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Enhancing Knowledge Transfer in Nano-Learning Through User Motivation and Satisfaction

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Abstract
This study investigates the effectiveness of nano-learning environments specifically short-form educational videos within higher education, focusing on the cultural, technological, and pedagogical dynamics that shape learner engagement and outcomes. Grounded in both quantitative and qualitative methodologies, the research explores how factors such as video length, content design, user motivation, engagement, and satisfaction influence learning effectiveness. Using Partial Least Squares Structural Equation Modelling (PLS-SEM) and thematic analysis of interviews with university educators in Chengdu, China, the study identifies that well-structured content and optimal video duration significantly enhance learner engagement, which in turn boosts short-video watch times and overall learning effectiveness. Additionally, the study reveals that while learners value personalization and flexibility, they also require structured support and cognitive depth. Platform algorithms, though enhancing motivation, may compromise autonomy and critical engagement. The study recommends the integration of reflective, culturally sensitive design features to balance personalization with deeper learning. The novelty of this research lies in its multidimensional analysis of nano-learning merging behavioural data with cultural and semantic insights to inform the development of inclusive, pedagogically sound micro-learning systems in global educational contexts.

Keywords: Nano-Learning, Short-Form Educational Videos, Learner Engagement, Learning Effectiveness, PLS-SEM, Personalization

INTRODUCTION

In the age of digital immediacy and mobile connectivity, short-form video platforms have transformed communication and learning habits. Their visual appeal, emotional engagement, and brevity align with modern attention patterns, making them highly relevant for contemporary education [1]. Thus, the proliferation of mobile devices and high-speed internet has transformed communication and learning, leading to the widespread use of short-form media like TikTok, Instagram Reels, and YouTube Shorts. These platforms cater to the modern preference for fast, visual, and emotionally engaging content, reshaping how knowledge is consumed [2]. Initially designed for entertainment, short videos now permeate education, particularly through emerging models like Nano-learning is a brief and focused instructional content typically under three minutes, tailored for digital natives with limited attention spans [3]. The rise of short video platforms (e.g., TikTok, YouTube Shorts) has fueled interest in Nano-learning considered as brief, focused learning burst through E-learning. However, theoretical development and empirical research remain limited, particularly in China. Nano-learning is often conflated with micro-learning without clear conceptual or empirical distinctions [2]. Key questions about the impact of time-limited content (under three minutes) on knowledge transfer, engagement, and satisfaction are underexplored, as are features like algorithm-driven personalization and multimedia integration [4]. E-learning has become increasingly vital in contemporary education, especially following the COVID-19 pandemic, which emphasized the need for accessible and flexible learning solutions) [5]. Among emerging strategies, Nano-learning is characterized by concise, targeted video-based content that enhances engagement, retention, and personalization, aligning well with the fast-paced digital lifestyles of modern learners [4]. While Nano-learning offers significant pedagogical benefits, it is not a replacement for traditional methods but rather a complementary tool that supports broader educational goals.This study explores the integration of short videos into E-learning, focusing on young adult learners (ages 18–39) in Chengdu, China a city known for its rapid digital adoption and educational innovation, particularly post-COVID-19. The research targets digitally native individuals engaged in lifelong learning, segmented into age groups (18–24, 25–30, 31–39) to capture generational differences in Nano-learning adoption.The objectives of this study are threefold. First, it aims to evaluate the effectiveness of short videos in facilitating knowledge transfer within Nano-learning environments. Second, it seeks to identify the key design and development factors that influence the creation of impactful short video content for Nano-learning. Third, the study explores the opportunities and challenges associated with integrating short videos into Nano-learning, with the goal of enhancing their educational value and overall impact within broader E-learning ecosystems.

LITERATURE REVIEW

2.1 Theory Application Overview

The theoretical foundation of this study integrates four complementary frameworks to examine short video-based nano-learning. First, the stimulus–organism–response (s-o-r) theory [6] explains how external stimuli such as video content and interface design trigger internal learner states (e.g., motivation, emotional engagement), leading to behavioral outcomes like attention or satisfaction. This is especially relevant for understanding how nano-learning prompts immediate cognitive and emotional processing. Second, uses and gratifications (U&G) theory [7] shifts focus to learner agency, highlighting that users actively choose short videos to fulfill cognitive, emotional, and social needs.In the context of nano-learning, u&g helps explain learner engagement, driven by personalization, interactivity, and self-directed learning [2]. Third, symbolic interaction theory [8] emphasizes meaning-making through interaction, showing how learners interpret visual cues, tone, and cultural symbols within short videos, shaping their understanding and engagement. Lastly, media ecology theory [9] views media as environments that structure perception and behavior. It contextualizes nano-learning within a digital ecosystem influenced by mobile technology, algorithms, and temporal constraints. Collectively, these theories offer a multidimensional lens to analyze how media form, user agency, symbolic content, and technological environments interact to shape learning behavior and outcomes in short video-based education.

Short videos, typically lasting a few seconds to three minutes, have emerged as a dominant digital content format designed for quick, visually engaging, and mobile-friendly communication [10]. Their rise is closely tied to shifts in media consumption habits, particularly on platforms like TikTok, YouTube Shorts, and Instagram Reels, which prioritize user-generated, algorithm-curated video content over traditional text or image-based interaction. Unlike earlier platforms such as Twitter and Facebook, which evolved from text-based communication, TikTok's native video infrastructure aligns more effectively with users' growing preference for rapid, immersive visual experiences [2].In educational contexts, this format's brevity aligns well with cognitive load theory, supporting short bursts of attention and improved retention, Thus, [11] indicates that videos lasting three to five minutes are ideal for maintaining concentration, particularly in multitasking, mobile environments. During the COVID-19 pandemic, short videos gained further relevance as tools for informal learning and public communication, offering immediate, personalized, and accessible content. Their adaptability was evident even on long-form platforms like YouTube, which introduced "YouTube Shorts" to meet user demand for micro-content. This trend underscores how short video consumption has reshaped user expectations and platform design across digital media ecosystems [12].

2.2 E-learning and Nano-learning

Education, a cornerstone of human development, has been transformed by globalization and digitalization, notably through the rise of E-learning, an approach leveraging electronic technologies to deliver flexible, accessible, and scalable learning [13]. Initially supplemental, E-learning evolved from static materials to interactive, multimedia-rich environments, accommodating diverse learners across time and space. Its advantages include overcoming geographical and financial barriers, enabling real-time or asynchronous communication, and empowering learners with autonomy [14]. The COVID-19 pandemic marked a pivotal moment, as prolonged institutional closures necessitated a shift to fully online education, normalizing platforms like Zoom and Moodle and accelerating the adoption of hybrid models [15]. Within this landscape, Nano-learning has emerged as a focused extension of Micro-learning, characterized by ultra-brief, goal-specific modules often under five minutes, designed for mobile and social platforms [2]. These modules deliver content in short bursts or "micro-moments," enhancing engagement and retention through minimal cognitive load and media-rich formats [16].

2.4 E-learning

E-learning has significantly transformed the way knowledge is accessed and delivered, evolving through distinct technological and pedagogical phases that contextualize the emergence of nano-learning and the widespread use of short videos in contemporary education [2]. Its foundation was laid in the 1970s with computer-based instruction and early internet developments [17], gaining momentum in the 1980s and 1990s through expanding telecommunication capabilities. Despite the rudimentary nature of early content primarily text and audio, and limited interactivity, this period established the groundwork for networked learning [18]. The 2000s introduced more interactive platforms enabled by better internet access and personal computing, transforming the web into a pedagogical space and giving rise to models like blended learning and MOOCs, which expanded access and promoted learner autonomy [19]. By the 2010s, E-learning matured into a viable alternative to traditional education, integrating video lectures, peer interactions, and affordable certification, though challenges like digital literacy and access inequity remained [20]. The onset of COVID-19 in 2020 marked a pivotal shift, making digital learning essential rather than optional and accelerating the adoption of platforms like Zoom, Google Classroom, and Coursera [21]. Simultaneously, the normalization of short-form content on platforms like TikTok influenced learner behavior, giving rise to nano-learning—concise, focused content designed to match modern attention spans and digital consumption habits [2]. While concerns about distraction and content quality persist [11], well-structured short videos have proven effective in enhancing learner motivation and retention. Overall, E-learning has evolved from simple distance education into a dynamic, technology-driven ecosystem, with nano-learning and short videos representing the latest innovation in creating more adaptive, interactive, and learner-centric educational experiences.

2.5 The short videos and Nano-learning

The integration of short videos with Nano-learning offers a compelling pedagogical response to the evolving preferences of digital-age learners. Both formats emphasize brevity, accessibility, and targeted content delivery, making their convergence both feasible and beneficial [2]. Nano-learning, designed for informal settings through ultra-compact learning units, aligns well with short videos typically under three minutes distributed via mobile apps and social platforms. These videos enhance Nano-learning by supporting temporal flexibility, visual clarity, and interactive engagement through likes, shares, and comments. Although concerns about overuse and distraction persist, the same algorithmic features that sustain attention in entertainment contexts can be strategically leveraged to maintain educational focus [11]. For example, TikTok's success in disseminating procedural content, such as handwashing during COVID-19, demonstrates the format's potential for delivering step-by-step instruction and boosting educational reach [22]. Moreover, short video-based Nano-learning addresses interaction gaps found in conventional E-learning by fostering user engagement and peer communication, which were noted as deficiencies in cross-border online learning experiences [23]. While the addictive nature of short video platforms poses a risk, intentional design focused on clarity and learning objectives can mitigate these issues. Ultimately, this model presents a responsive, modular, and engaging educational solution for 21st-century learners.

2.6 The factor driving users' satisfaction of E-learning and the short video

Understanding the drivers of user satisfaction in short video–based E-learning is vital for enhancing educational design. Engagement was closely linked to knowledge acquisition and deep learning, suggesting that emotional and behavioral involvement mediates educational outcomes. Short video attributes such as brevity, relevance, music, and interactivity are significantly influence satisfaction and attention [11]. Algorithmic content recommendations, based on user-generated media dynamics, personalize learning but risk reducing content diversity [24]. The Stimulus–Organism–Response (S–O–R) model and Flow Theory explain how cognitively stimulating and emotionally resonant videos enhance engagement and satisfaction through intrinsic motivation and immediate feedback. Interactive features like comments or quizzes foster community and psychological involvement, reinforcing satisfaction [24]. Ultimately, satisfaction emerges as both a product and predictor of performance, shaped by interconnected factors of personalization, interactivity, and emotional engagement. This conceptual basis supports further empirical exploration of Nano-learning systems.

2.7 Effectiveness in E-learning with the short videos

While E-learning has rapidly expanded across educational and professional sectors, its true effectiveness—especially in terms of measurable knowledge transfer (KT)—remains complex and underexplored. Effectiveness cannot be inferred from convenience alone; instead, it must be assessed through learners' ability to acquire, retain, and apply knowledge; it is considering a core metric of E-learning success, involves both subjective and objective indicators, including teaching evaluation, learner satisfaction, performance, and critique, by developing a validated quantitative framework for KT assessment using descriptive statistics and cluster analysis [4]. Similarly, [25] proposed a structural model identifying key variables are self-motivation, learning style, instructor feedback, facilitation, interaction, and course structure as significant predictors of satisfaction and learning outcomes.

2.8 Theoretical Framework for Nano-Learning in E-Learning Environments

This study employs a multidimensional theoretical framework to explore how short-form videos enhance Nano-learning in E-learning environments. The Stimulus–Organism–Response (S-O-R) model [26] explains how specific video features—such as brevity, interactivity, and music—act as stimuli that influence learners' internal states (e.g., attention, motivation), which then shape behavioral responses like sharing, rewatching, or continued engagement. Uses and Gratifications (U&G) Theory [7] further explains how learners actively choose short videos to fulfill various needs, including knowledge acquisition, emotional satisfaction, and social connection [27]. These theories highlight the learner's agency and responsiveness to media design, showing how the structure and content of short videos align with learners' goals for efficiency and engagement in digital education.Additionally, Symbolic Interaction Theory [7] provides insights into the meaning-making process, illustrating how learners construct and negotiate meaning through symbolic elements like visuals, hashtags, and comments. This theory underscores the social and interpretive nature of digital learning experiences. Media Ecology Theory [9] complements this by framing digital platforms as dynamic ecosystems that influence how content is consumed and understood. It emphasizes that the medium itself not just the message reshapes cognitive habits and learning behaviors. Together, these theories offer a comprehensive understanding of how short videos not only deliver content but transform learning experiences by engaging learners cognitively, socially, and culturally within evolving digital environments.

2.9 The Educational and E-learning Environment in China and the City-Brand Media Context of Chengdu

China's education system has transformed significantly, with higher university enrollment and growing societal emphasis on academic achievement. Economic growth remains the key driver of educational attainment, and additional education correlates with higher income [28]. Despite the expansion of higher education since 1999, deep urban-rural disparities persist, disadvantaging rural students and restricting equal access to opportunities. These gaps are worsened by regional economic differences, where industrialized areas offer better returns to education, reinforcing inequality [12]. Meanwhile, E-learning in China has gained traction, particularly after the COVID-19 pandemic, which shifted public and institutional perception toward recognizing its potential in widening access to education and reducing geographic and socio-economic barriers [23]. Chengdu, a rising first-tier city and capital of Sichuan, provides a unique setting to explore digital learning adoption. Unlike traditional first-tier cities, Chengdu has built a distinctive digital identity through strategic online branding campaigns, such as panda-themed promotions during the 2012 London Olympics, global volunteer initiatives, and international media partnerships [29]. These campaigns have cultivated a digitally literate population accustomed to media-rich interaction. Given its digitally engaged environment and innovative media culture, Chengdu offers an ideal context to investigate how urban media ecosystems facilitate the integration of short video platforms into Nano-learning and shape E-learning adoption in modern Chinese cities.

2.10 Conceptual Framework for Nano-Learning via Short Videos

This study adopts a conceptual model illustrated in figure 1, based on the Stimulus–Organism–Response (S-O-R) framework [30], integrated with Uses and Gratifications and Symbolic Interaction theories, to explore how short videos enhance Nano-learning.

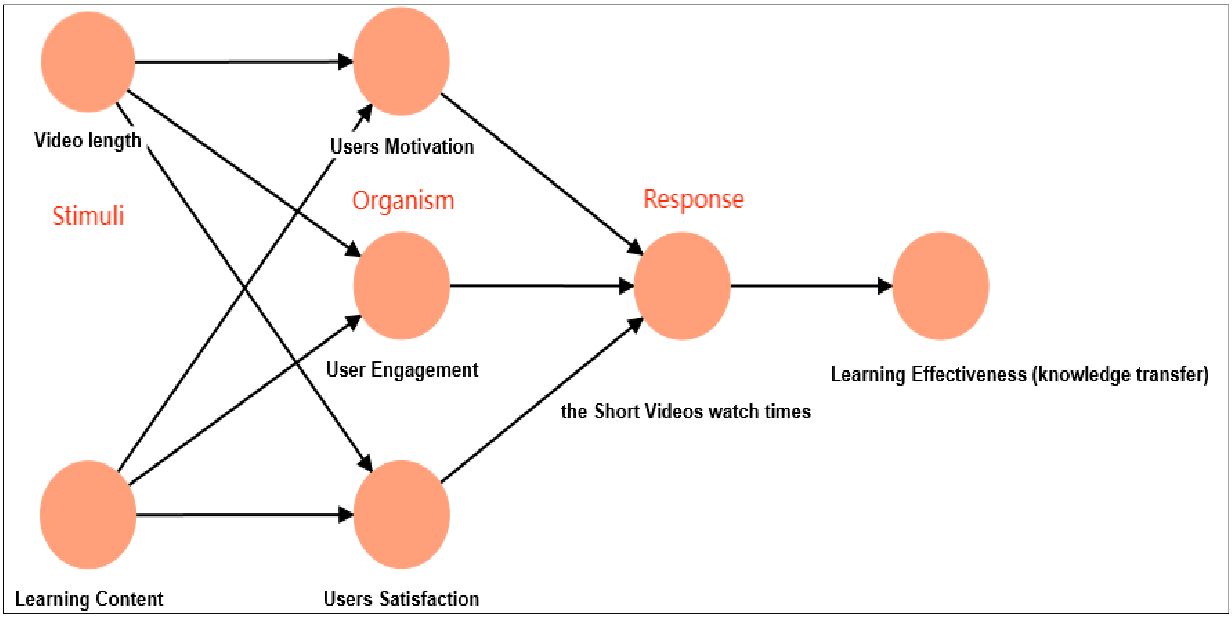

Figure 1 Conceptual Framework

RESEARCH METHODOLOGY

3.1 Population and Sample

This study targets young adult learners aged 18–40 in Chengdu, China—a digitally literate population highly engaged with short video content. A mixed-method sampling approach is used, combining random sampling for diversity and snowball sampling to reach niche Nano-learning communities.Participants are recruited via online platforms and educational networks, screened for age and prior experience with short video learning. A minimum sample size of 400 is set, based on [31-33] guidelines for large populations, ensuring statistical reliability at a 95% confidence level. Snowball sampling supplements recruitment, if necessary, especially through referrals from students and educators. Given the study's use of Structural Equation Modeling (SEM) to test complex relationships and mediations, a sample size above 400 enhances validity. Ethical protocols are observed, with voluntary participation and informed consent. This strategy ensures a representative, diverse, and methodologically sound dataset for both quantitative and qualitative analysis.

3.2 Research Measurements

This study adopts an abductive mixed-methods approach, combining questionnaire surveys and in-depth interviews to capture both quantitative trends and qualitative insights into Nano-learning via short videos. The bilingual (Chinese and English) questionnaire, developed based on the S-O-R model, employs forward–backward translation to ensure semantic accuracy. The instrument comprises three sections: screening questions, five-point Likert-scale items (1 = strongly disagree to 5 = strongly agree), and demographic details. It measures four key dimensions; information quality, content clarity, perceived utility, and personal relevance; across 21 items. Constructs such as video length and learning content are evaluated for clarity, usefulness, and engagement. Measurement items are adapted from validated literature to align with the study context. Likert scales ensure consistency and reduce respondent bias. Data from these instruments support hypothesis testing and structural analysis using SEM, offering a robust foundation for evaluating learning effectiveness in short video-based environments.

3.3 Research tools

This study utilizes a mixed-methods approach grounded in its conceptual framework, combining a structured questionnaire and in-depth interviews to investigate Nano-learning through short videos. The questionnaire quantitatively evaluates E-learning usage, satisfaction, and the effectiveness of short video content within China's social media platforms, with strong reliability (Cronbach's alpha 0.723–0.922) and validity (KMO = 0.651, Bartlett's test $p < .001$) confirmed through a pretest of 30 users. It includes demographic data, user habits, and Likert-scale items to assess content quality and relevance. Complementing this, semi-structured interviews with five experienced teachers provide qualitative insights into user motivation, engagement, satisfaction, and challenges, with data analyzed thematically to enrich and validate the survey results. Together, these instruments offer a comprehensive understanding of factors influencing the design, effectiveness, and broader application of short video-based Nano-learning in E-learning environments.

3.4 Data Collection Process

This study employed a mixed-methods approach to comprehensively investigate Nano-learning via short videos, aligning data collection with the research objectives, hypotheses, and conceptual framework. Quantitative data were gathered through a bilingual, self-developed web-based questionnaire based on the S-O-R model, distributed both online and offline in Chengdu to ensure diverse participation. The questionnaire collected demographic information, video usage habits, perceptions of educational content, and media evaluation, with data later analyzed using Structural Equation Modeling (SEM) to examine relationships among latent variables. Complementing this, qualitative data were obtained through five semi-structured in-depth interviews with educators experienced in Nano-learning, focusing on user motivations, engagement patterns, satisfaction, cognitive impacts, and challenges. Interviews were recorded, transcribed, and analyzed using thematic analysis to extract core themes and validate quantitative findings. This integration of empirical measurement with narrative insights offered a multidimensional understanding of short video-based learning, enhancing the study's validity and relevance for educational innovation in digital contexts.

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3.5 Data analysis

This study employed Structural Equation Modeling (SEM) to analyze the relationships among latent constructs within the S-O-R-based conceptual framework, enabling simultaneous evaluation of causal links and measurement validity. SEM was chosen for its ability to model complex relationships between unobservable variables such as motivation, engagement, satisfaction, and learning effectiveness. The measurement model was validated through Confirmatory Factor Analysis (CFA), assessing content and construct validity using factor loadings, AVE, and CR thresholds, with poorly performing items revised or removed. The structural model was then tested using fit indices (e.g., Chi-square/df, RMSEA, CFI, TLI, SRMR) to confirm the hypothesized pathways. Model refinement was conducted as needed, guided by theoretical justification and modification indices. To enhance interpretive depth, qualitative interview data contextualized the SEM findings, offering insights into user motivations, emotional engagement, and perceived effectiveness of short video content. This mixed-methods integration ensured both statistical robustness and rich contextual understanding of Nano-learning via short videos.

3.6 Ethical Considerations

Ethical considerations were integral to this study on Nano-learning via short video platforms, ensuring full respect for participants' rights, autonomy, and well-being throughout both quantitative and qualitative phases. Informed consent was obtained transparently, with participants fully briefed on the study's purpose, voluntary nature, and their right to withdraw at any time. Confidentiality was rigorously maintained through data anonymization, secure storage, and the use of pseudonyms. All procedures were designed to minimize risk and discomfort, with non-invasive questions and flexible scheduling to prioritize participant welfare. The research upheld academic transparency and integrity, documenting all methodological changes and adhering to recognized ethical standards such as those from the Declaration of Helsinki and APA guidelines. While formal IRB approval was not required, institutional ethical protocols were strictly followed. The study also addressed emerging ethical challenges specific to Nano-learning such as digital fatigue and algorithmic influence underscoring the need for evolving ethical frameworks in digital education research.

RESULTS AND ANALYSIS

4.1 Descriptive Statistical Analysis

Table 1 shows, a total of 553 valid responses were analyzed after excluding incomplete or inconsistent entries, all from Chengdu residents. The gender distribution was nearly balanced (50.63% male, 49.37% female), ensuring representativeness across genders. Most respondents were aged 31–40 (47.74%), followed by those aged 26–30 (35.8%), with fewer younger participants aged 18–25 (16.46%), indicating a predominance of middle-aged users. Notably, 97.29% reported using short video platforms, highlighting their widespread adoption and relevance as a medium for everyday content consumption and potential Nano-learning.

Table 1 Descriptive statistics of Quantitative Sample (N=553)

	Option	Frequency	Percentage (%)
Gender	Male	280	50.63
	Female	273	49.37

Age Group	18-25	91	16.46
	26-30	198	35.8
	31-40	264	47.74
Short Video Usage Habit	Yes	538	97.29
	No	15	2.71

4.2 Descriptive Statistics and Normality Assessment of Short Video Usage Items

Table 2 shows that, after excluding 15 participants who did not use short videos, data from 538 respondents were analyzed across 21 items (SV1–SV21) measured on a five-point Likert scale. The mean scores ranged narrowly between 3.42 and 3.57, indicating generally neutral to positive responses with no disagreement trends. Standard deviations around 1.24 to 1.32 reflect moderate variability, suggesting diverse respondent perspectives despite consistent central tendencies. Negative skewness values (-0.39 to -0.61) reveal a slight tendency for participants to agree with the statements, while the negative kurtosis (-0.62 to -0.90) indicates relatively flat distributions with fewer extreme responses. Although skewness and kurtosis values are statistically significant, their moderate magnitude supports the data's approximate normality, validating its suitability for further multivariate analysis.

Table 2 Descriptive statistics of Quantity and Data Normality Test (N=538 without non-using habit 15 participants)

Descriptive Statistics and Data Normality Test	Average Value	Std.	Skewness	Std. Error	Kurtosis	Std. Erro
SV1	3.49	1.276	-0.47	0.105	-0.756	0.21
SV2	3.43	1.243	-0.425	0.105	-0.739	0.21
SV3	3.52	1.243	-0.484	0.105	-0.701	0.21
SV4	3.42	1.275	-0.42	0.105	-0.778	0.21
SV5	3.47	1.295	-0.489	0.105	-0.759	0.21
SV6	3.42	1.292	-0.407	0.105	-0.806	0.21
SV7	3.53	1.279	-0.577	0.105	-0.672	0.21
SV8	3.43	1.267	-0.478	0.105	-0.696	0.21
SV9	3.53	1.273	-0.494	0.105	-0.78	0.21
SV10	3.57	1.291	-0.608	0.105	-0.686	0.21
SV11	3.55	1.272	-0.599	0.105	-0.621	0.21
SV12	3.46	1.287	-0.437	0.105	-0.826	0.21
SV13	3.53	1.255	-0.453	0.105	-0.763	0.21
SV14	3.47	1.32	-0.435	0.105	-0.903	0.21
SV15	3.47	1.257	-0.389	0.105	-0.817	0.21
SV16	3.45	1.259	-0.466	0.105	-0.702	0.21
SV17	3.51	1.292	-0.556	0.105	-0.724	0.21

SV18	3.43	1.251	-0.51	0.105	-0.636	0.21
SV19	3.46	1.262	-0.472	0.105	-0.703	0.21
SV20	3.46	1.27	-0.463	0.105	-0.75	0.21
SV21	3.44	1.321	-0.46	0.105	-0.822	0.21

4.3 Analysis of Survey Response Patterns and Perception Scores

Table 3, provides a concise analysis of the frequency distribution and perception scores for the 21 survey items (SV1–SV21), rated on a five-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree), based on 538 valid responses. The data indicate a consistent trend toward neutral to positive perceptions, with the majority of responses falling in categories 3, 4, and 5. Notably, “Strongly Agree” was the most frequent choice for many items, such as SV1 (27.7%) and SV9 (29%), reflecting strong endorsement. Negative responses (ratings 1 and 2) remained low across all items, underscoring limited disagreement. Effective percentages, which exclude invalid responses, aligned closely with raw frequencies, ensuring data reliability. Cumulative perception figures reveal that a substantial proportion of responses cluster at the favorable end of the scale; for example, 100% of SV1 responses fall at or above the "Agree" level. These trends collectively suggest that participants generally held positive views of the surveyed constructs, such as educational effectiveness, video watch time, and engagement. Nonetheless, the presence of neutral ratings signals variability in perception, warranting further analysis into potential demographic or behavioral influences.

Table 3 Descriptive statistics of Selection Frequency of Questionnaire (N=538)

		Frequency	Percentage	Effective Percentage	Accumulative Perception
SV1	1	55	10.2	10.2	10.2
	2	56	10.4	10.4	20.6
	3	146	27.1	27.1	47.8
	4	132	24.5	24.5	72.3
	5	149	27.7	27.7	100
SV2	1	52	9.7	9.7	9.7
	2	65	12.1	12.1	21.7
	3	146	27.1	27.1	48.9
	4	147	27.3	27.3	76.2
	5	128	23.8	23.8	100
SV3	1	47	8.7	8.7	8.7
	2	61	11.3	11.3	20.1
	3	141	26.2	26.2	46.3
	4	143	26.6	26.6	72.9
	5	146	27.1	27.1	100
SV4	1	60	11.2	11.2	11.2
	2	57	10.6	10.6	21.7

	3	153	28.4	28.4	50.2
	4	134	24.9	24.9	75.1
	5	134	24.9	24.9	100
	1	62	11.5	11.5	11.5
	2	50	9.3	9.3	20.8
SV5	3	145	27	27	47.8
	4	134	24.9	24.9	72.7
	5	147	27.3	27.3	100
	1	63	11.7	11.7	11.7
	2	52	9.7	9.7	21.4
SV6	3	161	29.9	29.9	51.3
	4	120	22.3	22.3	73.6
	5	142	26.4	26.4	100
	1	57	10.6	10.6	10.6
	2	54	10	10	20.6
SV7	3	122	22.7	22.7	43.3
	4	158	29.4	29.4	72.7
	5	147	27.3	27.3	100
	1	62	11.5	11.5	11.5
	2	50	9.3	9.3	20.8
SV8	3	150	27.9	27.9	48.7
	4	147	27.3	27.3	76
	5	129	24	24	100
	1	49	9.1	9.1	9.1
	2	65	12.1	12.1	21.2
SV9	3	130	24.2	24.2	45.4
	4	138	25.7	25.7	71
	5	156	29	29	100
	1	55	10.2	10.2	10.2
	2	56	10.4	10.4	20.6
SV10	3	113	21	21	41.6
	4	153	28.4	28.4	70.1
	5	161	29.9	29.9	100
	1	56	10.4	10.4	10.4
	2	50	9.3	9.3	19.7
SV11	3	125	23.2	23.2	42.9
	4	157	29.2	29.2	72.1
	5	150	27.9	27.9	100
	1	57	10.6	10.6	10.6
SV12	2	63	11.7	11.7	22.3
	3	140	26	26	48.3

	4	134	24.9	24.9	73.2
	5	144	26.8	26.8	100
SV13	1	46	8.6	8.6	8.6
	2	62	11.5	11.5	20.1
	3	147	27.3	27.3	47.4
	4	127	23.6	23.6	71
	5	156	29	29	100
SV14	1	60	11.2	11.2	11.2
	2	63	11.7	11.7	22.9
	3	137	25.5	25.5	48.3
	4	120	22.3	22.3	70.6
	5	158	29.4	29.4	100
SV15	1	48	8.9	8.9	8.9
	2	68	12.6	12.6	21.6
	3	151	28.1	28.1	49.6
	4	126	23.4	23.4	73
	5	145	27	27	100
SV16	1	57	10.6	10.6	10.6
	2	54	10	10	20.6
	3	150	27.9	27.9	48.5
	4	143	26.6	26.6	75.1
	5	134	24.9	24.9	100
SV17	1	60	11.2	11.2	11.2
	2	55	10.2	10.2	21.4
	3	122	22.7	22.7	44.1
	4	155	28.8	28.8	72.9
	5	146	27.1	27.1	100
SV18	1	61	11.3	11.3	11.3
	2	50	9.3	9.3	20.6
	3	145	27	27	47.6
	4	161	29.9	29.9	77.5
	5	121	22.5	22.5	100
SV19	1	57	10.6	10.6	10.6
	2	53	9.9	9.9	20.4
	3	150	27.9	27.9	48.3
	4	141	26.2	26.2	74.5
	5	137	25.5	25.5	100
SV20	1	56	10.4	10.4	10.4
	2	58	10.8	10.8	21.2
	3	144	26.8	26.8	48
	4	140	26	26	74

	5	140	26	26	100
SV21	1	69	12.8	12.8	12.8
	2	46	8.6	8.6	21.4
	3	151	28.1	28.1	49.4
	4	123	22.9	22.9	72.3
	5	149	27.7	27.7	100

4.4 Kaiser-Meyer-Olkin (KMO) Test and Bartlett's Test of Sphericity

The Kaiser-Meyer-Olkin (KMO) coefficient as shown in table 4, measures sampling adequacy for factor analysis by indicating how well variables correlate to reveal underlying factors. A high KMO value means the data is suitable for factor analysis, supporting construct validity, while a low value suggests poor suitability. KMO values are interpreted as: ≥0.90 (excellent), 0.80–0.89 (good), 0.70–0.79 (mediocre), 0.60–0.69 (fair), and below 0.60 (poor). In this study, the KMO value of 0.985 indicates excellent sampling adequacy. The Bartlett's test of sphericity ($\chi^2 = 6412.164$, $p < 0.001$) confirms that correlations among variables are significant, validating the use of factor analysis.

Table 4 The KMO and Bartlett test of the Formal Quantitative Study

KMO and Bartlett tests		
Number of KMO sampling suitability quantities		0.985
Bartlett sphericity test	Approximate chi square	6412.164
	Variance	210
	significance	<.001

4.5 Assessment of Convergent Validity Using AVE

Table 5 demonstrate acceptable convergent validity, with AVE values exceeding the 0.5 threshold, indicating that more than half of the variance in the indicators is explained by their respective latent constructs. Learning Content (0.757) and Short Videos Watch Times (0.739) show particularly strong validity, reflecting a high degree of alignment between the constructs and their indicators. The remaining constructs; Learning Effectiveness (0.613), User Engagement (0.645), Users Motivation (0.672), and Users Satisfaction (0.654) also exhibit solid convergent validity, confirming that the measurement items reliably represent their intended theoretical concepts.

	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
Learning Content	0.678	0.679	0.861	0.757
Learning Effectiveness	0.842	0.845	0.888	0.613

(knowledge transfer)				
User Engagement	0.816	0.817	0.879	0.645
Users Motivation	0.756	0.757	0.860	0.672
Users Satisfaction	0.735	0.735	0.850	0.654
Short Videos watch times	0.647	0.649	0.850	0.739

Table 5 Convergent Validity Analysis Using AVE

4.6 Discriminant Validity Assessment (Fornell-Larcker Criterion)

Discriminant validity was assessed using the Fornell-Larcker Criterion as shown in table 6, which compares the square root of the AVE for each construct with its correlations to other constructs. In this model, all constructs meet the criterion, as the square root of AVE for each construct (ranging from 0.783 to 0.870) exceeds its correlations with any other construct. This indicates that each construct shares more variance with its own indicators than with others, confirming that the constructs are distinct and conceptually separate. Therefore, the measurement model demonstrates strong discriminant validity, supporting the uniqueness and accuracy of the constructs measured.

Table 6 Discriminant Validity Analysis

Fornell-Larcker Criterion:	Learning Content	Learning Effectiveness (knowledge transfer)	User Engagement	Users Motivation	Users Satisfaction	the Short Videos watch times
Learning Content	0.870					
Learning Effectiveness (knowledge transfer)	0.771	0.783				
User Engagement	0.723	0.831	0.803			
Users Motivation	0.708	0.803	0.774	0.820		
Users Satisfaction	0.711	0.789	0.766	0.737	0.809	
the Short Videos watch times	0.685	0.750	0.728	0.688	0.694	0.860

4.7 Factor Loadings

Table 7 shows the outer loading analysis confirms that all indicators reliably represent their respective latent constructs, as all values exceed the 0.7 threshold. The strongest loadings are seen for Learning Content (SV3 = 0.875, SV4 = 0.865), Video Length (SV5 = 0.875, SV6 = 0.849), and Short Videos Watch Times (SV1 = 0.849, SV2 = 0.870), indicating highly reliable measures. Constructs like Users Motivation, Users Satisfaction, Learning Effectiveness, and User Engagement also show consistently strong loadings, confirming their effective representation. Overall, the measurement model demonstrates strong reliability, convergent validity, and discriminant validity, ensuring it is robust and suitable for further structural analysis.

Table 7 Factor Loadings

	Outer loadings
SV1 <- the Short Videos watch times	0.849
SV10 <- User Engagement	0.786
SV11 <- Users Motivation	0.837
SV12 <- Users Motivation	0.809
SV13 <- Users Motivation	0.813
SV14 <- Users Satisfaction	0.828
SV15 <- Users Satisfaction	0.805
SV16 <- Users Satisfaction	0.793
SV17 <- Learning Effectiveness (knowledge transfer)	0.810
SV18 <- Learning Effectiveness (knowledge transfer)	0.802
SV19 <- Learning Effectiveness (knowledge transfer)	0.771
SV2 <- the Short Videos watch times	0.870
SV20 <- Learning Effectiveness (knowledge transfer)	0.768
SV21 <- Learning Effectiveness (knowledge transfer)	0.763
SV3 <- Learning Content	0.875
SV4 <- Learning Content	0.865
SV5 -> Video length	0.875
SV6 -> Video length	0.849
SV7 <- User Engagement	0.822
SV8 <- User Engagement	0.787
SV9 <- User Engagement	0.816

4.8 Multicollinearity Test

The multicollinearity assessment using VIF values in table 8 shows that all predictor variables have VIFs well below the critical threshold of 5, indicating no significant multicollinearity concerns. Specifically, Learning Content, Learning Effectiveness, and Video Length each have VIFs of 1.896; User Engagement (3.153), Users Motivation (2.851), and Users Satisfaction (2.762) also fall within acceptable limits. The Short Videos Watch Times, with a VIF of 1.000, exhibits no multicollinearity at all. These results confirm that multicollinearity does not distort the model, ensuring the stability and reliability of path coefficient estimates. Hence, all variables can be retained for further analysis without adjustment.

Table 8 Results of The Multicollinearity Test

	Learning Content	Learning Effectiveness	User Engagement	Users Motivation	Users Satisfaction	Video length	the Short Videos watch times
Learning Content			1.896	1.896	1.896		
Learning Effectiveness (knowledge transfer)							

User Engagement					3.153
Users Motivation					2.851
Users Satisfaction					2.762
Video length		1.896	1.896	1.896	
the Short Videos watch times	1.000				

4.9 SEM Analysis Study

This study employs Structural Equation Modeling (SEM) using the Partial Least Squares (PLS) algorithm to examine and quantify the relationships among multiple latent variables. PLS-SEM is well-suited for predictive models with complex constructs measured through multiple indicators. It enables the assessment of both direct and indirect relationships, providing a comprehensive understanding of how the constructs interact. The following section presents the path coefficient results, highlighting the strength and direction of these relationships.

4.9.1 Hypothesis Study

The PLS-SEM model in figure 2, reveals that both Video Length and Learning Content significantly enhance User Engagement, Motivation, and Satisfaction, with path coefficients ranging from 0.401 to 0.467. Among these, Video Length has a slightly stronger influence. User Engagement exerts the greatest effect on Short Videos Watch Times (β = 0.362), followed by Satisfaction (β = 0.256) and Motivation (β = 0.220). In turn, Watch Times strongly predict Learning Effectiveness (β = 0.750), highlighting the central role of sustained video interaction in knowledge transfer. The model explains substantial variance in all endogenous constructs, with R^2 values between 0.562 and 0.638.

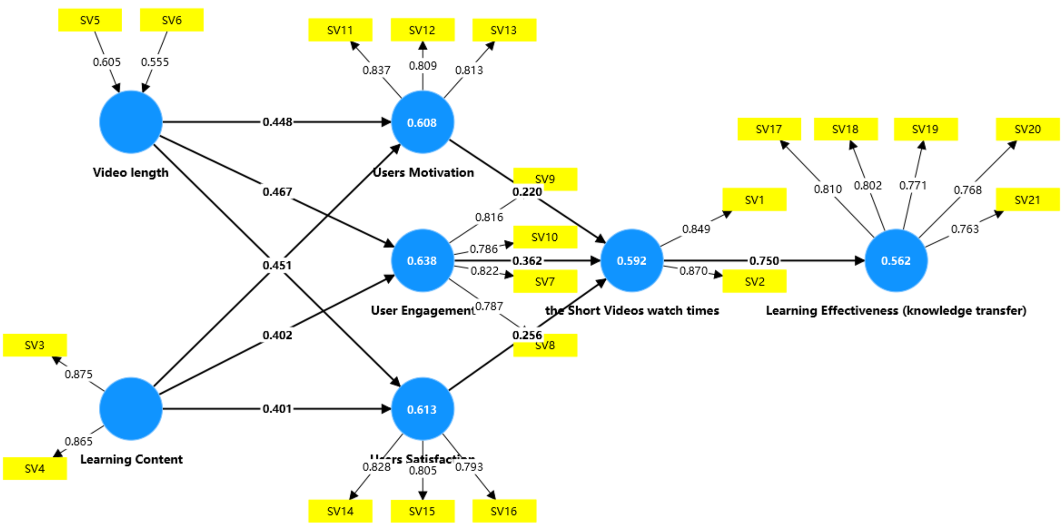

Figure 2 PLS Algorithm Results of the theoretical model

4.9.2 Path Coefficient Analysis and Structural Model Evaluation

The path coefficient analysis in table 9 reveals that both Learning Content and Video Length positively influence User Engagement, Users Motivation, and Users Satisfaction, with coefficients ranging from 0.40 to 0.47, indicating moderate to strong effects. Video Length shows a slightly stronger impact than Learning Content on these user attitudes, suggesting that optimal video duration enhances engagement, motivation, and satisfaction in short-video learning contexts. In turn, User Engagement, Users Motivation, and Users Satisfaction positively affect Short Videos Watch Times, though engagement (0.362) has a stronger influence than motivation (0.220) and satisfaction (0.256). Finally, Short Videos Watch Times exhibits the strongest effect on Learning Effectiveness (0.750), highlighting that greater video consumption substantially improves knowledge transfer. Overall, these results emphasize the crucial role of well-designed content and appropriate video length in driving user involvement, which ultimately leads to more effective learning outcomes.

Table 9 Results of The Path Coefficients

	Original sample (O)	Sample mean (M)	Std. deviation (STDEV)	T statistics (|O/STDEV|)	P values
Learning Content -> User Engagement	0.402	0.401	0.037	10.811	0.000
Learning Content -> Users Motivation	0.400	0.400	0.037	10.771	0.000
Learning Content -> Users Satisfaction	0.401	0.401	0.035	11.510	0.000
User Engagement -> the Short Videos watch times	0.362	0.363	0.049	7.316	0.000
Users Motivation -> the Short Videos watch times	0.220	0.220	0.044	5.010	0.000
Users Satisfaction -> the Short Videos watch times	0.256	0.254	0.046	5.542	0.000
Video length -> User Engagement	0.467	0.468	0.037	12.601	0.000
Video length -> Users Motivation	0.448	0.449	0.038	11.897	0.000
Video length -> Users Satisfaction	0.451	0.452	0.035	12.804	0.000
the Short Videos watch times -> Learning Effectiveness (knowledge transfer)	0.750	0.750	0.021	36.573	0.000

4.9.3 Mediation Effects Testing

The mediation analysis in table 10 confirms that Users Satisfaction, Users Motivation, and User Engagement significantly mediate the relationships between Learning Content and Video Length with Short Videos Watch Times, and ultimately with Learning Effectiveness. All indirect effects are statistically significant (p < 0.001, t > 1.96), indicating that improvements in content quality and video duration enhance satisfaction, motivation, and engagement, which in turn increase watch time and promote knowledge transfer. Among these, User Engagement shows the strongest mediating effect, highlighting its pivotal role in linking instructional design to behavioral and cognitive outcomes. This multi-step mediation structure emphasizes that emotional and cognitive activation are essential for effective learning in short video-based environments.

Table 10 Results of The Indirect Effect

	Original sample (O)	**Sample mean (M)**	**Std.Deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
Learning Content -> Users Satisfaction -> the Short Videos watch times	0.103	0.102	0.021	4.878	0.000
Learning Content -> Users Motivation -> the Short Videos watch times	0.088	0.088	0.020	4.323	0.000
Learning Content -> User Engagement -> the Short Videos watch times	0.145	0.146	0.025	5.865	0.000
Video length -> Users Satisfaction -> the Short Videos watch times	0.115	0.115	0.023	5.013	0.000
Video length -> Users Motivation -> the Short Videos watch times	0.099	0.099	0.021	4.651	0.000
Video length -> User Engagement -> the Short Videos watch times	0.169	0.170	0.027	6.204	0.000
Video length -> User Engagement -> the Short Videos watch times -> Learning Effectiveness (knowledge transfer)	0.127	0.128	0.021	6.000	0.000
Video length -> Users Motivation -> the Short Videos watch times -> Learning Effectiveness (knowledge transfer)	0.074	0.074	0.016	4.542	0.000
Video length -> Users Satisfaction -> the Short Videos watch times -> Learning Effectiveness (knowledge transfer)	0.086	0.086	0.018	4.901	0.000
Learning Content -> Users Satisfaction -> the Short Videos watch times -> Learning Effectiveness (knowledge transfer)	0.077	0.077	0.016	4.818	0.000
Learning Content -> User Engagement -> the Short Videos watch times -> Learning Effectiveness (knowledge transfer)	0.109	0.109	0.019	5.672	0.000
Learning Content -> Users Motivation -> the Short Videos watch times -> Learning Effectiveness (knowledge transfer)	0.066	0.066	0.016	4.230	0.000

User Engagement -> the Short Videos watch times -> Learning Effectiveness (knowledge transfer)	0.271	0.272	0.039	7.026	0.000
Users Motivation -> the Short Videos watch times -> Learning Effectiveness (knowledge transfer)	0.165	0.165	0.034	4.889	0.000
Users Satisfaction -> the Short Videos watch times -> Learning Effectiveness (knowledge transfer)	0.192	0.191	0.035	5.441	0.000

4.9.4 PLS Predict Analysis

The PLS Predict analysis in table 11 confirms that the model has strong predictive relevance and acceptable error levels. All Q^2predict values exceed zero, ranging from 0.316 to 0.444, indicating good predictive capability across all indicators, with SV9 performing best. RMSE and MAE values for both PLS-SEM and linear regression (LM) benchmarks remain low, supporting the model's accuracy. While the saturated model shows a good fit (SRMR = 0.049), the estimated model's SRMR (0.133) exceeds the recommended threshold, suggesting the need for model refinement. SV21 consistently shows the highest prediction error, signaling it may require further investigation. Overall, the model demonstrates robust out-of-sample predictive performance, especially for user behavior in nano-learning environments.

Table 11 Results of PLS-Predict

	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
SV17	0.378	1.020	0.864	0.954	0.790
SV18	0.386	0.981	0.833	0.915	0.751
SV19	0.348	1.020	0.872	0.968	0.797
SV20	0.316	1.051	0.901	1.012	0.834
SV21	0.331	1.081	0.922	1.027	0.851
SV10	0.383	1.016	0.816	1.018	0.814
SV7	0.398	0.993	0.806	0.997	0.811
SV8	0.403	0.980	0.792	0.984	0.797
SV9	0.444	0.949	0.793	0.951	0.794
SV11	0.427	0.963	0.775	0.968	0.779
SV12	0.417	0.984	0.813	0.988	0.815
SV13	0.367	1.000	0.832	1.002	0.837
SV14	0.384	1.037	0.853	1.036	0.853
SV15	0.406	0.970	0.776	0.975	0.779
SV16	0.401	0.975	0.799	0.978	0.801
SV1	0.375	1.010	0.828	1.011	0.821
SV2	0.426	0.943	0.780	0.942	0.776
	Saturated model		**Estimated model**		

SRMR	0.049	0.133

4.10 Interview-Based Qualitative Findings

The qualitative component of this study as shown in Table 12, involved semi-structured interviews with five university educators in Chengdu, China, to explore their experiences with Nano-learning and short-form educational videos. Conducted in quiet, private settings, the interviews lasted 13–34 minutes and were guided by 13 pre-defined questions focusing on student engagement, pedagogical integration, and instructional challenges. All sessions were recorded, transcribed, and analyzed using NVivo and WeiCiYun tools, which enabled thematic coding, sentiment analysis, and semantic network mapping. Texts were segmented and processed using the spaCy model for linguistic accuracy, yielding 51,451 words across 182 entries. The refined data provided valuable insights into teachers' perceptions and informed the study's broader analysis of Nano-learning's pedagogical impact.

Table 12 Participants information and interview time (time and quantity)

No.	Name	Gender	Position	Interview Duration (Min)	Draw Word Number
1	TIAN YI	MALE	Teacher	13	801
2	YANG	FEMALE	Teacher	23	1101
3	YU	MALE	Tutor	34	2358
4	MA	FEMALE	Teacher	28	2497
5	ZHANG	FEMALE	Teacher	21	1509

4.11 Visual Analysis Results of The Interview Results

4.11.1 Visual Analysis Results of Full Contents

Table 13 shows, a word frequency and semantic visualization analysis using NVivo and WeiCiYun revealed key themes in the interview corpus, centered on technology-enhanced pedagogy, student engagement, and content relevance. The top three words—"videos" (186), "students" (129), and "learning" (106)—highlight a strong emphasis on using short-form videos to enhance student learning. Other frequent terms such as "short," "think," and "content" reflect educators' critical consideration of Nano-learning's brevity and cognitive impact. Words like "teacher," "teaching," and "help" underscore the continued importance of instructor facilitation, while terms such as "class," "classroom," and "course" situate these practices within formal educational settings. Finally, words like "important," "tools," "engage," and "challenge" indicate a reflective awareness of the opportunities and limitations of digital instructional strategies. Overall, the results reveal a balanced perspective among educators, combining enthusiasm for innovation with thoughtful critique.

Table 13 High-Frequency Words in Interview Contents

No.	Words	Frequency	No.	Words	Frequency	No.	Words	Frequency
1	videos	186	11	need	38	21	Classroom	22
2	Students	129	12	like	33	22	Time	22
3	Learning	106	13	class	30	23	Course	20
4	short	83	14	interest	30	24	Many	20
5	think	65	15	points	29	25	Important	19
6	content	62	16	understand	29	26	Tools	18
7	teacher	53	17	example	28	27	Engage	16
8	Teaching	42	18	knowledge	27	28	Mentioned	16
9	help	40	19	Traditional	27	29	Quickly	16
10	use	40	20	Fragmented	24	30	Challenge	15

4.11.2 Sentiment Analysis of full Contents

Semantic network analysis is a robust method for revealing hidden relational structures in qualitative text by examining word co-occurrences and semantic proximity rather than mere frequency as shown in table 14. This study employed sentiment analysis using WeiCiYun with the VADER algorithm to examine emotional and attitudinal patterns in qualitative interview data on Nano-learning and educational technology. Sentiment was categorized as positive (39.01%), neutral (42.86%), or negative (18.13%) based on paragraph-level scoring, with corresponding sentence distributions of 223, 222, and 116, respectively. Neutral sentiment dominated, reflecting the reflective tone typical of semi-structured interviews, while positive sentiment highlighted enthusiasm for digital tools and innovation. Negative sentiment, though limited, pointed to concerns such as student attention spans and technological challenges, revealing a generally balanced emotional tone with optimism toward Nano-learning tempered by realistic concerns.

Table 14 Sentiment Analysis

Number of Positive paragraph	Number of Negative paragraph	Number of Neutral paragraph
71	33	78
Number of Positive Sentences	**Number of Negative Sentences**	**Number of Neutral Sentences**

223	116	222

4.12 Implications of the study

This study reveals that the effectiveness of nano-learning is shaped by cultural learning models, platform design, and evolving pedagogical authority. Far from being culturally neutral, nano-learning reflects learners' educational values, cognitive habits, and expectations of autonomy and support. While its flexibility and personalization enhance motivation and satisfaction, they also risk promoting fragmented attention and limiting critical thinking. As algorithms increasingly influence learning paths, autonomy becomes a negotiated space between user freedom and system-driven choices. Platform design significantly affects engagement, often prioritizing immediacy over depth. To foster meaningful learning, platforms must integrate reflective, inquiry-based, and culturally sensitive features. Ultimately, effective nano-learning requires a balanced design that aligns personalization with cognitive depth, autonomy with guidance, and efficiency with cultural relevance.

DISCUSSION

This study highlights the effectiveness of short video-based nano-learning through an integrated theoretical framework, primarily guided by the Stimulus–Organism–Response (S-O-R) model. It reveals that specific video attributes such as length and content relevance—act as external stimuli that influence learners' internal psychological states, including motivation, engagement, and satisfaction. These internal responses, in turn, drive observable behaviors like extended watch time and repeated viewing, which are positively associated with improved learning effectiveness. The results affirm that short, focused, and engaging video content supports learners in maintaining attention and achieving cognitive goals, making it a valuable format for digital education environments.Incorporating Symbolic Interaction Theory [8] and Media Ecology Theory [9] enriches the understanding of how learners construct meaning and interact with the digital learning environment. Symbolic cues within video content such as visuals, music, and social signals like likes and comments enable users to derive personal and social meaning, enhancing learning motivation and emotional engagement. Media Ecology Theory emphasizes that the nature of digital platforms shapes learners' experiences by altering attention, cognition, and communication processes [34]. Together, these insights suggest that pedagogically informed short videos can transform digital learning into a more interactive, personalized, and effective process. This underscores the importance of integrating media design, user psychology, and symbolic interaction in educational content development.

CONCLUSION AND RECOMMENDATIONS

This dissertation investigates nano-learning on short video platforms using mixed methods (SEM and content analysis) to examine how motivation, satisfaction, and platform design shape user engagement. Findings reveal that intrinsic motivation, content quality, and video length significantly enhance satisfaction, which in turn drives emotional and behavioral engagement. While motivation alone does not predict engagement, satisfaction is a key mediator, converting intent into sustained learning behavior. Content relevance and clarity boost engagement, which mediates the relationship between content quality and watch time. Platform features such as autoplay and algorithmic feeds facilitate learning flow but may fragment attention if not pedagogically aligned.The study extends the AMO and media affordance frameworks by showing how interface design and user agency interact to influence learning outcomes. High-agency users engage more deeply, using platform affordances strategically, while low-agency users risk superficial learning. Emotional and cognitive involvement, reinforced by repeated positive experiences, promotes long-term engagement. However, entertainment-driven features or poor content can disrupt this process. The research highlights satisfaction and engagement as central mechanisms that mediate and moderate learning effectiveness in nano-learning environments, offering practical and theoretical insights for optimizing digital pedagogy in attention-driven platforms.Based on these findings, the following recommendations are proposed: (1) Short video platforms should prioritize content clarity, relevance, and emotional resonance to enhance satisfaction and engagement; (2) Platform design must balance interactivity and usability with pedagogical coherence by minimizing distractions and supporting user-controlled pacing; (3) Developers should integrate features that build learner agency; such as personalized goals, reflective tools, and adaptive feedback to foster deeper learning engagement; (4) Educators and content creators must collaborate to design micro-content that aligns with learning objectives while leveraging platform affordances effectively. These steps can enhance the educational potential of nano-learning while maintaining user engagement and cognitive integrity.

LIMITATIONS AND FUTURE STUDIES

This study offers valuable insights into the cultural, technological, and pedagogical dimensions of nano-learning adoption but is subject to several limitations. The homogeneity of the sample mainly university students and digitally experienced young professionals limits generalizability, highlighting the need to include diverse age groups, cultural backgrounds, and marginalized learners in future research. The quantitative model excluded complex sociocultural variables, leaving cultural effects only partially explored; future studies should incorporate culturally sensitive measures to address this gap. Insights into algorithmic personalization were based on subjective reports without access to actual algorithms, limiting understanding of their true impact; interdisciplinary collaborations and algorithm audits are recommended. The focus on short-term outcomes such as satisfaction and engagement overlooks long-term cognitive effects like critical thinking and knowledge retention, necessitating longitudinal designs. Additionally, despite measures to minimize bias, qualitative interpretations remain subject to researcher perspective, suggesting a need for methodological triangulation and participant validation. External factors, including rapid technological change, post-pandemic learning shifts, and linguistic nuances, may also have influenced findings. Building on these limitations, future research should explore nano-learning's long-term cognitive impact, integrate cultural frameworks, examine the balance between personalization and learner autonomy, assess effectiveness across disciplines, evaluate platform interventions, and prioritize inclusive sampling particularly from the Global South to foster equitable, context-sensitive, and sustainable digital education.

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