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Predictors of teachers' actual classroom technology use: The role of technological knowledge, perception/motivation, and teaching approaches

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Abstract

Integrating blended learning under the Fourth Industrial Revolution imperative requires shifting educational focus from hardware distribution to frontline teacher readiness. This study evaluated the collective and unique predictive weights of teachers' *technological knowledge* (*TK*), perceptions and motivation, and general *teaching approaches* on actual classroom technology use within the resource-constrained Ethiopian secondary school context. A non-experimental, explanatory quantitative survey design was deployed with 53 educators in Central Ethiopia Region. Due to significant baseline non-normality across variables determined by a one-sample Kolmogorov-Smirnov test ($p < .05$), parameter estimates and objectives were tested via robust multiple linear regression utilizing 2,000 bootstrap resamples. The overall regression model was statistically highly significant, $F(3, 49) = 5.056$, $p = .004$, collectively explaining 23.6% ($R^2 = .236$) of the total variance in classroom technology utilization. Individually, *TK* was the sole statistically significant unique positive predictor ($\beta = .370$, $B = 0.201$, $p = .009$, bias-corrected accelerated 95% confidence interval [0.064, 0.376]), uniquely explaining 13.6% of the variance. Conversely, general *teaching approaches* ($\beta = .285$, $p = .089$) and *perception and motivation* ($\beta = .025$, $p = .864$) carried no significant unique predictive weight. Positive psychological perceptions are secondary to concrete technical mastery. Educational policymakers must prioritize hands-on, domain-specific technological capacity building over simple mindset advocacy to achieve sustainable classroom digital transformation.

Keywords: blended learning, teacher perceptions, teacher motivation, knowledge of technology, use of technology, regression analysis

INTRODUCTION

Evaluating an organization's preparedness for e-learning requires a multi-dimensional approach that spans human, environmental, and structural factors. Currently, the educational landscape of the 21st century has undergone significant changes, primarily steered by technological advancements, especially in artificial intelligence (AI) (AlAli & Wardat, 2024). As identified by Machaba and Bedada (2022), the success of these initiatives relies heavily on a comprehensive framework of indicators. At its core, psychological readiness measures the stakeholders' state of mind, which directly impacts their ultimate effectiveness and willingness to engage in digital learning. This is closely supported by sociological readiness, which examines the interpersonal dynamics and cultural context of the environment where the technology will be deployed, alongside human resource readiness, which ensures that a robust, appropriate human-support system is available to guide users through the transition.

According to Machaba and Bedada (2022), navigating the broader context also involves environmental readiness, which assesses the internal and external macro forces influencing organizational stakeholders, as well as content readiness, which ensures the subject matter and learning objectives align with the overall e-learning vision. Finally, the practical execution depends

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Contribution to the literature

- This study fills a crucial knowledge gap about how internal teacher characteristics influence classroom digital transformation by reorienting the empirical focus from hardware provision to frontline readiness in a resource-constrained Global South setting.
- In terms of methodology, it shows how to overcome significant non-normality in small-sample educational survey data by using non-parametric bootstrap resampling (2,000 resamples), providing a strong modeling foundation for comparable low-resource research contexts.
- By demonstrating that technological knowledge (13.6% unique variance explained) is the only significant driver of classroom technology use, the findings conceptually challenge popular educational technology models and demonstrate that concrete technical mastery has far greater predictive power than general teaching approaches or positive psychological mindsets.

heavily on technical and structural foundations: technological skill (aptitude) readiness qualifies the visible technical capabilities needed to meet information and communication technology goals, equipment readiness determines the availability of suitable and adequate physical hardware, and financial readiness ensures that the necessary funding is fully secured to sustain the entire implementation process. Besides this, modern educational landscapes are undergoing a profound paradigm shift driven by the expansion of the Fourth Industrial Revolution (4IR). For educational institutions to successfully transition from conventional, rote-heavy instructional frameworks to flexible, digital delivery models, the systematic implementation of blended learning has become indispensable (Abdulmunem, 2023). While macro-level educational policies frequently mandate the deployment of learning management systems and cloud infrastructure, the micro-level execution of these digital frameworks depends heavily on the frontline operators: the classroom teachers. Extensive literature indicates that simply distributing hardware or expanding institutional connectivity does not guarantee pedagogical transformation. Recent scholarship consistently challenges technological determinism in education. Bedada and Machaba (2022b), Bedada et al. (2026), and Machaba and Bedada (2022) find that misalignment between institutional policies, pedagogical strategies, and faculty development creates barriers regardless of infrastructure investment. Similarly, Selwyn et al. (2025) argue that the expansion of digital platforms in schools has led to the "enshittification" of education—a loss of pedagogical value despite increased connectivity. Regli et al. (2026) demonstrate that providing digital devices without corresponding teacher training, leaderships, curriculum redesign, or reliable Internet access results in isolated interventions rather than systemic transformation. Instead, the successful integration of technology is an intricate process governed by psychological and behavioral variables. To understand why some educators seamlessly diversify their classrooms with digital tools while others resist technological adoption, researchers must analyze the interplay between subjective attitudes and objective technical interactions. This ongoing fragmentation is exacerbated by an institutional vacuum within localized teacher preparation programs. Many local colleges of teacher education (CTEs) operate without standardized, contextually tailored pedagogical frameworks that account for the material realities of rural and semi-urban classrooms. In pre-service training environments, digital tools are rarely modeled systematically by instructional faculties or assessed as core components of teaching practicums (Fabian et al., 2024). As a result, newly deployed teachers enter the workforce with a profound mismatch between their nominal computer literacy and their actual capacity to execute technology-enhanced instruction within specific subject matters.

To resolve this stagnation, educational technology research must move past descriptive accounts of resource scarcity and examine the underlying mathematical and behavioral predictors that govern how teachers interact with digital systems. This study addresses this need by modeling classroom technology usage as an ecosystem driven by three primary predictors: *technological knowledge* (*TK*) (the structural capability), *teaching approaches* (the pedagogical vehicle), and teachers' perception (the psychological gatekeeper).

Statement of the Problem

"Despite the widespread drive for digital upskilling, many people remain passive users of technology, engaging with technology only at a surface level – consuming content – without fully understanding how it works" (Carroll & Dastjerd, 2026, p. 4). Digitization and blended learning have eased teaching, learning, and research by creating accessible online platforms. However, in Ethiopia, educational technology is not yet responsive to all students' needs because severe digital divides persist across the country. By using innovative, technology-integrated learning methods tailored to specific content areas, teachers are expected to hone vital 21st century skills among their students, including creativity, critical thinking, communication, and collaboration (Wark & Ally, 2020).

Over the years, the Federal Democratic Republic of Ethiopia Ministry of Education and various higher education institutions (HEIs) have made substantial investments aimed at building connectivity and expanding information and communications technology (ICT) infrastructure. Yet, beyond its limited capacity to absorb a growing number of secondary graduates, higher education faces severe contemporary challenges, including low instructional quality, un-readiness for the digital age, and weak linkages between education, research, innovation, and socio-economic development. While the government has intervened via summer capacity building for secondary teachers using the technological pedagogical content knowledge (TPACK) model and e-learning for strengthening for higher education (Bedada, 2024), the broader state of digital e-learning remains limited due to a lack of concrete policies and localized guidelines to set standard technological expectations across HEIs. This low penetration of systematic e-learning has compromised the overall quality, affordability, and accessibility of education, making the entire sector highly vulnerable to external shocks (Bedada, 2021; Bedada & Machaba, 2022b; Machaba & Bedada, 2022). This structural vulnerability was deeply pronounced during the COVID-19 pandemic when HEIs were closed and completely unable to reach their student bodies. While HEIs are faced with compounding demands to transform their campuses into modern technological hubs, the impact of rapid digitization on indigenous knowledge systems has been simultaneously neglected, raising concerns regarding equity, inclusion, and cultural preservation (Gumbo, 2023).

This operational breakdown is thoroughly documented in regional literature. National assessments indicate that a major obstacle to the success of digitalization in Ethiopian schools is the critical gap in in-service teachers' pedagogical-digital skills, combined with a history of sporadic, uncoordinated implementation models (Bedada et al., 2026; Woldemariam et al., 2025). This is compounded by an acute baseline deficit in high schools, where language and science educators operate with minimal digital literacy and an absolute shortage of high-quality localized digital tools (Hunduma et al., 2023; Welesilassie & Gerencheal, 2025).

The systemic reality of the sub-Saharan classroom in particular Ethiopian teachers routinely battle inconsistent ICT usage due to poor infrastructure, limited support and weak policy implementation (Kebede et al., 2025) This reality forcing them to operate with extremely low instructional confidence when attempting to transition to blended learning models into daily classroom practice (Carroll & Dastjerd, 2026; Thepnuan & Yan, 2026). Consequently, when institutions attempt to deploy advanced systems without addressing baseline teacher readiness, it leads to a total failure of digital content delivery within actual subject matters, leaving the tech-integration process stuck at basic word processing operations (Aidoo & Chebure, 2024; Bedada et al., 2026; Kebede et al., 2025). Furthermore, because of the absence of standardized contextual frameworks, the implementation of technology in local teacher training colleges remains highly ineffective and fragmented, failing to meet the foundational targets outlined in national development roadmaps (Teferra et al., 2018).

Furthermore, the education technology plan (2020-2030) proposed the use of e-formative assessments and national e-examinations to facilitate a learner-centered digital transformation. While the Ministry of Education successfully piloted national online entrance examinations for selected schools in urban centers like Addis Ababa, it could not implement this scale nationwide, leaving the traditional paper-based exam schedule in place for the vast majority of rural students. Many researchers argue that the dominant teaching and learning processes in Ethiopia rely heavily on conventional, rote methods that fail to align with the 4IR—an alignment that is mandatory now that global learners can access knowledge anywhere and at any time (Bedada & Machaba, 2022a; Machaba & Bedada, 2022).

The 4IR has matured faster than forecasted, disrupting business, society, and traditional educational structures (Sackey & Bester, 2016; Schwab, 2016; Tapscott, 2009). Locally funded research indicates that the primary barriers to successful technology integration include massive delays in implementing a nationwide, e-cloud-based ICT infrastructure, a lack of clear coordination for the pedagogical use of ICT, and insufficient capacity-building training for both teachers and school leaders. Because the 4IR influences school vision, planning, curriculum design, and knowledge sharing developing nations must prepare citizens who possess not only specialized academic knowledge but a rich plethora of digital soft skills.

As shown in historical transitions, the development of global education must be reinvented to align with the current industrial revolution (Machaba & Bedada, 2022). Traditional educational methods are entirely unable to cope with these swift scientific changes (Alotabi, 2014), forcing schools to adapt to technological innovations to meet basic goals. However, if this transition is unmanaged or rushed without training, it leads to institutional failure rather than success, often manifesting as teacher resistance, systemic technological dropouts, student dependency, and the unproductive loss of instructional time on social media platforms.

Objective of the Study

Objective 1 (O1): To determine how collectively teachers' *TK*, *perception/motivation*, and general *teaching approaches* (including blended learning) predict their actual classroom technology use.

Objective 2 (O2): To identify the unique predictive weight of each individual factor while controlling the other variables in the model.

Research Questions

RQ1: To what extent do teachers' *TK*, *perception/motivation*, and *teaching approaches* collectively predict actual classroom technology use?

RQ2: What is the unique predictive weight of each factor on technology use when controlling for the other variables in the model?

Significance of the Study for the Ethiopian School Context

This study holds critical significance for Ethiopian schools, where the government has increasingly invested in educational technology infrastructure such as smartboards, tablets, and digital learning platforms yet faces persistent challenges in translating these resources into actual classroom practice. By identifying the extent to which teachers' *TK*, perceptions and motivation, and *teaching approaches* (including blended learning) collectively predict their actual *use of technology*, the findings will provide evidence-based guidance for the Ministry of Education, regional education bureaus, and school principals to design targeted, context-sensitive interventions. For instance, if the study reveals that motivation and perceptions are stronger predictors than *TK*, teacher training programs (e.g., those under the general education quality improvement program [GEQIP]) can shift focus from purely technical skills to mindset change and attitude cultivation. Conversely, if *TK* emerges as the dominant unique predictor, pre-service and in-service curricula can prioritize hands-on digital competency development. Furthermore, given Ethiopia's diverse school contexts ranging from urban schools with reliable electricity and Internet to rural schools with severe resource constraints the study's predictive model can help prioritize which psychological and pedagogical levers to invest in first, ensuring that limited professional development budgets yield maximum impact on actual technology integration. Ultimately, this research supports Ethiopia's broader digital education transformation agenda (e.g., the digital Ethiopia 2025 strategy) by moving beyond technology access to meaningful, sustained classroom adoption that enhances teaching and learning outcomes.

LITERATURE REVIEW

Introduction

While this study is conceptually informed by the baseline requirements of the TPACK taxonomy, the empirical construct measured herein is strictly delimited to foundational technical literacy specifically, standalone *TK*. This investigation isolates this baseline technical proficiency rather than its complex intersections, such as technological pedagogical knowledge (TPK) or technological content knowledge (TCK).

The 4IR and the Structural Imperative for Digital Soft Skills

The intrusion of the 4IR into institutional space has fundamentally redefined long-term planning, school visions, and curriculum frameworks worldwide (Alvarez-Aros et al., 2024). Under the paradigm of "Education 4.0," the primary objective of secondary schooling shifts away from acting as a simple storehouse of factual knowledge. Because digital tools allow immediate information retrieval, the modern labor market increasingly prioritizes high-level digital soft skills—such as complex computational thinking, collaborative digital problem solving, and adaptive virtual communication (Alvarez-Aros et al., 2024; Chirinda et al., 2022).

Fulfilling this demand requires educational frameworks that move away from rigid, one-size-fits-all traditional modules toward decentralized, responsive, and technology-mediated learning hubs. However, the execution of this curricular evolution is heavily dependent on the digital competence of classroom teachers (Chirinda et al., 2022). If the frontline teaching force lacks the integrated capacity to model these tools within daily lessons, national development roadmaps remain purely theoretical, failing to equip students with the soft skills necessary to escape digital marginalization.

Systemic Infrastructure Barriers and the Policy-Practice Nexus

Within the sub-Saharan context, the execution of macro-level digital policies is consistently hindered by structural bottlenecks. Empirical investigations indicate that despite significant policy goodwill expressed in national frameworks—such as Ethiopia's education sector development program VI—public secondary schools endure severe resource deficits (Areri, 2025; Hunduma & Seyoum, 2023; Hunduma et al., 2023). These deficiencies include a lack of functional computer labs, missing domain-specific software, and a total absence of technical maintenance budgets, meaning that a single hardware malfunction can permanently remove a device from service.

This baseline scarcity is further compounded by a connectivity paradox. Teachers are expected to deliver blended and online learning materials within environments defined by unstable electrical grids and slow, interrupted Internet connections (Abich & Eriku, 2023; Gumede & Ngobe, 2024). These issues are highly magnified across geographic regions; rural secondary schools endure a disproportionate share of structural neglect compared to urban administrative centers (Areri, 2025). This intense operational unpredictability discourages educators from taking pedagogical risks, prompting them to abandon digital media entirely during periods of infrastructural volatility.

TK: From Literacy to TPACK

To understand how teachers overcome or succumb to these barriers, contemporary research utilizes the TPACK framework (Koehler & Mishra, 2009). In the mid-2026 academic landscape, *TK* is no longer treated as isolated technical skill (such as knowing how to boot a machine or navigate the Internet). Instead, it is conceptualized as an integrated cognitive domain where technology directly intersects with pedagogical methods (TPK) and subject matter content (TCK) (George-Reyes et al., 2026). Moreover, ''the effectiveness of interactive digital content based on the TPACK model is in developing skills for producing educational aids and cognitive achievement'' (Aldalalah et al., 2025, p. 1). Recent literature has expanded this construct to explore "AI-TPACK," tracking how teachers utilize intelligent tools and adaptive learning data to differentiate instruction (George-Reyes et al., 2026). However, empirical findings show a persistent asymmetry: while modern in-service teachers frequently self-report adequate standalone *TK*, their comprehensive capacity to synthesize technology, pedagogy, and content (TPACK) remains low (Abubakir & Alshaboul, 2023) This deficit forms a primary cognitive barrier to effective technology integration.

Teaching Approaches as the Pedagogical Vehicle

A teacher's dominant teaching approach serves as the practical mechanism that determines how digital tools are deployed in the classroom. Active, student-centered teaching methodologies such as inquiry-based science, flipped classrooms, and data-driven formative assessments inherently require and predict sophisticated technology usage. In these active learning environments, technology is used constructively to gather data, foster collaboration, and allow students to create knowledge. Conversely, traditional, teacher-centered lecture approaches constrain technology's potential. When educators default to teacher-centric instruction due to poor professional preparation, technology integration stalls completely (Bedada & Machaba, 2022a). Rather than utilizing technology to transform learning experiences, teachers revert to utilizing high-end digital tools for primitive, analog-style tasks, such as displaying text-heavy bullet points or typing up administrative notices via basic word processing applications (Aidoo & Chebure, 2024).

Modern instructional models increasingly rely on technology-driven *teaching approaches* that optimize student learning through interactive, AI-feedback, and adaptive assessments. Interactive assessment transforms evaluation into an engaging, real-time dialogue by utilizing tools like digital content curation platforms and collaborative apps, moving classrooms away from passive testing and toward active, ongoing participation. Building on this immediacy, AI-feedback assessment automates targeted, formative critiques, giving students personalized feedback right at the moment of learning while freeing educators to focus on high-impact interventions. Finally, adaptive assessment leverages algorithm-driven platforms to continuously analyze individual student performance data, dynamically adjusting the difficulty and nature of content in real time to match the learner's unique pace. Together, these assessment paradigms shift teaching from a rigid, one-size-fits-all model into a responsive, equitable, and data-driven learning ecosystem.

Teachers' Perceptions: The Psychological Gatekeeper

Even when a teacher possesses sufficient *TK* and an innovative curriculum, actual classroom integration must pass through a psychological gatekeeper: teachers' perceptions and attitudes (Elsayary et al., 2026). Grounded in the technology acceptance model (TAM), this variable assesses an educator's perceived usefulness (PU) and perceived ease of use (PEOU) regarding digital tools. Contemporary studies show that a teacher's perception of whether a tool directly enhances student learning outcomes is the strongest direct predictor of their behavioral intention to use it (Elsayary et al., 2026). Because professional competence naturally builds self-efficacy, these psychological perceptions are heavily shaped by internal readiness and the stability of the external school ecosystem (Chan et al., 2026; Wentzel & Miele, 2016). If a teacher experiences high technological anxiety or views digital systems as an unreliable administrative burden, their negative perceptions can completely stall the integration process, leading to systemic avoidance or defensive non-use (Elsayary et al., 2026).

METHODOLOGY

Research Design

This study utilizes a non-experimental, explanatory quantitative survey design. This approach relies on descriptive and inferential statistics to evaluate the predictive weight of psychological and behavioral independent variables on a single dependent pedagogical variable.

Participants and Sampling

The sample consists of N = 53 educators who recently completed a structured professional development initiative designed around digital technology integration, content knowledge, and pedagogical

Table 1. One-sample K-S test

Variables			*Perception and motivation*	*KT*	*Use of technology*	*Teaching approaches*
N			53	53	53	53
Normal parameters[a,b]	M		11.70	32.9434	15.3585	44.9811
	SD		1.514	4.62192	2.50457	5.75624
Most extreme differences	Absolute		.371	.119	.167	.153
	Positive		.232	.084	.121	.111
	Negative		-.371	-.119	-.167	-.153
Test statistics			.371	.119	.167	.153
Asymptotic significance (2-tailed)[c]			.000	.060	.001	.003
Monte Carlo significance (2-tailed)[d]	Significance		.000	.060	.001	.004
	99% CI	Lower bound	.000	.000	.054	.000
		Upper bound	.000	.000	.066	.002

Note. [a]Test distribution is normal; [b]Calculated from data; [c]Lilliefors significance correction; & [d]Lilliefors' method based on 10,000 Monte Carlo samples with starting seed 2,000,000

knowledge (Bedada et al., 2026), and who were also involved in teaching activities during the 2026 academic year. The sample size provided adequate statistical power for parametric testing, Spearman's rank-order correlation, and ordinary least squares (OLS) multiple linear regression; a detailed discussion of this is provided in the results section of the study (Bonett & Wright, 2000).

Ethical Considerations and Data Collection

Ethical clearance was first requested and obtained from the Wachemo University Institutional Review Board (IRB). Following this official approval, the data collection process was initiated. Prior to their involvement in the study, the voluntary willingness of each participant was secured to ensure informed consent and uphold ethical research standards.

Analysis

Data was processed using SPSS version 27. First, internal consistency was verified using Cronbach's alpha (α). Second, assumption for normality and model test were employed. Third, descriptive statistics establish baseline tendencies. Fourth, a Spearman's rank-order correlation between perceptions, *TK*, *use of technology*/tool interactions, and *teaching approaches* were computed depending upon the nature of the data. Finally, simultaneous multiple linear regression was conducted to determine which specific technological interactions serve as the most critical predictors of pedagogical diversification.

RESULTS

Instrument Reliability and Validity

All subscales demonstrated acceptable reliability for the main study. Specifically, *knowledge towards technology*/blended learning (α = 0.604, 9 items), The *use of technology* for teaching (α = 0.58, 4 items), and *teaching approaches*/blended (α = 0.915, 12 items) all met the criteria for inclusion according to the study (George & Mallery, 2016; Shirawia et al., 2023; Taber, 2018). Despite variations in the alpha values, each subscale is considered sufficiently reliable to proceed with the main analysis with some criterion defined.

Inferences for Assumption and Model Test

The need for a normality test in the study is essential because it determines whether the data distribution meets the assumptions required for subsequent statistical analyses. Specifically, parametric tests (e.g., t-tests, analysis of variance (ANOVA), Pearson correlation) assume that the data are approximately normally distributed, while non-parametric tests (e.g., Mann-Whitney U, Kruskal-Wallis, Spearman's rho) are used when normality is violated. Given that the subscales in this study vary in their reliability values—some with lower α (e.g., the *use of technology* for teaching, α = 0.58, 4 items; *knowledge towards technology*/blended learning, α = 0.604, 9 items, *perception and motivation* (α = 0.869, 3 items)—normality testing becomes even more critical. It helps justify the choice of statistical methods, ensuring valid and accurate interpretation of results. Common normality tests include the Shapiro-Wilk test (suitable for smaller sample sizes) and the Kolmogorov-Smirnov (K-S) test, often supplemented by visual inspections such as Q-Q plots and histograms. Therefore, conducting normality tests is a necessary preliminary step before performing any inferential statistics in the main study.

Data Screening and Normality Diagnostics

Prior to executing the primary parametric analyses, the distributional assumptions of the dataset were rigorously evaluated using the one-sample K-S test. To maximize statistical precision given the moderate sample size (N = 53), Lilliefors significance corrections alongside Monte Carlo simulation techniques (utilizing 10,000 random samples) were applied.

As detailed in **Table 1** and **Table 2**, *TK* was found to be normally distributed within acceptable parameters (p

Table 2. Descriptive statistics for study variables

	N	M	SD	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	SE	Statistic	SE
Perception and motivation	53	11.70	1.514	-1.709	.327	4.612	.644
Knowledge towards technology	53	32.9434	4.62192	-.517	.327	.303	.644
Use of technology	53	15.3585	2.50457	-.112	.327	-.665	.644
Teaching approaches	53	44.9811	5.75624	.389	.327	.100	.644
Valid N (listwise)	53						

Table 3. Collinearity diagnostics and hetroskedasticity test of technology use

Model	Unstandardized coefficients		Standardized coefficients	t	p	Correlations			Collinearity statistics	
	B	SE	β			Zero-order	Partial	Part	Tolerance	VIF
(Constant)	2.687	3.568		.753	.455					
Perception and motivation	.042	.242	.025	.172	.864	.161	.025	.021	.731	1.368
KT	.201	.068	.370	2.956	.005	.384	.389	.369	.993	1.007
Teaching approaches	.124	.064	.285	1.950	.057	.317	.268	.243	.730	1.371

= .060). However, the remaining three variables demonstrated severe and statistically significant deviations from a normal distribution: *perception/ motivation* (p < .001), *teaching approaches* (p = .004), and the dependent variable, the *use of technology* (p = .001). Because severe non-normality can dramatically inflate standard errors and distort regular OLS p-values in moderate samples, a robust non-parametric bootstrapping method (employing 2,000 resamples) was adopted for the core regression analyses to ensure maximum validity and inference accuracy.

By integrating the descriptive data with the normality testing for the 53 surveyed participants, it becomes clear that the shape and spread of each variable's data directly dictate its statistical distribution shown in **Table 2**. *Knowledge towards technology* features a mean (M) score of 32.94 (standard deviation [SD] = 4.62), and its mild negative skewness (-.517) and low kurtosis (.303) allow it to safely satisfy the assumption of normality under the K-S test (p = .060, which is > .05). In contrast, the remaining three variables significantly violate the normality assumption (p < .05). This is most pronounced in *perception and motivation* (M = 11.70, SD = 1.51), which displays a severe negative skewness of -1.709 and a highly peaked, heavy-tailed leptokurtic distribution (kurtosis = 4.612), resulting in a highly significant deviation from normality (p < .001). Similarly, the *use of technology* (M = 15.36, SD = 2.50, kurtosis = -.665) and *teaching approaches* (M = 44.98, SD = 5.76, skewness = .389) both exhibit structural asymmetries that cause them to reject normality with significance values of p = .001 and p = .004, respectively.

Based on the above scenario and the data in **Table 1** and **Table 2**, a Spearman's rank-order correlation was chosen and conducted to assess the relationships between teachers' perceptions and motivation, *TK*, technology use, and *teaching approaches*. Preliminary descriptive analysis indicated that the *perception and motivation* variable violated the assumption of normality due to significant negative skewness and high kurtosis (see **Table 1**, as consolidated by **Table 2**). Consequently, the non-parametric Spearman's rho was utilized as a robust alternative to Pearson's r.

The Spearman technique resolves non-normality by converting the raw, skewed scores of the *perception and motivation* variable into ordinally scale-free numerical ranks. This mathematical transformation entirely neutralizes the distorting influence of the high kurtosis (4.612) and severe skewness, allowing for an accurate, un-biased assessment of the monotonic relationships between the variables. By applying this non-parametric framework, the subsequent correlation matrix yields stable, mathematically sound coefficients that can reliably inform the structural dynamics of tech-pedagogy implementation within the target educational context.

Multi-Collinearity Diagnostics

To guarantee that the independent variables independently contribute to the model without problematic overlapping variance, collinearity diagnostics were conducted. The evaluation criteria dictated that a variance inflation factor (VIF) exceeding 5.0, or a tolerance value dropping below 0.10, would suggest structural multicollinearity. The empirical diagnostics revealed that tolerance values ranged tightly from .730 to .993, while VIF statistics spanned between 1.007 and 1.371 (see **Table 3**). Because all VIF indices are exceptionally close to the baseline value of 1.0, multi-collinearity is absent from this framework, validating the structural safety of the multivariate parameters.

Objective Testing

To resolve the core objectives of this study, a multiple linear regression model was constructed to measure the predictive weight of teachers' *perception and motivation*, *TK*, and *teaching approaches* on actual classroom technology use.

Table 4. Multiple regression model summary of *technology use*

Model	R	R^2	Adjusted R^2	SE	ΔR^2	ΔF	df1	df2	p	Durbin-Watson
1	.486[a]	.236	.190	2.255	.236	5.056	3	49	0.004	2.104

Note. [a]Predictors: (Constant), *teaching approaches*, *KT*, & *perception and motivation*; ΔR^2: R^2 change; & ΔF: F change

Table 5. ANOVA metrics for combined predictors

Model		Sum of squares	N	Mean square	F	Significance
1	Regression	77.105	3	25.702	5.056	.004
	Residual	249.083	49	5.083		
	Total	326.189	52			

Note. Predictors: (Constant), *teaching approaches*, *KT*, & *perception and motivation* & Dependent variable: *Use of technology*

Table 6. Spearman rank-order correlations among study variables

			Perception and motivation	*KT*	*Use technology*	*Teaching approaches*
Spearman's rho	*Perception and motivation*	Correlation coefficient	1.000	.137	.181	.505**
		Significance (2-tailed)	.	.328	.194	.000
		N	53	53	53	53
	KT	Correlation coefficient	.137	1.000	.412**	.041
		Significance (2-tailed)	.328	.	.002	.768
		N	53	53	53	53
	Use technology	Correlation coefficient	.181	.412**	1.000	.261
		Significance (2-tailed)	.194	.002	.	.059
		N	53	53	53	53
	Teaching approaches	Correlation coefficient	.505**	.041	.261	1.000
		Significance (2-tailed)	.000	.768	.059	.
		N	53	53	53	53

Note. **Correlation is significant at the 0.01 level (2-tailed)

Analysis of the collective effect of TK, perception and motivation, and teaching approaches on technology use

Collective predictive weight: RQ1: To what extent do teachers' *TK*, *perception/motivation*, and *teaching approaches* collectively predict actual classroom technology use?

The multiple linear regression analysis presented in **Table 4** was conducted to predict technology use from *perception and motivation*, *TK*, and *teaching approaches*. In fulfillment of the first research objective, the combination of the three predictor variables collectively exerted a statistically highly significant predictive power over actual classroom technology execution. With the help of **Table 4** the model was significant, $F(3, 49) = 5.056$, $p = .004$, $R^2 = .236$, adjusted $R^2 = .190$). Only *TK* was a significant individual predictor (B = 0.201, standard error [SE] = 0.068, $\beta = .370$, t = 2.956, p = .005). Neither *perception and motivation* (p = .864) nor *teaching approaches* (p = .057) significantly predicted technology use. As we have discussed earlier in section we need to check collinearity. In **Table 3** we see that collinearity diagnostics indicated no multicollinearity concerns, with tolerance values ranging from .730 to .993 and VIF values ranging from 1.007 to 1.371. So, the data transformation was not necessary Therefore, we can further go to analyses the three predictors together. Hence, together, the three factors accounted for 23.6% of the total variance in technology usage ($R^2 = .236$, Adjusted $R^2 = .190$) see **Table 4**. The overall model summary statistics indicated that this collective predictive weight was highly statistically significant, $F(3, 49) = 5.056$, $p = .004$. This establishes that teachers' combined *TK*, psychological motivation, and structured *teaching approaches* represent an important, statistically viable framework for determining actual technological praxis. The baseline ANOVA framework proved that this collective predictive weight is highly dependable and could not have occurred by sampling error, $F(3, 49) = 5.056$, p = .004 (see **Table 5**). Nearly a quarter of the operational differences in how teachers utilize tools in secondary schools is explained directly by this collective model.

The study examined the relationships between the predictor variables and the dependent variable**.** From **Table 6** we see that the analysis revealed two statistically significant, positive correlations. First, a moderate-to-strong positive correlation was observed between *perception and motivation* and *teaching approaches*, $r_s = .505$, $p < .001$. This indicates that higher levels of motivation and perceptions are strongly associated with more robust *teaching approaches*. Second, a moderate positive correlation was found between *TK* and the *use of technology*, $r_s = .412$, p = .002, suggesting that greater *TK* is meaningfully linked to increased technology implementation.

Conversely, no statistically significant relationships were found between *perception and motivation* and *TK* (r_s = .137, p = .328), or between *TK* and *teaching approaches* (r_s = .041, p = .768). While the correlation between *use of*

Table 7. Integrated model coefficients, collinearity diagnostics, and robust bootstrap intervals

Predictor variable	UB	SB	RS (p)*	PC	PCR	Robust BCa 95% CI	Collinearity VIF
1 (Constant)	2.687	-	.483	-	-	[-5.826, 8.316]	-
Perception and motivation	.042	.025	.864	.025	.021	[-0.405, 0.723]	1.368
KT	.201	.370	.009	.389	**.369**	[0.064, 0.376]	1.007
Teaching approaches	.124	.285	.089	.268	.243	[-0.055, 0.257]	1.371

Note. UB: Unstandardized B; SB: Standardized beta; RS: Robust significance; PC: Partial correlation; & PCR: Part correlation

technology and *teaching approaches* did not reach formal statistical significance at the conventional 5% level (r_s = .261, p = .059), it demonstrates a marginal positive trend that may warrant further exploration with a larger sample size. A powerful, statistically significant positive relationship exists between a teacher's total interaction scores and their *teaching approaches* (r_s = .54, p < .001). Educators who frequently interact with digital tools demonstrate a definitive statistical shift away from traditional lecturing toward student-centered practices.

Regression analysis: The predictive weight of classroom technology use

Unique predictive weights: RQ2: What is the unique predictive weight of each factor on technology use when controlling the other variables in the model?

To address the primary objective of this research, a multiple linear regression analysis was executed to evaluate the collective predictive capability of teachers' internal characteristics and pedagogical frameworks on their classroom technology implementation. The model targeted the *use of technology* as the continuous dependent variable, predicted simultaneously by *TK*, *perception and motivation*, and *teaching approaches* can be represented by the formula. The multiple linear regression model can be expressed as follows:

$$TechUse = b_0 + \beta_1 * (TechKnowledge) + \beta_2 * Perception/Motivation + \beta_3 * TeachingApproaches, \quad (1)$$

which represents the predicted value of the continuous dependent variable (*actual use of classroom technology*), and b_0 represents the model intercept or constant. In this statistical equation, β_1, β_2, and β_3 serve as the partial regression coefficients that quantify the unique, simultaneous predictive strength of the independent variables *perception/motivation*, *TK*, and *teaching approaches*, respectively while controlling all other factors in the model indicated in **Table 3**.

Due to the severe univariate non-normality identified in **Table 1** and **Table 2** the *perception/motivation* scale during preliminary descriptive diagnostics (skewness = -1.709, kurtosis = 4.612), standard OLS inference parameter vulnerabilities were mitigated by enabling robust bootstrap estimation configured to 2,000 bias-corrected accelerated (BCa) resamples. The model satisfied standard linear regression criteria; independent residual distributions were confirmed via a Durbin-Watson statistic of 2.104, falling within the optimal range around 2.0. Hence, in fulfillment of **RQ2**, individual parameter estimates were evaluated to capture the unique predictive weight of each independent variable while holding all concurrent factors in the model completely constant because the data violated normality, robust BCa 95% confidence intervals (CIs) were generated from 2,000 bootstrap iterations indicated in **Table 7** and **Table 3**.

Multivariate Parameter Estimates and Unique Predictive Weights

To isolate the unique predictive weight of each independent variable on actual classroom technology use while concurrently controlling for all other variables in the model, individual parameter estimates were evaluated. Because the baseline data screening revealed significant violations of multivariate normality, all standard errors, significance values p, and 95% CIs were derived using a non-parametric bootstrapping method utilizing 2,000 empirical resamples with BCa intervals. This robust statistical architecture prevents alpha inflation and guarantees inferential validity. The complete results of this simultaneous regression matrix are presented in **Table 7**.

Evaluation of individual predictors

The parameter in **Table 7** estimates reveal a clear, hierarchical divergence in how cognitive, psychological, and pedagogical factors uniquely drive classroom technology execution: -

TK: *TK* emerged as the primary and sole statistically significant unique positive predictor of actual technology use within the multivariate framework (B = 0.201, β = .370, p = .009). The absolute mathematical rigor of this effect is firmly validated by its robust bootstrap CI, which remains entirely in positive territory and well clear of zero BCa 95% CI [0.064, 0.376]). The unstandardized coefficient (B = 0.201) indicates that when holding all other variables completely constant, every single-unit increase on the Knowledge scale results in an operational expansion of 0.201 units in actual classroom technology utilization. Furthermore, the part (semi-partial) correlation metric (r_{part} = .369) demonstrates that *TK* uniquely explains 13.6% ($[part]^2$ = $[\mathbf{.369}]^2$ = .136) of the total variance in technology execution entirely on its own.

Teaching approaches: In contrast, *teaching approaches* (reflecting general pedagogical delivery and blended learning strategies) displayed a moderate positive directional path but failed to achieve traditional statistical significance (B = 0.124, β = .285, p = .089). This lack of unique predictive weight is further confirmed by its robust bootstrapped CI, which narrowly straddles zero by crossing into negative space (BCa 95% CI [-0.055, 0.257]). The *teaching approaches* framework showed a positive trend toward predicting the outcome variable, suggesting a meaningful practical effect that did not quite reach the conventional threshold for statistical significance. This marginal trend suggests that while advanced, student-centered teaching frameworks naturally align with digital tools, their capacity to uniquely predict actual technology use is heavily constrained when accounting for baseline technical knowledge.

Perception and motivation: Most notably, *perception and motivation* carried virtually zero unique predictive weight within the controlled regression model (B = 0.042, β = .025, p = .864). Its partial $r_{partial}$ = .025) and part (r_{part} = .021) correlations approached absolute zero, and its robust CI heavily spanned across zero (BCa 95% CI [-0.405, 0.723]). This critical finding demonstrates that positive psychological mindsets, high internal motivation, or favorable attitudes fail to convert into active classroom technological execution if an instructor lacks solid technical capacity.

Methodological and practical implications of the model

The empirical model of **Table 7** uncovers a profound diagnostic reality regarding digital transformation within structurally constrained educational environments. First, the complete collapse of *perception and motivation* (β = .025, p = .864) within the simultaneous equation proves that psychological readiness is a necessary but entirely insufficient condition for practice. Grounded in self-efficacy theory and the cost-benefit approach to human decision-making, the TAM identifies PU and PEOU as the primary psychological drivers of an individual's intention to use a system (Chan et al., 2026). While an educator may be highly motivated and value digital media, resource-volatile environments (characterized by localized infrastructure deficits, power instability, and minimal technical support) create a barrier that cannot be overcome by pure mindset alone. Without concrete technical mastery as captured by the highly significant *TK* metric positive attitudes stall entirely, forcing teachers into defensive non-use or basic, passive administrative consumption.

Second, the structural validity of these individual coefficients is protected by the collinearity diagnostics. The VIF for all three predictors ranged tightly between 1.007 and 1.371, falling drastically below the standard conservative threshold of 5.0 (and the ideal threshold of 2.5). Correspondingly, tolerance values remained exceptionally high (ranging from .730 to .993). This absolute absence of multi-collinearity confirms that the isolated predictive weight of *TK* is structurally sound and completely unpolluted by shared variance or mathematical redundancy among the independent scales.

DISCUSSION

The empirical findings of this study provide crucial, field-based clarity regarding the micro-level behavioral and structural dynamics that dictate technology integration within the resource-constrained environments of Ethiopian secondary education. While our model demonstrates the significant role of individual teacher factors, it leaves 76.4% of the variance unexplained, pointing directly to the critical influence of unmeasured school-level barriers. In practice, a teacher's pedagogical and technological readiness cannot translate into effective classroom integration if baseline school infrastructure is lacking. Challenges such as unstable electricity, limited Internet connectivity, and inadequate access to working devices create an immediate bottleneck for daily lesson delivery. We acknowledge the limited statistical power resulting from our sample size (N = 53). Additionally, the model explains 23.6% of the variance (R^2 = .236), meaning that over 76% of the variance remains unaccounted for. However, in behavioral and educational field studies, R^2 nearly 25% represents a substantial effect size (Cohen, 1988). The remaining unexplained variance is highly likely driven by critical contextual and environmental variables not captured in the survey instrument, such as recurring localized power outages, infrastructural deficits, and administrative support dynamics, which heavily moderate technology implementation in developing educational landscapes.

Furthermore, even when hardware is available, teachers are often constrained by a lack of institutional support, including a lack of school leadership encouragement, rigid timetables, and absent on-site technical assistance. Because these structural, school-wide variables were outside the scope of our quantitative model, they represent the missing variance highlighting that sustainable technology integration is heavily dependent on the school environment rather than individual teacher effort alone. Crucially, the simultaneous multiple linear regression analysis reveals a sharp divergence from common theoretical assumptions when these variables are evaluated concurrently rather than in isolation. While bivariate relationships may suggest that psychological and general pedagogical frameworks are highly related to practice, the multivariate model proves that *TK* (β = .370, B = 0.201, p = .009) serves as the primary and sole statistically significant unique predictor of actual classroom technology use. This structural reality directly challenges pure technological determinism and forces a critical re-evaluation of classic TAM applications in developing regions (Abubakir & Alshaboul, 2023; Elsayary et al., 2026; Fabian et al., 2024). In baseline bivariate contexts, a strong relationship appears between teacher perceptions/motivation and *teaching approaches* (r_s = .505, p < .001), suggesting that psychological readiness acts as a gateway to innovative instructional design. However, when entered into the simultaneous regression equation, the predictive weight of *perception/motivation* completely collapses (β = .025, p = .864). This empirical drop-off reveals a profound pedagogical insight for sub-Saharan public school environments: while positive perceptions, internal self-efficacy, and high motivation are desirable traits, they carry virtually zero unique predictive weight if concrete technical mastery is absent. Teachers in rural and semi-urban Ethiopian classrooms routinely battle unstable electrical grids, slow Internet connectivity, and a lack of maintenance support (Abich & Eriku, 2023; Areri, 2025; Kebede et al., 2025). Within this highly volatile operational ecosystem, pure psychological motivation fails to convert into physical classroom execution; without deep, structural *TK*, positive attitudes stall at defensive non-use or surface-level administrative tasks (Aidoo & Chebure, 2024; Elsayary et al., 2026). The regression model confirms this by demonstrating that *TK* uniquely explains 13.6% (part^2 = .136) of the variance in technology execution entirely on its own. This empirical reality highlights the critical policy-practice divide embedded within local CTEs and national upskilling initiatives. As Carroll and Dastjerd (2026) caution, a profound mismatch exists between nominal, passive computer literacy and the active capacity to execute technology-enhanced instruction within specific subject domains. This is the classic cognitive bottleneck of the TPACK framework (Koehler & Mishra, 2009). While contemporary in-service teachers may display basic standalone computer literacy, their integrated capacity to synthesize technology alongside active, student-centered *teaching approaches* remains fragmented (Abubakir & Alshaboul, 2023; Bedada et al., 2026). Interestingly, *teaching approaches* (including blended learning) displayed a moderate positive directional path that trended toward significance (β = .285, p = .089) but ultimately failed to cross the traditional α = .05 threshold when controlling for concurrent variables. This marginal trend suggests that while *teaching approaches* (student-centered practices) such as interactive assessments, algorithm-driven AI-feedback, and adaptive assessments (Selwyn et al., 2025) coexist naturally with digital tools, their execution is structurally constrained by the baseline technical knowledge environment. When educators revert to traditional, teacher-centered lecture models due to low instructional confidence, advanced electronic interfaces are immediately reduced to primitive electronic writing boards for text-heavy bullet points (Aidoo & Chebure, 2024; Carroll & Dastjerd, 2026). Ultimately, navigating the structural demands of the 4IR requires moving past superficial resource accumulation (Sackey & Bester, 2016; Schwab, 2016). If advanced digital platforms are deployed without resolving the baseline deficit in teachers' practical *TK*, it results in isolated, fragile interventions that trigger institutional failure, equity gaps, and the loss of instructional value (Gumbo, 2023; Regli et al., 2026; Selwyn et al., 2025).

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study demonstrates that classroom technology usage within Ethiopian secondary education is a complex, hierarchical ecosystem where objective technical capability forms the foundational infrastructure for psychological and pedagogical expressions. Shifting past technological determinism, the inferential data confirm that the simple macro-level distribution of hardware cannot secure systemic educational transformation. While educational literature frequently emphasizes mindset cultivation and psychological motivation as core gatekeepers of blended learning, this study proves that in resource-constrained developing environments, concrete *TK* is the active, primary mechanism driving behavior. When infrastructural expansion outpaces deep, practical teacher capability, professional confidence collapses, and technology integration permanently stalls at passive, surface-level consumption. Sustainable digital transformation under the 4IR demands localized, context-responsive frameworks that prioritize hands-on technical mastery as an indispensable prerequisite for pedagogical innovation and mindset cultivation.

Recommendations

Based on the empirical findings and multivariate contexts validated in this study, the following targeted interventions are recommended for the Ethiopian secondary school sector:

- **Prioritize practical knowledge in professional development (GEQIP-E):** The Ministry of Education and regional education bureaus must immediately reorient in-service training frameworks away from abstract "mindset advocacy" or basic standalone software tutorials. Funding should be directed exclusively toward intensive, hands-on TPACK and AI-TPACK methodologies that train teachers to actively troubleshoot infrastructure volatility and execute data-driven digital instruction within their specific subject matters.

- **Standardize and assess digital practicums in CTEs:** Local CTEs must integrate context-specific digital pedagogy as a core, mandatory, and formally assessed component of pre-service teaching practicums. Newly deployed teachers must enter the workforce with proven capability to integrate tools under realistic sub-Saharan classroom conditions, eliminating the operational gap between nominal computer literacy and actual instructional execution.
- **Design context-specific blended learning guidelines:** HEIs and secondary school administrative networks must collaborate to formulate localized, clear e-learning policy guidelines. These frameworks must reject generalized Western-centric models and establish realistic, standard technological expectations tailored precisely to the material realities of rural and semi-urban classrooms.
- **Stabilize the baseline digital ecosystem:** Institutional stakeholders and government bodies must invest in stabilizing basic digital infrastructures—such as solar-powered electrical backups, localized offline-capable digital repositories, and technical maintenance funds. Reducing the operational volatility of the classroom environment is a mandatory prerequisite to reduce teacher anxiety and encourage educators to take pedagogical risks with digital media.

Limitations of the Study

Several methodological limitations must be considered when interpreting the findings of this study. First, the sample size is relatively small (N = 53) and restricted to secondary school teachers within a single region in Central Ethiopia, which inherently restricts the statistical power of the simultaneous multiple linear regression and limits the generalizability of the findings to broader national or international contexts. Doing research in resource-limited regional contexts is very hard and as a result of this we call for future study to include large number of participants to apply structural equation modeling or observed path analysis model. Because the study was underpowered, there is an elevated risk of a type II error concerning the "general *teaching approaches*" variable (β = 0.285, p = .089), meaning a potentially meaningful pedagogical predictor could not achieve formal statistical significance. Second, the model explained 23.6% of the total variance (R^2 = 0.236), indicating that more than 76% of the variance in actual classroom technology use is driven by external variables omitted from this individual-level model—such as institutional support, infrastructural access, electricity reliability, and device-to-student ratios. Third, even though some researchers support the internal consistency (reliability) values for the *knowledge towards technology*/blended learning (α = 0.604) and the *use of technology* for teaching (α = 0.58) subscales fell below the traditional structural threshold of 0.70 (George & Mallery, 2016; Tabachnick & Fidell, 2013; Taber, 2018). This measurement error may have attenuated our regression coefficients, necessitating cautious interpretation and requiring structural item expansions in future validation studies. Lastly, the cross-sectional survey design captures a single point in time, which prevents the establishment of explicit causal relationships between a teacher's technical knowledge base and their active instructional technology utilization rather than predictive associations.

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