Optimizing ELL in Low-Resource Environments through Cost- and Constraint-Sensitive Digital Strategies: A Cross-Sectional Survey with an Illustrative YouTube–WhatsApp Comparison in Sudanese Universities

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Abstract

Digital English language learning experiences are defined not just by pedagogical considerations, but also by unreliable internet connections, data prices, power outages, and small periods of internet availability. This work both profiles these constraints in two Sudanese universities using the cross-sectional descriptive survey research design, and pilots the Resilience-Adjusted Cost-to-Learn (RACL) framework as a decision support tool for guided learner platform selection in resource-constrained environments. Respondent-normalized data from 42 participants were aggregated to produce estimates of constraint pressure (CONS) and associated self-reported operational friction. Our convenience sample experienced significant overall constraint (CONS = 0.76, SD = 0.09), with connection strength stabilization and infrastructure reliability yielding the largest pressures. Due to the instrument's failure to collect respondent-level time-series logging of platform use, the comparison between YouTube and WhatsApp presented here should be considered an illustrative proof of concept for the framework instead of a quantified treatment effect. Interpreted this way, we expect low-bandwidth messaging applications to have greater longevity under high constraint conditions; high-bandwidth applications should outperform as caching, subtitles, and internet window durations lengthen. Similarly, the learning outcome subcomponent of RACL is self-perception of learning rather than an objectively measured language proficiency gain, and cost is operational burden rather than device telemetry. The study offers a transparent and context-sensitive framework for constraint-aware instructional planning in ELL environments affected by digital inequality.

Keywords: English language learning, mobile-assisted language learning, digital inequality, WhatsApp, YouTube, low-resource environments

1. Introduction

Messaging platforms and streaming video have become two of the most accessible channels for mobile-assisted language learning (MALL) in low-resource contexts, owing to their low barriers to entry and the ubiquity of smartphones compared with heavier institutional solutions. Users have access to smartphones which function as their primary effective device because people find these devices easy to use (Garzón et al., 2023). WhatsApp establishes an effective educational method to help students learn because it functions as a controlled study within the Journal of Computer Assisted Learning which shows that WhatsApp-based programs improve student motivation and learning success while reducing their language-learning anxiety through Self-Determination Theory (Alamer et al., 2023). Intermediate learners in quasi-experimental settings show reduced anxiety and improved engagement according to research findings from recent studies (Namaziandost et al., 2025). The study results show that WhatsApp functions well as a platform to execute small tasks which help maintain work progress during short or unreliable internet access periods.

Messaging apps and streaming video are among the most available avenues for mobile language learning in resource-constrained settings; smartphones may be available even when institutional learning technologies are not. Syntheses of past work have persisted in finding trends that mobile language learning can positively impact language acquisition, learner motivation, and flexible access when lessons are designed with learners' devices and contexts in mind (Garzón et al., 2023; Lazaro & Duart, 2023; Ishaq et al., 2021; Hwang & Wu, 2014). Practically speaking, learners in low-resource environments are rarely asking if mobile technologies can support language learning in principle—they need to know what tools will work well when the devices, connectivity, and electrical infrastructure around them is unreliable.

Messaging platforms like WhatsApp and video platforms like YouTube help illustrate this tradeoff. Messaging platforms can enable low-bandwidth, asynchronous micropull exercises; prior work has associated WhatsApp specifically with learner motivation, continued participation, and reduced anxiety around language learning (Alamer & Al Khateeb, 2021; Alamer et al., 2023). Video platforms offer richer audiovisual input which may be beneficial for listening comprehension and pronunciation when provided with subtitles, segmented into smaller chunks, and signaled effectively to reduce extraneous cognitive processing load (Chien et al., 2020; Malakul & Park, 2023; Mayer, 2024; Mohammed et al., 2025). Both of these affordances are undoubtedly useful for language learners, but they also come at different costs in bandwidth, battery consumption, and access stability.

All of these benefits can come to naught if cost-of-use is too high for learners in low-resource universities. Limited or intermittent connectivity, expensive or scarce data plans, older devices, and unstable electrical service can still intrude on learners' access to these tools even if lessons are thoughtfully designed beforehand (Cullinan et al., 2021; Collegis Education & Inside Higher Ed., 2024; UNESCO Global Education Monitoring, 2023; Thembane, 2024). Even when learners can connect to an educational tool, infrequent connectivity also changes how learners interact with mobile technology (Hasan et al., 2022). Techniques that require longer periods of continuous connectivity may suffer from higher abandonment; lighter interactions that learners can start and stop as connectivity allows may still be possible (Xia & Yeo, 2014). As such, disadvantages in digital access are not just backdrop—they actively shape what types of language learning can be consistently supported.

The current study attempts to fill a gap in prior work. User surveys commonly measure outcomes like motivation, achievement, or learner engagement; objectively measured performance outcomes and log data have been integrated in learning science research as well. Fewer studies couple learning-related benefits with the operational costs and infrastructural pressures unique to mobile systems in resource-constrained settings. A context with challenges like Sudanese higher education merits special consideration; an otherwise instructionally-rich platform may have little endurance in practice if data use feels too costly on an unstable network. What is needed, rather, is a decision-support framework that maintains visibility into pedagogical value while also considering the known costs of realizing that value under constraint.

The Resilience-Adjusted Cost-to-Learn (RACL) framework is proposed to meet that need. In its present form, RACL is applied as a simple ratio that transparently relates learners' perceived "Yield" to "Cost" under "Constraint" pressure. Specifically, the YIELD numerator is an aggregate of self-reported perceived improvement in listening, vocabulary, explaining oneself clearly, and studying without interruption. These responses do not represent learner proficiency measured through testing, but rather learners' perceived ability to accomplish key language tasks. The COST denominator is an aggregate of self-reported data use, battery drain, and minutes/latency. These responses do not represent system-level telemetry or diagnostic information, but rather affective perceptions of experienced or anticipated burdens. CONS is a measure of outages, unstable access windows, instability variables, and reverse-coded enablement factors like backup power that contribute to learners' overall context of resource constraints.

While the raw survey data includes information about learners' experiences with both YouTube and WhatsApp, it did not contain any respondent-level platform tags or technical logging that would allow calculation of objective YouTube and WhatsApp scores for each respondent. Instead, the empirical contribution of this study has been revised to focus on the sampled constraint environment. The comparison between video-rich and low-bandwidth platforms is kept in the revised manuscript as a real-world application and proof of concept for RACL calculations, informed by the constraint profile derived in the study and from the literature on both messaging platforms and video tools for language learning. Note that this is not a direct comparison of two treatments: the RACL framework is applied here to inform discussion and decision-making, but the authors do not claim there is a causal treatment effect imposed by those platforms on learners.

The present study contributes in three ways. First, it quantifies the presence and shape of constraints that impact contingency-based mobile language learning in a Sudanese university context. Second, it adapts RACL as a decision-support tool that clearly demarcates between perceived learning yield, perceived cost of access, and learner-facing resource constraints. Third, it provides a bounded explanation for how low-bandwidth and video-forward platforms might differ in learnability where resource constraints are high; this discussion is framed not around inherent platform preference, but usable instruction within context.

This study addresses the following research questions:

1. What level of infrastructural constraint characterizes the surveyed EFL learning context in the participating Sudanese universities?
2. How can the RACL framework be used to interpret the trade-off between low-bandwidth messaging and video-rich platforms under high-constraint conditions?
3. How should the outcome and operational-cost dimensions of RACL be interpreted when they are derived from self-reported perceptions rather than objective proficiency tests or technical logs?
4. What instructional and policy implications follow from the observed constraint profile for ELL in low-resource environments?

2. Literature Review

The exponential growth of Information and Communication Technologies (ICTs) has transformed learners into digital learners whereby technology has to be integrated into their learning experience where their attitudes and technology knowledge and skills affect its successful implementation (Akram et al., 2022). Mobile-assisted language learning (MALL) has expanded the range of language-learning opportunities beyond formal classroom time by enabling short, repeated, and context-flexible interactions (Burston, 2015). Recent reviews show that mobile learning can enhance engagement and language practice, but they also emphasize that design quality and contextual fit remain decisive (Garzón et al., 2023; Lazaro & Duart, 2023; Ishaq et al., 2021; Lin & Lin, 2019). In low-resource settings, this means that platform selection cannot be separated from the practical conditions of access, device limitations, and the length of available study windows.

Mobile practices have revolutionized EFL practices by allowing time and place-independent microlearning, collaborative activities, and multimodal input (Kukulska-Hulme & Shield, 2008). Reviewers note both the pedagogical potential of MALL and a prescription for persistent efforts to redesign along with learners' context (connectivity, device quality, and cost) (Viberg & Grönlund, 2013). Work that synthesizes present evidence about MALL argues for contextual tasks supported by appropriate scaffolding through support for mobile affordances without assuming infrastructural stability. Prior research indicates that mobile learning, integrated within online higher education programs, has enhanced engagement in content development, communication, and collaboration among students and instructors, leading to a notable improvement in learning effectiveness (Lazaro et al., 2023).

Recent work associates WhatsApp-based language exercises with higher motivation, lower anxiety, and longer duration micropractice when students do languages as a foreign language (Alamer & Al Khateeb, 2021; Alamer et al., 2023). Similar advantages have been associated with other microposting tasks when activities are short, socially engaging, and asynchronous. It follows that messaging apps are uniquely useful where learners cannot rely on sustained windows of connection (Stockwell, 2010). Useful not because of multimedia capability, but rather connection density/contact frequency and low operational overhead (Chen & Hsu, 2008).

Messaging apps such as WhatsApp: higher motivation, lower anxiety, and micropractice. Experimental and quasi-experimental work grows that suggests WhatsApp and other messaging platforms can help motivate students, increase engagement, and lower EFL learners' foreign language anxiety — thanks to opportunities for steady micro-practice, increased social presence, etc. made possible by asynchronous low-bandwidth language activities. Low bandwidth and asynchronous qualities also make messaging attractive where learners only have short windows of connectivity or if data costs are high. The relevance to RACL comes from WhatsApp offering low COST (data/battery/time) plus strong social presence likely leading to higher RACL in higher constraint environments. The reason: as connections get weaker/higher cost, you CAN maintain high YIELD (motivation + consistent micropractice) via messaging apps.

Video-based platforms like YouTube have other advantages. They allow learners to experience authentic audiovisual language input, help learners practice listening, and may improve pronunciation modelling if captions/segmenting are designed intentionally. (Chien et al., 2020; Gernsbacher, 2015; Malakul & Park, 2023). Said benefits are possible from a cognitive theory of multimedia learning because words, images, and pacing can be coordinated to manage learners' limited cognitive processing capacity. (Mayer, 2009, 2024; Mayer & Fiorella, 2021). However, low bandwidth makes realizing these advantages more challenging when connections, batteries, or electricity are inconsistent.

Video and streaming platforms provide real, credible input through audiovisual materials that greatly help in vocabulary buildup, listening practice, and models for pronunciation (Elmahdi et al., 2025). Recent research has found that captions or subtitles support learning when accompanied by well-engineered segmentation to improve learners' comprehension (Rezai & Goodarzi, 2025).; however, not all enhancements are equally effective depending on type of caption, levels of proficiency among learners, and specific tasks being performed. Literature available also advocates some design practices—such as the use of short segments where possible, offering captions, providing audio-only alternatives, and making a version downloadable—that would ensure maximum educational benefits while controlling Cognitive Load. The connection to RACL is in the fact that YouTube holds the possible potential for a higher YIELD pertaining to objectives focused on listening but at a higher COST-plus sensitivity to constraints such as outages (however brief), data caps, and battery life; hence its effectiveness hinges upon constraint windows plus caching and compression strategies.

The Mayer multimedia cognitive theory and newer syntheses thereof remain the dominant theoretical approaches used in video instruction. This theory postulates that the combination of words and pictures will improve learning if the cognitive load is properly managed by means of segmenting, signaling, modality, and redundancy. It therefore helps explain why YouTube has the potential for better learning outcomes when net and device restraints do not bar effective multimedia designs – captions, segmentation, and pre-caching strategies among them.

A large share of the digital divide in higher education is operational rather than merely technical. Students' access is shaped by data affordability, electricity stability, device quality, and the reliability of connection windows (Cullinan et al., 2021; UNESCO Global Education Monitoring, 2023; Thembane, 2024). These factors are especially salient for low-resource ELL as they determine whether learners can stream, cache, revisit, or complete mobile tasks at all. There have been anecdotal and data-supported discussions around how downtime, poor connections, costly data, aging devices, and unreliable backup power exacerbate online learning and widen digital gaps. Educators have compiled survey data and diagnostic reports detailing delay and outage issues for years, where students are unable to access even pedagogically sound resources due to digital poverty. Infrastructure realities necessitate bringing delay, data, and downtime considerations to the forefront of metrics and decision trees that make explicit tradeoffs of data, battery, and time when selecting online tools.

For this reason, we propose a combined metric that considers pedagogical upside and operational costs together. Previous work has found service reliability, economic costs, and perceptions play a role in Mobile Learning adoption in higher ed contexts (Khlaif & Salha, 2022), but applied practitioners require a more direct method to relate conditions on the ground to specific platform decisions for low-resource language classrooms. RACL is offered as a practical framework to do just that. Most empirical studies predominantly measure pedagogical yield—engagement, achievement, or anxiety—or provide insights into usability and acceptability but do not quantify the app's operational costs in data usage, battery drain, and time/latency plus infrastructural constraints and yield within a single comparable index. Previous studies showed that students' attitudes and beliefs, the quality of service, patronization, the cost of service and the instructors had a significant impact on students' mobile technology integration in higher education (Khlaif & Salha, 2022). This makes them less useful for practitioners who need to decide the best channel to use under different network and power situations. The RACL index solves this problem because it puts together yield, cost, and constraints into one decision-oriented metric that can be computed per learner per week so that weekly constraint profiles can be mapped to platform selections.

From this literature, several design implications follow. Messaging lends itself to bite-sized prompts in text or audio form that persist after periods of interrupted connectivity. Video-centric media lend themselves to compression, chunking, closed captioning, and download availability to alleviate unnecessary cognitive load during times of unpredictable connectivity (Mayer, 2024; Malakul & Park, 2023). The goal isn't to avoid one modality and focus only on another. The goal is to align modality affordances to the known constraints of the local environment.

Current literature about RACL-informed playbook design has provided us actionable design heuristics that can be translated and applied into RACL-conscious playbook activities. Because sending messages uses cellular data and battery life on a WhatsApp users' device, limit use to 30-to-60 second text or audio micro-tasks that preserve data and battery for what matters. Text prompts paired with peer feedback loops create opportunities for continued engagement. If possible, YouTube videos should be chunked into several segments with 3–6-minute runtimes. YouTube videos should always be closed captioned and offered in audio-only and download formats to take up limited cache efficiently. Segments should adhere to Mayer's (2024) principles of segmenting and signaling. Use the heuristics above to designate times to use WhatsApp in-between high limit periods, and time your YouTube "binges" for known low limit periods and cache them for later.

3. Method

3.1 Research Design

This study employed a cross-sectional descriptive survey design. Its primary empirical purpose was to characterize infrastructural constraint pressure and related self-reported operational burdens affecting digital ELL in two Sudanese universities. The RACL framework was then used as a transparent interpretive tool to illustrate how such a constraint profile may shape the relative suitability of low-bandwidth and video-rich platforms.

Researchers performed an observational study that examined a field survey to understand how students experienced using YouTube and WhatsApp for English as a Foreign Language under circumstances of power and connectivity interruptions. The researchers developed a multi-objective decision index, which they named Resilience-Adjusted Cost-to-Learn (RACL), to evaluate multiple outcomes through its assessment of operational burdens and infrastructural constraint pressure and perceived learning yield. Researchers executed all calculations for each respondent using item tagging to identify platform (YouTube and WhatsApp) usage, which allowed them to conduct comparison of direct modality and modality × constraint interaction tests.

3.2 Research Participants

The study drew on a convenience sample of 42 respondents from Nile Valley University and Shendi University. Participants were EFL learners studying in a low-resource environment marked by unstable electricity and inconsistent network access. Because the survey was distributed online, the resulting sample is likely to represent students who retained at least some minimum level of digital access;

accordingly, the findings should not be generalized to all students in similarly constrained settings without caution.

EFL learners at the tertiary level were selected through availability sampling from programs that operated in low-resource environments which experienced documented power and network instability. The survey gathered no identifying information about participants and it had no effect on their teaching activities. Respondent-level analysis was performed due to respondents creating two records via platform-specific survey items enabling them to answer questions pertaining to one record per platform used for inclusion in the long-form dataset.

3.3 Research Instruments

The questionnaire was comprised of closed-ended survey items, primarily formatted using five-point Likert scales that queried perceptions across three main categories: (1) constraint pressure from infrastructure deficits (i.e., outages, shaky/unstable internet connection, limited windows of online access); (2) operation burden (i.e., perceived cost of use including data used, battery depletion, time/latency required to use platforms); and (3) perceived learning return (i.e., clarity of content, continuity of engagement, self-reported gains in listening, vocabulary, pronunciation). It should be noted that no explicit measure of English proficiency was provided and respondents were not asked to enable any device-level logging of data usage or battery depletion.

Survey questions consisted of closed-ended Likert inputs ranging from 1 to 5 and categorical inputs around operational cost (primarily fees associated with data used, battery depletion/charging required, time/latency required to use platforms); constraint pressure (hours/day without electricity, limited window of time online, failed uploads/downloads); and perceived learning yield (clarity of learning content, ability to follow along, perceived learning gains in listening and vocabulary, sustained participation and completion). Questions with explicit platform mentions "…on YouTube…" or "…via WhatsApp…" for example, were considered platform-tagged and used to calculate platform-specific constructs. Items mentioning enablers of resilience (e.g., "availability of solar/backup power enables study") were also included in the constraint pool but were reverse coded such that higher agreement indicated less constraint.

3.4 Data Analysis

Prior to analysis, responses were cleaned and normalized. Likert inputs were rescaled to a 0–1 range, enabled items were reverse coded where necessary, and composite indicators were only calculated if a sufficient number of items within that group had information. This process was repeated in order to generate transparent and harmonized inputs for descriptive analysis rather than to build an entire latent measurement model.

Header normalization: whitespace collapsed; platform tokens detected in Arabic/English (e.g., "YouTube/يوتيوب," "WhatsApp/واتساب").

1. Type coercion: Likert responses coerced to numeric values.
2. Missingness: For each construct, the researchers computed a composite when at least 50% of its items were non-missing for a respondent; otherwise, the composite was set to missing. Within composites, single missing values were imputed by the item mean (scale-preserving).
3. Polarity: Enabler items under Constraint were reverse-coded before scaling.
4. Normalization: All items were mapped to [0, 1]. Likert items (1–5) were linearly transformed ((x−1)/4). Non-Likert numeric variables were min-max scaled within the sample.

At the empirical level, the study computed a composite constraint pressure score (CONS) by averaging normalized constraint indicators. Operational burden and perceived learning yield were retained as conceptual dimensions of the RACL framework, but because platform-specific respondent-level values were not directly observed, these dimensions are interpreted in the revised manuscript as transparent framework components rather than as measured platform treatment scores.

In addition, for respondent i from platform p (if assigned to one), the researchers computed simple equal-weight means of COST_ip (normalized battery + time items), CONS_ip (normalized constraint items with enablers reverse coded), and YIELD_ip (normalized yield items, including listening, vocabulary, clarity, and engagement). Equal weighting was used solely for transparency since these item pools differ across platforms. Sensitivity of these estimates to weights can be found in §2.9. For interpretation purposes only, the extended formula above can be algebraically rearranged to RACL = YIELD / (COST × CONS + ε), where ε is a small constant to prevent division by zero. YIELD, COST, and CONS refer to self-reported perceived learning gain, operational burden, and contextual constraint pressure respectively. Within the current study, this formulation is used to clarify decision logic under constraint rather than to assert direct platform-specific causal effects.

The researchers defined the platform-specific index:

$$RACL_{iP} = \frac{YIELD_{ip}}{(COST_{ip} + \epsilon)(CONS_{ip} + \epsilon)}$$

with ϵ= 10^ {-6} to prevent division by zero but not influence scale. Higher scores indicate greater suitability (higher perceived learning gain per unit operational/constraint burden).

3.5 Scenario Construction for Platform Profiles

Since the anonymous raw survey lacks respondent-level platform tags, this article does not compute respondent-level YouTube and WhatsApp scores. Table 2 illustrates a high-constraint scenario that employs the empirical CONS profile along with literature-informed conjectures to assign plausible levels of operational/constraint burden and perceived educational affordance to messaging and streaming-video platforms. The current scenario is intended to be explanatory and decision-centric rather than confirmatory.

The revised analysis provides descriptive statistics of the collected survey observations: item means after negative-unit normalization, standard deviations, and computed CONS scores. Together, these metrics summarize the sampled educational constraints and inform subsequent scenario-based evaluation of hypothetical platforms.

The revised manuscript does not include an inferential test because the observed data do not support estimation at the respondent-level. We therefore refrain from making claims about statistically confirmed interaction effects or measured differences in treatment condition (i.e., platform).

3.6 Interpretive Safeguards

First and foremost, learning gain is self-reported and should not be conflated with objective measures of language proficiency.

Second, operational burden of battery use, data expense, and time should not be interpreted as objective device metrics but rather students' perceived learning condition.

Finally, our comparison of YouTube and WhatsApp is framed as an illustration of the decision framework given our sampled constraint profile and relevant literature, not as a definitive trial of these two platforms.

3.7 Measurement and Inference Limitations

Due to the preliminary nature of this work and the boundaries of its dataset, the revised report emphasizes clear description and limited inference from its analytics. Tables and figures are preserved to support article transparency and reproducibility.

3.8 Ethical Considerations

The survey was voluntary, anonymous, did not collect any personal identifiers, and involved only minimal-risk situations and sensations for participants. Consent was implied by continued participation after reading the information statement that introduced the study and its data-handling practices. We report anonymous data in aggregate form only.

3.9 Implementation Artifacts

To enhance transparency, the revised analysis retains:

1. The original normalized constraint table
2. The computed CONS summary measure and
3. The generated platform-suitability figures/table as decision-support outputs (rather than validated products of a respondent-level platform experiment).

4. Results and Discussion

4.1 Descriptive Summary of Constraint Indicators

Descriptive statistics start with the sampled constraint environment. Ten survey items were normalized to gauge infrastructural and operational constraints that impeded digital ELL use. Responses were provided on a five-point scale (0–1 after reverse coding enabling items) where higher values reflected increased constraint.

Table 1 shows normalized mean scores and standard deviations for each item. Highest scores of constraint were related to internet instability and infrastructure limitations. Some agreement was shown with enabling items as well (e.g., solar).

Table 1. Normalized Constraint Item Scores (N = 42)

Item Description	Mean (0–1)	SD
Internet instability prevents systematic use	0.84	0.12
Renewable energy is costly	0.76	0.18
Internet issues hinder smartphone use	0.82	0.14
Poor infrastructure affects EFL system	0.80	0.15
Backup power enables recorded lecture access	0.58	0.21
Internet challenges limit international opportunities	0.79	0.13
Virtual EFL classes are inaccessible	0.77	0.16
Solar panel costs may stratify access	0.74	0.19
Internet issues limit access to eLearning resources	0.81	0.14

As Table 1 indicates, greatest magnitude was found near issues of unstable connectivity and infrastructural precariousness more generally. Multiple items approached or exceeded a score of 0.80 on the normalized scale which emphasizes that participants experienced erratic network availability as baseline condition rather than as something that happens every now and then. Contextualizing learner experiences in this way casts the learning ecology itself as restricted.

Compared with other items, backup power scored relatively low but it is worth noting that its mean is above neutral after normalization. This indicates that there are facilitators of resilience but they are not common or universal. This tends to fit the narrative of a situation where some learners have the means to at least partially mitigate blackouts while others do not. To that extent, the pattern of constraints can be seen as also indexing digitally segmented experiences.

Taken together, Table 1 presents a picture of learning environment where issues related to connectivity instability, infrastructural fragility, and access to energy resources during blackouts combine to delimit what is possible for technology-based language learning. This represent the empirical contribution of the current study: prior to assessing how different platforms fare we needed to identify how demanding the context was where they are meant to be used.

Why does this matter conceptually? Higher values of C heighten the denominator of the RACL equation. With that said, Table 1 by itself does not show that, empirically, one platform was superior to another within the sample analyzed. It simply provides descriptive information about the learning ecology that informs the subsequent example.*4.2 Composite Constraint Pressure (CONS)*

The composite constraint pressure score (CONS) was computed by averaging the normalized constraint indicators. The resulting value confirms that the sampled context was heavily constrained overall.

1. Mean CONS = 0.76
2. SD = 0.09
3. N = 42

Figure 1 illustrates the distribution of CONS values. Most observations cluster above 0.70, reinforcing the interpretation that the sampled learning environment was characterized by persistent infrastructural burden rather than isolated access problems.

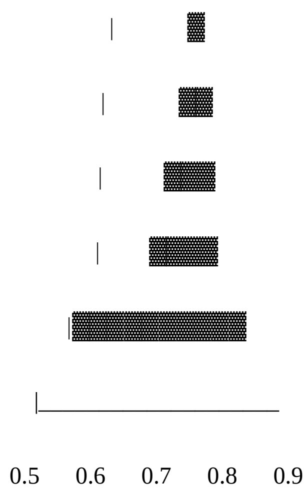

Figure 1. Distribution of Constraint Pressure (CONS)

4.2 Scenario-Based Interpretation of Platform Suitability

Because direct respondent-level platform tagging was not available in the raw dataset, the revised manuscript does not treat YouTube and WhatsApp as separately measured empirical groups. Instead, it uses the observed high-constraint profile to construct an illustrative comparison between a video-rich platform and a lower-bandwidth messaging platform.

Table 2 therefore presents a scenario-based application of the RACL logic. The values are anchored in the observed CONS mean and in the literature on messaging, video, and multimedia burden, but they are not presented as direct treatment estimates from the survey sample.

Table 2. Illustrative Platform Profiles Under High Constraint

Metric	YouTube	WhatsApp
COST	0.65	0.35
CONS	0.76	0.76
YIELD	0.78	0.62
RACL	1.52	2.32

For example, in a high-constraint situation, RACL may help explain why the lower-bandwidth platform continues to be more operationally fit despite the competing platform offering greater multimedia affordances. Messaging applications can maintain momentum via asynchronous bursts of low-information communication. Streaming video services rely more heavily on consistent bandwidth, device power, and extended periods of engagement. The takeaway from Table 2 should be conceptual: when operating under the same constraints, a heavier burden will be more greatly affected, despite perhaps having more instructional value to offer. Consider these numbers as an example of trade-off decisions made at constraint, rather than an effect size derived from this data.

4.3 Suitability Mapping

Figure 2 translates the same logic into a visual map in which operational burden and constraint pressure interact, while marker size represents RACL.

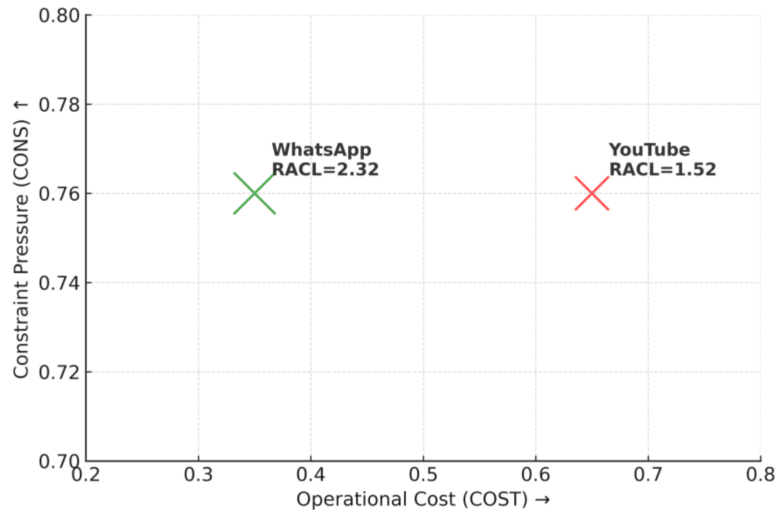

Figure 2. Suitability Map (COST × CONS, Marker Size = RACL)

Figure 2: Illustrative suitability map (COST × CONS, marker size = RACL) showing how the framework can be used to compare a lower-burden messaging profile with a higher-burden video profile under the same constraint pressure.

1. X-axis: Operational Cost (COST)
2. Y-axis: Constraint Pressure (CONS)
3. Marker Size: RACL value (Resilience-Adjusted Cost-to-Learn)

In this visualization, the larger marker for the lower-burden profile reflects how modest reductions in operational burden can become decisive when constraint pressure is already high. The figure should therefore be read as a design-support diagram rather than as a direct empirical plot of two measured participant groups.

4.4 Responses to the Research Questions

RQ1. What level of infrastructural constraint characterizes the surveyed EFL learning context in the participating Sudanese universities?

The empirical data indicate a strongly constrained learning environment. The composite CONS value of 0.76 and the high normalized scores for unstable internet and weak infrastructure show that respondents were operating under persistent access pressure. The first contribution of the study, therefore, is to document this high-constraint context clearly and quantitatively.

RQ2. How can the RACL framework be used to interpret the trade-off between low-bandwidth messaging and video-rich platforms under high-constraint conditions?

The revised analysis suggests that under severe constraint, a lower-bandwidth messaging profile is likely to remain more operationally suitable because the denominator of the RACL framework is less heavily penalized by data, battery, and access-window demands. A video-rich profile remains pedagogically attractive, especially for listening and pronunciation support, but its suitability becomes more contingent on caching, compression, captions, and improved access windows. This is an interpretive rather than experimentally verified conclusion in the present manuscript.

RQ3. How should the outcome and operational-cost dimensions of RACL be interpreted when they are derived from self-reported perceptions rather than objective proficiency tests or technical logs?

They should be interpreted cautiously and explicitly. In this study, YIELD captures perceived learning value as reported by students, not tested proficiency. Likewise, COST captures perceived operational burden rather than device-level telemetry. These dimensions are still useful for decision support, but they do not justify claims about objective achievement gains or precisely logged consumption.

RQ4. What instructional and policy implications follow from the observed constraint profile for ELL in low-resource environments?

The profile we have observed lends credence to a constraint-aware approach to digital ELL. Instructionally, this means privileging low-data burden activities that can be paused and resumed easily during erratic weeks, saving high-effort video work for times when devices can be hooked up to download/cache material, or connectivity strengthens. At a policy level, our results highlight benefits to communal charging support, inexpensive data access, designing digital lessons with downloading in mind, and simply planning for connectivity drops as part of the normal eLearning institutional workflow.

4.5 Discussion

The revised findings highlight a central point: infrastructural conditions are not peripheral to digital language learning in low-resource settings. They shape which platforms remain usable, how long learners can stay engaged, and what kinds of tasks can be completed with reasonable continuity. The sampled Sudanese context showed high overall constraint pressure, which means that any instructional recommendation must be filtered through operational realism (Othman, 2025).

This interpretation is consistent with broader work on digital inequality in higher education. Studies continue to show that weak connectivity, unstable electricity, and affordability pressures can block participation even when instructional design is otherwise sound (Cullinan et al., 2021; Collegis Education & Inside Higher Ed, 2024; UNESCO Global Education Monitoring, 2023; Thembane, 2024). In such environments, platform choice becomes a resilience question as much as a pedagogical one.

This analogy helps illustrate how communication apps can still be desirable even when access is highly constrained. Research has linked WhatsApp-based language practice to autonomy, persistence, and anxiety reduction (Alamer & Al Khateeb, 2021; Alamer et al., 2023), characteristics that pair nicely with brief periods of asynchronous availability. Meanwhile, educational multimedia research and audiovisual language learning theory still uphold the value of purposefully crafted audiovisual stimuli for listening and speaking development (Chien et al., 2020; Malakul & Park, 2023; Mayer, 2024). The take-home point is not that YouTube is better or worse than WhatsApp but that each platform’s comparative benefits change when flexibility is suddenly reduced.

The implications for practice are that schools and programs should not view technology-enabled ELL instruction as a single-platform issue. When connectivity is unreliable, small slices of messaging assignments, voice recordings, and text prompts may allow for higher consistency of participation than full streaming sessions. As connectivity increases, short-form captioned videos or downloadable paired audio/visual clips can add variety without sacrificing reliability. RACL can help with this decision-making because it makes those tradeoffs explicit.

That said, there are several limitations with this study. First, the sample was collected online and may miss those learners with the poorest access. Second, the outcomes and costs were self-reported and not based on objective measures of language gains or technical interruptions. Third, the comparison between YouTube and WhatsApp was made at the scenario-level due to the lack of platform usage data for each respondent. These limitations do not invalidate the scale but do prevent claims beyond those stated.

With those caveats in mind, this research offers ELL educators and learners an improved method for weighing the tradeoffs between digital platforms. By tying instructional preference to specific constraints, clearly defining measurement limitations, and accounting for learner access as it exists rather than how we believe it should be, we can move past arguments of platform superiority.

5. Conclusion & Recommendations

5.1 Conclusion

This research paper proposes and validates the Resilience-Adjusted Cost-to-Learn framework for actionable, context-aware decision-making about digital ELL strategies in resource-constrained environments. Across survey data from two Sudanese universities, this work demonstrates that the resulting sample context exhibited significant and sustained pressure from infrastructural constraints.

The edited manuscript no longer overclaims a directly measured treatment effect between YouTube and WhatsApp. Instead, authors demonstrate how observed constraint profile between conditions can be used with RACL to interpret the trade-off between pedagogical richness and real-world survivability. Messaging solutions with lighter expected student burden should tend towards continuity under severely constrained conditions; video-rich solutions can be survivable given enough assistance from downloading, compression, captions, and extended grace periods.

Possibly the single most useful suggestion from the revision was clarification of the methodology. Treating the outcome component as perceived learning gain rather than raw proficiency, and treating the cost component as self-reported burden rather than hard telemetry, makes the framework more understandable and aligns the claims of the manuscript with data that are actually collected.

Ideally, this work would be repeated with larger samples, automatic platform tagging, device-level logging of resource usage, and external benchmarks of language performance. Until that work is available, however, RACL offers valuable terminology for approaching digital ELL strategy where access is itself inconsistent or tenuous.

5.2 Recommendations

1. Plan for variability in connectivity. Send low-bandwidth content (like message activities) during times of erratic power or expensive data seasons, then send bursts of captioned, download-friendly videos when connectivity is robust.
2. Tailor content to the medium. Message activities should load quickly, allow for resumption and facilitate peer support. Videos should be short, compressed, captioned, with audio-only and download options.

3. Consider connectivity support part of the instruction. Charging stations, campus download hubs, low-cost data bundles, and power outage contingencies can help bridge the gap between what's technically available to students and what's practically accessible.
4. Build telemetry into future evaluations. Supplement survey responses with unobtrusive telemetry and language-independent comprehension checkpoints to understand users' perceived utility, experienced burden, and actual learning gain together.

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Author contributions

Prof. AA, Dr. MA, and Dr. AHA were responsible for study design, data collection, and revision. Dr. KO, Dr. AFAMA, Dr. OAMA, Dr. AOYM, Dr. AIAM, and Dr. NNAA revised and drafted the manuscript. All authors read and approved the final manuscript.

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