.26**	−.43***
6. External regulation	.45***	.32***	−.36***	.28***	−.44***
7. Amotivation	.22**	.13	−.13	.24**	−.27***
8. Internal professional motivation	−.46***	−.19*	.27***	−.38***	.48***
9. External positive motivation	.09	.16*	−.21*	.22**	−.25**
10. External negative motivation	.39***	.34***	−.35***	.45***	−.49***
Note: Compiled by the authors.					

* $p < .05$. ** $p < .01$. *** $p < .001$.

One-way analyses of variance (ANOVAs) were conducted to examine differences across five age groups (25–34, 35–44, 45–54, 55–64, and 65+ years). As shown in Table 3, all comparisons yielded significant results with large effect sizes.

Intrinsic motivation significantly decreased with age, $F(4, 149) = 56.88$, $p < .001$, $\eta^2 = .60$. Young faculty (25–34 years) reported the highest intrinsic motivation ($M = 4.01$, $SD = 0.62$), while older faculty (65+) reported the lowest ($M = 1.93$, $SD = 0.38$). Conversely, external negative motivation significantly increased with age, $F(4, 149) = 25.89$, $p < .001$, $\eta^2 = .41$, with oldest faculty showing the highest scores ($M = 5.84$, $SD = 0.51$) compared to youngest faculty ($M = 4.35$, $SD = 0.68$).

Technology anxiety showed a strong age-related increase, $F(4, 149) = 34.94$, $p < .001$, $\eta^2 = .48$, with means ranging from 2.96 ($SD = 0.41$) in the youngest group to 4.33 ($SD = 0.36$) in the oldest group. Digital self-efficacy demonstrated the inverse pattern, $F(4, 149) = 65.43$, $p < .001$, $\eta^2 = .64$, declining from 5.57 ($SD = 0.71$) to 2.27 ($SD = 0.53$) across age groups.

The largest effect size was observed for digital competence, $F(4, 149) = 123.49$, $p < .001$, $\eta^2 = .77$, with a substantial decline from 3.00 (SD = 0.35) in the youngest group to 1.57 (SD = 0.21) in the oldest group. Resistance to change, $F(4, 149) = 54.41$, $p < .001$, $\eta^2 = .59$, and emotional exhaustion, $F(4, 149) = 16.60$, $p < .001$, $\eta^2 = .31$, also increased significantly with age.

Table 3 – Descriptive Statistics and ANOVA Results by Age Group

Variable	25–34	35–44	45–54	55–64	65+	F	p	η²
	(n = 27)	(n = 50)	(n = 38)	(n = 29)	(n = 10)			
Intrinsic motivation	4.01	3.58	3.03	2.57	1.93	56.88	< .001	.60
External negative motivation	4.35	4.67	4.84	5.59	5.84	25.89	< .001	.41
Technology anxiety	2.96	3.42	3.68	4.06	4.33	34.94	< .001	.48
Digital self-efficacy	5.57	4.54	4.01	3.17	2.27	65.43	< .001	.64
Resistance to change	3.43	3.90	4.36	4.71	4.92	54.41	< .001	.59
Digital competence	3.00	2.61	2.28	1.94	1.57	123.49	< .001	.77
Technology acceptance	4.20	3.37	3.13	2.54	2.18	56.80	< .001	.60
Emotional exhaustion	3.12	3.59	3.86	4.27	4.67	16.60	< .001	.31
Note: Compiled by the authors.								

Note: Effect size interpretation: $\eta^2 = .01$ (small), $\eta^2 = .06$ (medium), $\eta^2 = .14$ (large).
Compiled by the authors.

Independent samples t-tests were conducted to examine gender differences. No significant differences were found between female (n = 93) and male (n = 61) faculty members on any variable (all ps > .05). Effect sizes were uniformly small (Cohen's d range: −0.21 to 0.20). Female faculty reported slightly higher intrinsic motivation (M = 3.27, SD = 0.78) compared to males (M = 3.14, SD = 0.74), $t(114.9) = 1.00$, $p = .322$, $d = 0.17$. Similarly, no significant differences emerged for technology anxiety, $t(117.3) = -0.57$, $p = .568$, $d = -0.10$, or digital self-efficacy, $t(121.1) = 1.21$, $p = .230$, $d = 0.20$.

Multiple regression analyses were conducted to identify predictors of key outcome variables. Table 4 summarizes the results of five regression models. The regression model predicting intrinsic motivation was significant, $F(6, 147) = 42.93$, $p < .001$, $R^2 = .64$. Age emerged as the strongest predictor ($\beta = -1.09$, $p < .001$), indicating that older faculty reported substantially lower intrinsic motivation. Self-efficacy was also a significant predictor ($\beta = -0.20$, $p = .016$), though the negative coefficient suggests a suppression effect when controlling for age. Technology acceptance showed a marginal negative association ($\beta = -0.14$, $p = .068$).

The model predicting technology anxiety was significant, $F(5, 148) = 27.51$, $p < .001$, $R^2 = .48$. Age was the only significant predictor ($\beta = 0.71$, $p < .001$), indicating that anxiety increases substantially with age. Neither external negative motivation (SDT: $\beta = 0.06$, $p = .415$; professional: $\beta = 0.02$, $p = .765$) nor self-efficacy ($\beta = 0.07$, $p = .508$) contributed unique variance when age was controlled.

The model predicting self-efficacy was significant, $F(5, 148) = 54.49$, $p < .001$, $R^2 = .65$. Age again emerged as the dominant predictor ($\beta = -0.81$, $p < .001$). Intrinsic motivation showed a significant negative relationship ($\beta = -0.18$, $p = .020$), which may reflect multicollinearity with age. External negative professional motivation ($\beta = -0.07$, $p = .250$) and resistance ($\beta = -0.07$, $p = .367$) were not significant predictors.

The model predicting technology acceptance (TAM) was significant, $F(5, 148) = 41.70$, $p < .001$, $R^2 = .59$. Age was the primary predictor ($\beta = -0.80$, $p < .001$). Intrinsic motivation showed a marginal effect ($\beta = -0.16$, $p = .070$), while self-efficacy ($\beta = 0.04$, $p = .630$), anxiety ($\beta = -0.03$, $p = .705$), and digital competence ($\beta = 0.03$, $p = .796$) were not significant.

The model predicting emotional exhaustion (burnout) was significant but explained less variance, $F(5, 148) = 13.94$, $p < .001$, $R^2 = .32$. Age showed a marginally significant positive trend ($\beta = 0.34$, $p = .061$), and technology anxiety exhibited a similar trend ($\beta = 0.16$, $p = .097$). Neither external negative motivation ($\beta = 0.04$, $p = .593$), self-efficacy ($\beta = -0.02$, $p = .858$), nor intrinsic motivation ($\beta = -0.08$, $p = .452$) were significant predictors.

Table 4 – Summary of multiple regression analyses

Outcome Variable	R^2	R^2adj	F	df	Significant Predictors
Intrinsic motivation	.64	.62	42.93***	6, 147	Age (β = −1.09***), Self-efficacy (β = −0.20*)
Technology anxiety	.48	.46	27.51***	5, 148	Age (β = 0.71***)
Digital self-efficacy	.65	.64	54.49***	5, 148	Age (β = −0.81***), Intrinsic motivation (β = −0.18*)
Technology acceptance	.59	.57	41.70***	5, 148	Age (β = −0.80***)
Emotional exhaustion	.32	.30	13.94***	5, 148	Age (β = 0.34†)
Note: Compiled by the authors.					

Note: β = standardized coefficient. * $p < .10$. * $p < .05$. *** $p < .001$.

Compiled by the authors.

K-means cluster analysis was conducted to identify distinct faculty profiles based on motivation and barrier variables. Six variables were included: intrinsic motivation, external negative motivation, technology anxiety, digital self-efficacy, resistance to change, and digital competence. All variables were standardized prior to analysis. The optimal number of clusters was determined by examining within-cluster sum of squares and the ratio of between-cluster to total variance. A four-cluster solution was selected, explaining 58.6% of the total variance. Table 5 presents cluster profiles.

Cluster 1: Pragmatic Adapters (n = 46, 29.9%) showed moderate scores across all variables, with average intrinsic motivation (M = 3.19), moderate anxiety (M = 3.76), and average self-efficacy (M = 4.15). This cluster was predominantly composed of faculty aged 45–54 years (67.4%).

Cluster 2: Digital Enthusiasts (n = 42, 27.3%) demonstrated above-average intrinsic motivation (M = 3.59), low anxiety (M = 3.22), low resistance (M = 3.75), and relatively high self-efficacy (M = 4.52). This cluster was dominated by faculty aged 35–44 years (83.3%).

Cluster 3: Resistant Skeptics (n = 42, 27.3%) exhibited the lowest intrinsic motivation (M = 2.42), highest external negative motivation (M = 5.66), highest anxiety (M = 4.10), lowest self-efficacy (M = 2.97), and highest resistance (M = 4.77). This cluster was predominantly composed of senior faculty: 66.7% aged 55–64 and 23.8% aged 65+.

Cluster 4: Digital Leaders (n = 24, 15.6%) showed the most favorable profile: highest intrinsic motivation (M = 4.06), lowest external negative motivation (M = 4.20), lowest anxiety (M = 2.96), highest self-efficacy (M = 5.77), lowest resistance (M = 3.45), and highest digital competence (M = 3.01). This cluster was almost exclusively young faculty: 95.8% aged 25–34 years.

Table 5 – Cluster profiles: means and demographic composition

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Total
	Pragmatic	Enthusiasts	Skeptics	Leaders	Sample
n (%)	46 (29.9%)	42 (27.3%)	42 (27.3%)	24 (15.6%)	154
Profile Variables					
Intrinsic motivation	3.19	3.59	2.42	4.06	3.22
External negative motivation	4.80	4.67	5.66	4.20	4.91
Technology anxiety	3.76	3.22	4.10	2.96	3.58
Digital self-efficacy	4.15	4.52	2.97	5.77	4.18
Resistance to change	4.33	3.75	4.77	3.45	4.15
Digital competence	2.36	2.62	1.89	3.01	2.41
Age Distribution (%)					
25–34 years	0.0	9.5	0.0	95.8	17.5
35–44 years	30.4	83.3	0.0	4.2	32.5
45–54 years	67.4	7.1	9.5	0.0	24.7
55–64 years	2.2	0.0	66.7	0.0	18.8
65+ years	0.0	0.0	23.8	0.0	6.5
Note: Compiled by the authors.					

The results revealed several consistent patterns:

1. Age as a universal predictor: Age emerged as the strongest predictor in all regression models, explaining substantial variance in intrinsic motivation ($\beta = -1.09$), technology anxiety ($\beta = 0.71$), self-efficacy ($\beta = -0.81$), and technology acceptance ($\beta = -0.80$).
2. Detrimental effects of external negative motivation: External negative motivation consistently showed positive correlations with all psychological barriers (anxiety, negative attitudes, resistance) and negative correlations with protective factors (confidence, self-efficacy), with effect sizes ranging from $r = .34$ to $r = -.55$.
3. Protective role of intrinsic motivation: All components of intrinsic motivation were negatively associated with barriers and positively associated with self-efficacy, supporting Self-Determination Theory predictions.
4. Independence of identified regulation: Notably, identified regulation showed no significant relationships with psychological barriers, suggesting that internalized acceptance of digitalization's importance operates independently of anxiety or resistance.
5. Distinct faculty typology: Four distinct faculty types were identified, strongly differentiated by age, with "Resistant Skeptics" (predominantly senior faculty) showing the most challenging profile for digital transformation initiatives.

Discussion

The research results showed number of patterns that can be important in the context of study of digital transformation and psychological barriers of faculty members.

First, age emerged as the dominant predictor across all regression models, explaining variance in intrinsic motivation ($\beta = -1.09$), technology anxiety ($\beta = 0.71$), digital self-efficacy ($\beta = -0.81$), and technology acceptance ($\beta = -0.80$). This finding is critically important for the further technology adoption in the sphere of higher education.

Second, the correlation analyses demonstrated that intrinsic motivation was consistently negatively associated with psychological barriers (technology anxiety, resistance to change) and positively associated with protective factors (digital self-efficacy, confidence). Conversely, external negative motivation showed the opposite pattern, with strong positive correlations with anxiety ($r = .46$) and resistance ($r = .43$), and a strong negative correlation with self-efficacy ($r = -.55$).

Third, identified regulation showed no significant correlations with psychological barrier variables, suggesting that internalized acceptance of digitalization's value operates independently of anxiety or resistance. Fourth, cluster analysis identified four distinct faculty types–Digital Leaders, Digital Enthusiasts, Pragmatic Adapters, and Resistant Skeptics–that were strongly differentiated by age.

The present findings strongly support the application of Self-Determination Theory to understanding faculty technology adoption. Consistent with SDT predictions [12], autonomous forms of motivation (intrinsic motivation) were associated with more favorable attitudes toward technology, lower anxiety, and higher self-efficacy. Faculty members who engage with educational technologies out of genuine interest and satisfaction appear to experience fewer psychological barriers and demonstrate greater openness to digital innovation.

Conversely, controlled forms of motivation (external and introjected regulation) were associated with heightened psychological barriers. The finding that external negative motivation showed the strongest negative correlation with digital self-efficacy ($r = -.55$) is particularly noteworthy.

Age was the strongest predictor in all five regression models, often overshadowing other theoretically important variables. This finding extends previous research on age-related differences in technology adoption by demonstrating that age effects persist even when controlling for motivation, self-efficacy, and other psychological factors.

The age effect observed in this study likely reflects multiple underlying processes. First, generational differences in technology exposure during formative years may create lasting differences in comfort and familiarity with digital tools. Second, age-related changes in cognitive flexibility and learning capacity may make technology adoption more effortful for older adults. Third, career stage differences may influence motivation: younger faculty seeking tenure may perceive stronger incentives for technology adoption, while senior faculty with established reputations may see less benefit from changing their pedagogical approaches.

The four-cluster solution provides a practically useful typology for understanding faculty diversity in technology adoption. Each cluster represents a distinct profile with specific characteristics and support needs.

Digital Leaders (15.6%). This cluster, composed almost exclusively of young faculty (95.8% aged 25–34), represents the vanguard of digital transformation. These individuals demonstrate the highest intrinsic motivation, lowest anxiety, highest self-efficacy, and greatest digital competence. They require minimal direct support for technology adoption but represent valuable resources for peer mentoring and institutional change leadership.

Digital Enthusiasts (27.3%). Dominated by faculty aged 35–44 (83.3%), this cluster shows above-average intrinsic motivation and self-efficacy with relatively low anxiety and resistance. These individuals are positively disposed toward technology but may benefit from advanced training opportunities. They represent a natural bridge between Digital Leaders and more hesitant colleagues.

Pragmatic Adapters (29.9%). This largest cluster, predominantly aged 45–54 (67.4%), shows moderate scores across all variables. These faculty members are neither enthusiastic nor resistant; they adopt technologies when they perceive clear benefits and adequate support. For this group, demonstrating practical applications, providing hands-on training, and ensuring reliable technical support are essential.

Resistant Skeptics (27.3%). Composed primarily of senior faculty (66.7% aged 55–64, 23.8% aged 65+), this cluster presents the greatest challenge for digital transformation initiatives. With the lowest intrinsic motivation, highest anxiety, lowest self-efficacy, and highest resistance, these individuals require intensive, patient, and respectful support. Importantly, coercive strategies are likely to be counterproductive given the strong association between external negative motivation and psychological barriers.

Conclusion

The current research examined the psychological barriers of faculty members in the context of digital transformation of higher education. The findings showed that age can be seen as the dominant predictor of motivation, anxiety and self-efficacy. The created cluster typology can be seen as the practical framework for the development of further strategies.

Several limitations of this study should be acknowledged. First, the cross-sectional design precludes causal inferences. While the regression analyses identified predictors, the direction of causality cannot be established. Longitudinal research is needed to clarify causal mechanisms.

Second, the sample was drawn from universities in a single country, limiting generalizability to other cultural and institutional contexts. Technology attitudes and adoption patterns may differ across national contexts due to infrastructure differences, cultural values, and educational traditions. Cross-cultural replication studies are warranted.

Third, all measures were self-reported, introducing potential biases including social desirability and common method variance. Objective measures of technology use frequency and competence would strengthen future research. Additionally, the reliability coefficients for some subscales were below conventional thresholds, reflecting limitations that should be addressed in future studies.

Fourth, the age categories used in this study were relatively broad, potentially masking important within-group variability. Future research might examine age as a continuous variable or use finer-grained categories to better understand developmental trajectories.

Several directions for future research emerge from this study. First, longitudinal studies are needed to examine how motivation and psychological barriers change over time as faculty gain experience with digital technologies. Second, intervention studies should test whether strategies derived from this research–differentiated by age group, targeting identified regulation, avoiding coercive approaches–are more effective than traditional faculty development models.

The findings show that to successfully implement digital transformation in the higher education it is necessary to provide individualized strategies of digitalization for certain types of faculty members. The understanding of psychological dynamics can lead to more effective technology adoption scenarios and can facilitate digital transformation in higher education institutions.

Higher education institutions in Kazakhstan should not blindly follow the digitalization pathway, but understand the psychological needs and fears of their main driving source – faculty members.

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ЖОҒАРЫ БІЛІМ БЕРУДІҢ ЦИФРЛЫҚ ТРАНСФОРМАЦИЯСЫ КОНТЕКСТІНДЕГІ ОҚЫТУШЫЛАРДЫҢ МОТИВАЦИЯЛЫҚ ФАКТОРЛАРЫ МЕН ПСИХОЛОГИЯЛЫҚ КЕДЕРГІЛЕРІ: ЭМПИРИКАЛЫҚ ЗЕРТТЕУ

Аңдатпа

Жоғары білімнің цифрлық трансформациясы оқытушылардан жаңа технологияларды меңгеруді талап етеді, алайда олардың енгізілу деңгейі әлі де айтарлықтай өзгермелі болып қалуда. Бұл зерттеуде университет оқытушылары арасындағы мотивациялық факторлар, психологиялық кедергілер және технологияларды қабылдау арасындағы өзара байланыстар зерделенді. Өзін-өзі анықтау теориясына (ӨАТ) және технологияларды қабылдау моделіне (ТҚМ) сүйене отырып, біз мотивацияның әртүрлі түрлерінің технологиялық мазасыздықпен, өзгерістерге қарсылықпен және цифрлық өзін-өзі тиімділікпен қалай байланысатынын зерттедік. Мемлекеттік, жеке және ұлттық зерттеу университеттерінің 154 оқытушысының қатысуымен көлденең қималы сауалнама жүргізілді. Қатысушылар академиялық мотивацияны (АМШ), технологиялық мазасыздықты (ШКРҚ), өзгерістерге қарсылықты, цифрлық өзін-өзі тиімділікті, технологияларды қабылдауды, цифрлық құзыреттілікті және кәсіби тұтануды (MBI) өлшейтін валидтелген құралдарды толтырды. Деректер корреляциялық талдау, дисперсиялық талдау (ANOVA), көп реттік регрессия және k-орташалар әдісімен кластерлік талдау арқылы өңделді. Нәтижелер жасты барлық регрессиялық модельдердегі үстем предиктор ретінде анықтады: ол ішкі мотивацияның ($\beta = -1{,}09$), технологиялық мазасыздықтың ($\beta = 0{,}71$), цифрлық өзін-өзі тиімділіктің ($\beta = -0{,}81$) және технологияларды қабылдаудың ($\beta = -0{,}80$) дисперсиясының едәуір бөлігін түсіндірді. Сыртқы теріс мотивация психологиялық кедергілермен күшті оң корреляция ($r = {,}39$–${,}46$) және өзін-өзі тиімділікпен теріс корреляция ($r = -{,}55$) көрсетті. Айта кетерлігі, идентификацияланған реттеу кедергілермен маңызды байланыс танытпады. Кластерлік талдау оқытушылардың төрт түрін анықтады: «Цифрлық көшбасшылар», «Цифрлық энтузиастар», «Прагматикалық адаптерлер» және «Скептик-қарсыластар», олар жас бойынша айқын ажыратылды.

Тірек сөздер: цифрлық трансформация, жоғары білім, оқытушылардың мотивациясы, өзін-өзі анықтау теориясы, технологиялық мазасыздық, өзгерістерге қарсылық, цифрлық өзін-өзі тиімділік.

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МОТИВАЦИОННЫЕ ФАКТОРЫ И ПСИХОЛОГИЧЕСКИЕ БАРЬЕРЫ ПРЕПОДАВАТЕЛЕЙ В КОНТЕКСТЕ ЦИФРОВОЙ ТРАНСФОРМАЦИИ ВЫСШЕГО ОБРАЗОВАНИЯ: ЭМПИРИЧЕСКОЕ ИССЛЕДОВАНИЕ

Аннотация

Цифровая трансформация высшего образования требует от преподавателей освоения новых технологий, однако уровень их внедрения по-прежнему существенно варьируется. В данном исследовании изучались взаимосвязи между мотивационными факторами, психологическими барьерами и принятием технологий среди университетских преподавателей. Опираясь на теорию самодетерминации (ТСД) и модель принятия технологий (МПТ), мы исследовали, каким образом различные типы мотивации соотносятся с технологической тревожностью, сопротивлением изменениям и цифровой самоэффективностью. Было проведено поперечное анкетирование с участием 154 преподавателей государственных, частных и национальных исследовательских университетов. Участники заполняли валидированные инструменты для измерения академической мотивации, технологической тревожности (ШКРК), сопротивления изменениям, цифровой самоэффективности, принятия технологий, цифровой компетентности и профессионального выгорания (MBI). Данные анализировались с применением корреляционного анализа, дисперсионного анализа (ANOVA), множественной регрессии и кластерного анализа методом k-средних. Результаты показали, что возраст являлся доминирующим предиктором во всех регрессионных моделях, объясняя значительную долю дисперсии внутренней мотивации ($\beta = -1{,}09$), технологической тревожности ($\beta = 0{,}71$), цифровой самоэффективности ($\beta = -0{,}81$) и принятия технологий ($\beta = -0{,}80$). Внешняя негативная мотивация обнаружила сильные положительные корреляции с психологическими барьерами ($r = {,}39$–$,46$) и отрицательные корреляции с самоэффективностью ($r = -{,}55$). Примечательно, что идентифицированная регуляция не показала значимых связей с барьерами. Кластерный анализ позволил выделить четыре типа преподавателей: «Цифровые лидеры», «Цифровые энтузиасты», «Прагматичные адаптеры» и «Скептики-резистенты», которые существенно дифференцировались по возрасту.

Ключевые слова: цифровая трансформация, высшее образование, мотивация преподавателей, теория самодетерминации, технологическая тревожность, сопротивление изменениям, цифровая самоэффективность.

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