

Technology Acceptance as a Pathway from Universal Design for Learning to Student Engagement: A Mixed-Methods Structural Equation Modelling Study of an Inclusive E-Learning Platform

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ABSTRACT:

This study examines the impact of integrating Universal Design for Learning (UDL) principles into an e-learning platform on student engagement and technology acceptance. Through a mixed-methods approach combining questionnaires (n=146), analysis of platform usage data, and analysis of forum interactions, this research utilizes the Unified Theory of Acceptance and Use of Technology (UTAUT) model as an analytical framework. Hierarchical multiple regression analysis revealed that the four dimensions of the UTAUT model positively predict student engagement—performance expectancy ($\beta = .389$, $p < .001$), effort expectancy ($\beta = .183$, $p = .002$), social influence ($\beta = .151$, $p = .017$), and facilitating conditions ($\beta = .125$, $p = .043$)—together explaining 65.9% of the variance in engagement ($R^2 = .659$, $F(10,135) = 24.87$, $p < .001$).

Structural equation modelling produced good model fit ($\chi^2/df = 2.14$, $RMSEA = .063$, $CFI = .946$, $TLI = .941$, $SRMR = .052$) showing the proposed associations between UDL factors and engagement through UTAUT dimensions. Findings from factor analysis showed that 72.4% of the total variation was explained by four UDL factors. These were content multimodality (23.1%), interface personalization (21.3%), assessment flexibility (15.8%), and collaborative supports (12.2%). Mediation analysis, with bootstrapping, demonstrated that content multimodality had the strongest indirect effect on engagement through performance expectancy ($\beta = .181$, 95% CI = [.118, .256]). The current study contributes to the field of inclusive digital learning by demonstrating how content multimodality and collaborative supports have the greatest effect on user perceptions and behaviors as UDL factors. Benefits autonomy, accessibility and community engagement are perceived by users and support the previous quantitative findings. Finally, there is an ethical imperative to include UDL for e-learning platform design. This research gives evidence-based inputs to the field and

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demonstrates how UDL engagement would benefit various populations of learners in the digital realm.

Keywords: Universal Design for Learning; e-learning; engagement; UTAUT; structural equation modelling

1. Introduction

Recent years have witnessed a dramatic change in the pedagogical practices as well as the entire framework of education due to the processes of digital transformation (Bates, 2022). E-learning platforms have emerged that provide learners with unprecedented temporal and spatial flexibility not experienced before (Singh & Thurman, 2019). This trend was accelerated by the COVID-19 pandemic, which increased the adoption of educational technologies in higher learning institutions (Adedoyin & Soykan, 2020). Nevertheless, the digital revolution raises an important concern: does the advancement of technology actually help all learners? There is substantial evidence indicating that the transition to online learning exacerbates pre-existing educational inequalities and inequities (Reich, 2020; Lambert, 2020). In the current educational environment, where equity and inclusion are paramount, it is essential to investigate whether e-learning platforms can effectively address the diverse needs of all learners, particularly those with distinct learning profiles or disabilities. This is where Universal Design for Learning (UDL) becomes an essential framework for addressing these issues (Meyer et al., 2014). Initially developed by CAST (Center for Applied Special Technology), UDL presents a systematic approach grounded in three fundamental principles: providing multiple avenues for engaging learners, offering various formats for delivering information, and permitting different methods for students to demonstrate their understanding (Rose & Meyer, 2002; CAST, 2018). These principles are to remove barriers to learning and increase learning opportunities for all. UDL is becoming popular among educators, but there's a lack of sufficient, empirical studies on UDL, and especially in e-learning (Al-Azawei et al., 2016; Rao et al., 2021). Although UDL is theoretically superior (Capp, 2017) or studies

have been done on UDL in traditional classroom settings (Tobin & Behling, 2018), not many have been done on the effects of using UDL in e-learning on student engagement.

This is extremely concerning, as engagement has a substantial impact on persistence and performance in online learning (Martin & Bolliger, 2018; Czerkawski & Lyman, 2016). To correct this, this study has adopted an innovative approach to integrate UDL and the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which was developed by Venkatesh and his colleagues (2003). The UTAUT model focuses on the components that influence the acceptance and use of technology.

It focuses on four primary factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. (Venkatesh et al, 2016)

Using this theoretical lens, this study aims to address a fundamental question: what is the impact of employing UDL in an e-learning system on student engagement and acceptance, and what is the impact in terms of the UTAUT model?

With regard to the existing body of knowledge, using self-determination theory (Deci & Ryan, 2008), a key hypothesis is formulated: It is hypothesized that integrating UDL in an e-learning environment would positively influence the four UTAUT model elements (performance expectancy, effort expectancy, social influence, and facilitating conditions) and therefore, increase student engagement. In order to test this hypothesis, we developed and tested an e-learning environment that implements UDL principles in a structured way with a group of university students.

2. Literature review

UDL Principles in Digital Learning Environments

UDL has also emerged as an important framework to foster inclusivity in digital learning environments. Developed from the concept of meeting the needs of students with disabilities, UDL has grown to encompass the many facets of learning (Rose & Meyer, 2002). This implementation is founded on three principles: multiple means of engagement, multiple means of representation, and multiple means of expression (CAST, 2018).

Al-Azawei et al. (2016) have shown how these principles may be implemented in digital environments using various features of technology. Some ways of representation may be realized, for instance, by providing texts, audio and an interactive activity all at the same time. Diversity of expression can be accomplished through the use of various forms of assessment (He, 2014). Multiple and/or different forms of scaffolding can be offered by adaptive systems (Tobin & Behling, 2018).

Components of the UTAUT Model

The UTAUT model was developed by Venkatesh et al. (2003) and synthesizes eight other models concerning how individuals adopt and use technology.

At its core, this framework highlights four key factors that shape our intention to adopt a technology and how effectively we use it: performance expectancy, effort expectancy, social influence, and facilitating conditions.

Performance expectancy is basically how much someone thinks using the technology will help them achieve their goals. In an educational perspective, it relates to how students perceive the platform's usefulness in improving learning outcomes (Khechine et al., 2014). Effort expectancy on the other hand, is concerned with the ease of use of the technology. Venkatesh et al. (2016) note the relevance of this concept to early learning of a new tool.

According to the study results, the UTAUT model is applicable within educational technology studies. For example, the four dimensions of the model predicted a considerable amount of variance in users' intentions to use learning management systems, as confirmed by Ain et al. (2016).

Intersection Between UDL Principles and Technology Acceptance

The integration of UDL and technology acceptance models (TAMs) is an interesting, emerging area of research. Kumar and Owston (2016) helped define this area with their research involving the use of both automated and student-centered methods to assess the accessibility of e-learning environments. The researchers concluded that barriers to accessibility negatively affect the online learning experience of students.

Kumar and Owston (2016) suggest that e-learning systems designed with accessibility and universal design in mind would improve student perceptions of the systems and positive feelings about using the systems.

Identified Gap in the Literature

In spite of the above progress, the literature points to the fact that opportunities to measurably demonstrate the impact of UDL on learner engagement, and in relation to the UTAUT model, is lacking.

As Al-Azawei et al. (2016) comment in their content analysis of the scholarly publications of UDL, the great majority of the studies adopt a qualitative or descriptive approach, with very few rigorous empirical evaluations that assess the efficacy of UDL interventions.

This is evident in the domain of e-learning, where Evmenova (2018) suggests that a great body of literature takes a case study approach and neglects larger scale systematic analyses. For the intersection of TAMs, and in particular UTAUT, the research is still in its infancy.

There are studies on the accessibility and multimodal delivery of content in e-learning (Kumar & Owston, 2016; Dinmore, 2019), but, to the best of our knowledge, no study has

examined the integration of UDL into e-learning environments and its impact on the four components of UTAUT and, in extension, learner engagement.

3. Methodology

Research Design

This research takes a sequential explanatory mixed-methods approach to understand the impact of integrating UDL into the e-learning platform on student engagement, based on the UTAUT model. The combination of both approaches supports methodological triangulation and results cross-validation (Creswell & Plano Clark, 2018).

The quantitative phase employs a structured questionnaire based on the UTAUT model to assess student perceptions, and analyzes usage data from the platform. The qualitative phase utilizes analyses of student perceptions expressed in open-ended responses and interviews with a purposive subsample of students.

UDL Platform Development

The e-learning platform used for this study was designed according to the ADDIE model (n. Analysis, Design, Development, Implementation and Evaluation) and enhanced through the addition of UDL principles at each stage. During the Analysis phase, a detailed evaluation of learners' needs ($n = 35$) was conducted, using preliminary questionnaires with students with different learning profiles.

At the Design phase, a pedagogical blueprint was developed with integration of the three UDL principles. For each learning objective, it was planned: (1) Multiple means for engagement (choice of paths or learning journeys, personalized feedback, gamification), (2) multiple means of representation (text, audio, video, and interactive infographics), and (3) multiple means of expression and evaluation (assessment) which included: multiple-choice questions, writing, multimedia creations and discussion forum.

Sample Description

The sample comprises 146 French Language and Literature majors from the sixth semester of the

Faculty of Arts and Humanities (FLSH), Ibnou Zohr University, Agadir.

The average age of participants is 22.7 years ($SD = 3.2$), with a gender distribution of 68% female ($n=99$) and 32% male ($n=47$). Among participants, 18% ($n=26$) reported having specific learning needs.

Sample size calculation: Sample size was determined using Cohen's (1988) formula for multiple regression analysis with 4 predictors (UTAUT dimensions), medium effect size ($f^2 = 0.15$), statistical power of 0.80, and $\alpha = 0.05$, yielding minimum $n = 85$. Our sample of 146 participants ensures adequate statistical power (observed power = 0.92).

Data Collection Instruments

UTAUT-UDL Questionnaire

The questionnaire created for this research is based on the UTAUT instrument validated by Venkatesh et al. (2003) and focused on e-learning platforms. It is also extended to embrace dimensions of UDL. The questionnaire was administered online, twice, mid-semester and end-of-semester, and is made up of 42 items which are grouped into six major components. The six components are defined below:

- Performance Expectancy (7 items, $\alpha = 0.89$): "The platform improves my learning performance"
- Effort Expectancy (6 items, $\alpha = 0.87$): "It is easy to use this platform"
- Social Influence (5 items, $\alpha = 0.82$): "My peers encourage me to use this platform"
- Facilitating Conditions (6 items, $\alpha = 0.85$): "I have the necessary technical support"
- Engagement (10 items, $\alpha = 0.91$): "I feel involved in my learning"
- UDL Elements Perception (8 items, $\alpha = 0.88$): "Multiple options help me learn"

All items use a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

Objective Engagement Data

Objective engagement metrics for each participant were extracted from platform logs and included frequency of use, duration of use, types of content interacted with, participation in forums, usage diversity, completion of activities, and preferences in modes of interaction.

Statistical Analyses

Preliminary Analyses

- Descriptive analyses: means, standard deviations, skewness, kurtosis
- Normality tests: Shapiro-Wilk and Kolmogorov-Smirnov
- Outlier detection: z-scores > 3.29 and Mahalanobis distance
- Reliability analyses: Cronbach's Alpha and McDonald's omega

Main Analyses

Hierarchical Multiple Regression Analysis

The main hypothesis was tested with a hierarchical multiple regression, with engagement being the dependent variable:

- Model 1: Control variables (age, gender, technological experience)
- Model 2: Addition of four UTAUT dimensions
- Model 3: Addition of interactions between UTAUT dimensions

Assumptions tested:

- Linearity: scatterplots and Ramsey RESET tests
- Independence: Durbin-Watson test
- Homoscedasticity: Breusch-Pagan test
- Multicollinearity: VIF < 5, Tolerance > 0.20

Structural Equation Modeling (SEM)

A Structural Equation Model (SEM) was built to find causal relationships between UDL principles, UTAUT dimensions and engagement.

Fit indices evaluated:

- χ^2 and χ^2/df (< 3 acceptable, < 2 good)
- RMSEA (< 0.08 acceptable, < 0.05 good) with 90% CI
- CFI and TLI (> 0.90 acceptable, > 0.95 good)
- SRMR (< 0.08 acceptable, < 0.05 good)

Estimation: Maximum likelihood with bootstrap (n = 5000) for confidence intervals

Mediation Analyses

To analyze UTAUT dimensions mediate the relation with UDL principles with respect to engagement using bootstrap method (Hayes, 2018).

Procedure:

- Direct and indirect effects calculated with PROCESS macro v4.1
- 95% bootstrap confidence intervals (10,000 samples)
- Sobel tests for validation

Moderation Analyses

Moderation analyses to test whether prior technological experience moderates the main relationships.

Complementary Analyses

- Exploratory Factor Analysis (EFA) with Varimax rotation
- K-means cluster analysis to identify user profiles
- t-tests and ANOVA for group comparisons
- Pearson correlations between all continuous variables

Missing Data Treatment

Missing data (< 5% for all variables) were handled through multiple imputation (m = 20) using the MICE (Multiple Imputation by Chained Equations) algorithm.

Qualitative Analyses

Qualitative data from interviews and open-ended responses were analyzed through a systematic

thematic analysis (Braun & Clarke, 2006) using NVivo 12 for induction and deduction.

Ethical Considerations

This research received approval from the Ethics Committee of Ibnou Zohr University (Protocol #2022-FLSH-03). Informed consent was obtained from all participants, and data anonymity was preserved.

Software Used

- SPSS 29.0: descriptive analyses, multiple regression, ANOVA
- AMOS 29.0: structural equation modeling
- R 4.2.0: advanced analyses and visualizations (packages: lavaan, semPlot, ggplot2)
- NVivo 12: qualitative analysis
- PROCESS v4.1: mediation and moderation analyses

4. Results

Preliminary Analyses

Data Quality and Assumptions

Screening of the data revealed no univariate outliers (z -scores > 3.29), and two multivariate

Descriptive Statistics

outliers based on Mahalanobis distance ($\chi^2 > 22.46$, $p < .001$). After reviewing each case, it was decided to keep the outliers. The analysis of the missing data showed that all variables had fewer than 3% missing values and were missing randomly (Little's MCAR test $\chi^2 = 127.45$, $df = 118$, $p = .259$).

There were adequate distributions of the variables (Shapiro-Wilk $p > .05$) in 89% of cases. Transforming the variables that had a slight deviation from normality (log transformation) improved the distribution of the variables.

Reliability and Validity

Internal consistency reliability was excellent for all scales: Performance Expectancy ($\alpha = .891$, $\omega = .894$), Effort Expectancy ($\alpha = .874$, $\omega = .877$), Social Influence ($\alpha = .823$, $\omega = .826$), Facilitating Conditions ($\alpha = .847$, $\omega = .851$), Engagement ($\alpha = .913$, $\omega = .915$), and UDL Perception ($\alpha = .882$, $\omega = .885$).

Confirmatory factor analysis for the measurement model showed acceptable fit: $\chi^2 = 647.23$, $df = 284$, $p < .001$; $\chi^2/df = 2.28$; RMSEA = .067 (90% CI [.058, .076]); CFI = .934; TLI = .928; SRMR = .058.

Table 1. Descriptive Statistics and Correlations

Variable	M	SD	1	2	3	4	5	6
1. Performance Expectancy	5.42	1.18	—					
2. Effort Expectancy	5.67	1.09	.673**	—				
3. Social Influence	4.89	1.34	.521**	.468**	—			
4. Facilitating Conditions	5.23	1.21	.587**	.634**	.445**	—		
5. UDL Perception	5.78	1.03	.692**	.589**	.434**	.561**	—	
6. Engagement	5.51	1.14	.731**	.612**	.528**	.598**	.746**	—

Note. N = 146. ** $p < .01$.

The analysis of the platform usage showed that students on average logged into the platform 4.86 times per week ($SD = 2.14$). Their average session duration was 28.43 minutes ($SD = 12.67$). The usage diversity index was at an intermediate to advanced level ($M = 0.67$, $SD = 0.18$).

Hierarchical Multiple Regression Analysis

Table 2. Hierarchical Regression Analysis Predicting Engagement

Variables	Model 1	Model 2	Model 3
Step 1: Control Variables			
Age	-.143*	-.062	-.058

Gender (1=Female)	.167*	.089	.085
Tech Experience	.234**	.121*	.118*
Step 2: UTAUT Dimensions			
Performance Expectancy		.394***	.389***
Effort Expectancy		.187**	.183**
Social Influence		.146*	.151*
Facilitating Conditions		.128*	.125*
Step 3: Interactions			
PE × EE			.092
PE × SI			-.074
PE × FC			.108
R ²	.089	.642	.659
ΔR ²	.089***	.553***	.017
F	4.62***	32.18***	24.87***
Durbin-Watson			1.94

Note. N = 146. PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Conditions. *p < .05, **p < .01, ***p < .001.

The final model explained 65.9% of the variance in engagement ($F(10, 135) = 24.87, p < .001$). Performance Expectancy emerged as the strongest predictor ($\beta = .389, p < .001$), followed by Effort Expectancy ($\beta = .183, p = .002$), Social Influence ($\beta = .151, p = .017$), and Facilitating Conditions ($\beta = .125, p = .043$).

Assumptions Testing:

- Linearity: Satisfied (RESET test: $F = 1.23, p = .297$)
- Independence: Satisfied (Durbin-Watson = 1.94)
- Homoscedasticity: Satisfied (Breusch-Pagan: $\chi^2 = 8.45, p = .583$)
- Multicollinearity: No concerns (VIF range: 1.34-2.67; Tolerance range: .375-.745)

Structural Equation Modeling

Model Specification and Fit

The hypothesized structural model provided a representation of the relationships among UDL factors, UTAUT dimensions, and engagement. The model was a good representation of the data:

Model Fit Indices:

- $\chi^2 = 423.67, df = 198, p < .001$
- $\chi^2/df = 2.14 (< 3.0 = \text{acceptable})$
- RMSEA = .063 (90% CI [.054, .072]) ($< .08 = \text{acceptable}$)
- CFI = .946 ($> .90 = \text{acceptable}$)
- TLI = .941 ($> .90 = \text{acceptable}$)
- SRMR = .052 ($< .08 = \text{acceptable}$)

Table 3. Structural Path Coefficients

Path	β	SE	CR	p	95% CI
UDL Factors → UTAUT Dimensions					
Content Multimodality → Performance Expectancy	.468	.087	5.38	< .001	[.297, .639]
Content Multimodality → Effort Expectancy	.382	.091	4.19	< .001	[.203, .561]
Interface Personalization → Effort Expectancy	.447	.089	5.02	< .001	[.272, .622]
Collaborative Supports → Social Influence	.513	.096	5.34	< .001	[.325, .701]
Assessment Flexibility → Facilitating Conditions	.389	.092	4.23	< .001	[.208, .570]
UTAUT Dimensions → Engagement					

Performance Expectancy → Engagement	.387	.076	5.09	< .001	[.238, .536]
Effort Expectancy → Engagement	.223	.081	2.75	.006	[.064, .382]
Social Influence → Engagement	.174	.073	2.38	.017	[.031, .317]
Facilitating Conditions → Engagement	.142	.072	1.97	.049	[.001, .283]

Note. β = standardized coefficient; SE = standard error; CR = critical ratio; CI = confidence interval.

Factor Analysis of UDL Elements

Performing exploratory factor analysis (EFA) with Varimax rotation showed that there are four unique UDL factors, which explain 72.4% of the total variance.

Table 4. UDL Factor Structure

UDL Elements	Factor 1	Factor 2	Factor 3	Factor 4
Content Multimodality (23.1% variance)				
Video explanations available	.834	.156	.201	.089
Audio narration options	.812	.178	.134	.145
Interactive infographics	.789	.234	.112	.198
Text-to-speech functionality	.756	.298	.189	.076
Interface Personalization (21.3% variance)				
Customizable dashboard	.201	.845	.167	.123
Adjustable font sizes	.178	.823	.145	.198
Color contrast options	.234	.798	.201	.089
Layout preferences	.167	.771	.234	.167
Assessment Flexibility (15.8% variance)				
Multiple choice options	.189	.198	.812	.156
Multimedia submissions	.234	.145	.789	.201
Oral presentation alternatives	.156	.234	.767	.178
Self-paced assessments	.201	.289	.743	.234
Collaborative Supports (12.2% variance)				
Peer discussion forums	.145	.167	.198	.823
Group project tools	.198	.234	.234	.798
Peer feedback systems	.234	.189	.167	.776
Study group formation	.167	.201	.289	.754

Note. Factor loadings > .40 are bolded. Extraction method: Principal Components Analysis. Rotation: Varimax with Kaiser normalization.

Mediation Analysis

Mediation analysis using bootstrapping (10,000 samples) examined whether the dimensions of UTAUT mediate the relationship between UDL factors and engagement.

Table 5. Mediation Analysis Results

Mediator Path	Direct Effect	Indirect Effect	Total Effect	95% CI (Indirect)
Content Multimodality → Engagement				
Via Performance Expectancy	.267*	.181***	.448***	[.118, .256]
Via Effort Expectancy	.363*	.085**	.448***	[.032, .145]
Interface Personalization → Engagement				
Via Effort Expectancy	.189*	.100**	.289***	[.041, .167]
Collaborative Supports → Engagement				

Via Social Influence	.234*	.089**	.323***	[.035, .152]
Assessment Flexibility → Engagement				
Via Facilitating Conditions	.198*	.055*	.253**	[.012, .108]

Note. CI = confidence interval. * $p < .05$, ** $p < .01$, *** $p < .001$. Each mediator was tested in a separate simple mediation model; the total effect is therefore identical across models.

Results suggest partial mediation for all of the relationships. The most significant indirect effect was found to be for Content Multimodality and Performance Expectancy ($\beta = .181$, 95% CI [.118, .256]).

Moderation Analysis

Moderation analysis looked at if and how previous technical experience moderates the relation between UTAUT dimensions and engagement.

Table 6. Moderation Effects of Technological Experience

Interaction Term	β	SE	t	p	ΔR^2
PE × Tech Experience	.167	.067	2.49	.014	.023*
EE × Tech Experience	.089	.071	1.25	.213	.008
SI × Tech Experience	-.034	.068	-0.50	.617	.001
FC × Tech Experience	.123	.069	1.78	.077	.015

Note. PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Conditions. * $p < .05$.

The relationship between Performance Expectancy and Engagement was moderated by Technological Experience ($\beta = .167$, $p = .014$).

Simple Slopes analysis indicated that Performance Expectancy had a stronger effect on Engagement with respect to students with high Technological Experience ($\beta = .456$, $p < .001$) than students with low Technological Experience ($\beta = .289$, $p = .002$).

Usage Pattern Analysis

Cluster Analysis

K-means cluster analysis identified three distinct user profiles based on platform usage patterns:

Table 7. User Profile Characteristics

Profile	n (%)	Session Freq.	Duration (min)	Forum Posts	Content Views	Modality Diversity
High Engagers	42 (28.8%)	7.23 (1.45)	41.67 (8.92)	15.34 (6.78)	87.45 (12.34)	0.89 (0.12)
Moderate Users	67 (45.9%)	4.78 (1.23)	26.89 (7.45)	8.67 (4.23)	54.23 (9.67)	0.67 (0.15)
Low Engagers	37 (25.3%)	2.34 (0.89)	15.23 (5.67)	3.45 (2.89)	28.67 (8.45)	0.34 (0.18)

Note. Values represent M (SD). ANOVA revealed significant differences between all groups ($p < .001$).

Modality Preferences

Analysis of content interaction logs revealed distinct patterns in modality usage:

- Text-based content: 42% primary usage, with higher preference among Low Engagers (67%)
- Video content: 38% primary usage, preferred by High Engagers (89% utilized videos)
- Interactive elements: 20% primary usage, mostly utilized by High Engagers (78%)
- Audio content: Supplementary usage across all groups (M = 23% of total time)

Table 8. Relationship Between UDL Features and Engagement Metrics

UDL Feature	Frequency of Use	Duration	Forum Participation	Content Completion
Multiple Engagement Options	$r = .451^{***}$	$r = .378^{***}$	$r = .234^{**}$	$r = .489^{***}$
Varied Representation	$r = .389^{***}$	$r = .423^{***}$	$r = .345^{***}$	$r = .456^{***}$
Flexible Expression	$r = .367^{***}$	$r = .298^{**}$	$r = .467^{***}$	$r = .398^{***}$
Collaborative Tools	$r = .298^{**}$	$r = .234^{**}$	$r = .523^{***}$	$r = .345^{***}$

Note. N = 146. $^{**}p < .01$, $^{***}p < .001$.

Qualitative Insights Integration

Thematic analysis of qualitative data (n = 87 open-ended responses, 12 interviews) identified five major themes:

1. Autonomy and Choice (28.3%): "Having multiple ways to access content makes me feel in control of my learning."
2. Accessibility (23.7%): "The audio options help me when I'm tired of reading."
3. Community Engagement (19.2%): "The forum discussions are more active when we can post in different ways."
4. Self-regulation (16.8%): "I like that I can learn at my own pace and in the way that works best for me."
5. Technical Challenges (12%): "Sometimes there are too many ways to get to the content, it's a little overwhelming at first."

Our qualitative data backed up our quantitative data, particularly pertaining to the importance of choice and flexibility.

5. Discussion

Structural Relationships and Model Fit

The fit indices of our structural equation model (SEM) indicate good model fit (RMSEA = .063; CFI = .946; TLI = .941; SRMR = .052). Therefore, we can conclude that the relationships between the UDL factors and the UTAUT constructs and engagement, are empirically supported by our data. According to Hu and Bentler (1999), these fit indices fulfill the requirements for an acceptable model fit. Thus, we can conclude that the hypothesized relationships of our model are well-founded and reflect a good fit.

The most important finding from our study was the relatively large effect of content multimodality on students' perception of performance expectancy ($\beta = .468$, $p < .001$). This effect indicates that the use of various modalities to present learning content was found to engage a greater number of learners, and consequently improved students' expectations about their performance in learning.

UTAUT Dimensions as Mediating Variables

According to our mediational analysis, UTAUT dimensions are the strongest mediating variables between UDL and engagement. Of these, the strongest effect was found for content multimodality and performance expectancy ($\beta = .181$, 95% CI [.118, .256]).

Regression Coefficients indicate that Performance Expectancy is the most important factor effecting engagement and is the largest predictor of engagement, with a standardized coefficient of $\beta = .389$ ($p < .001$). Students who use UDL to help them learn and are able to determine the features of UDL that help them best, are significantly more engaged than those who do not. This finding supports self determination theory (Deci & Ryan, 2008) in that UDL features are clear, learning is beneficial, and students feel they are successful, resulting in an increase in their intrinsic motivation and engagement.

Interface Personalization and Effort Expectancy

A strong relationship between interface personalization and effort expectancy ($\beta = .447$, $p < .001$) support the theory that certain types of learning environments place a reduced cognitive load on the student and enhance their

engagement. For the sample, students personalized the learning environment to a significant extent ($\beta = .183$, $p = .002$). This suggests that personalization of a learning environment improves usability perceptions.

Social Learning and Collaborative UDL Features

UDL goes beyond individual learning to include community learning, as evidenced by the significant relationship between the path from collaborative supports and social influence ($\beta = .513$, $p < .001$). Social learning is strengthened by peer engagement, which is supported by the effect of social learning on engagement ($\beta = .174$, $p = .017$).

Moderation Effects and Individual Differences

An important moderation effect of Technology Experience on the Performance Expectancy-Engagement relationship ($\beta = .167$, $p = .014$), reveals important differences among students in the way they respond to UDL features. For students with higher Technology Experience, the relationships was stronger ($\beta = .456$) as compared to those with lower Technology Experience ($\beta = .289$). This indicates that for students with better digital literacy, the expected benefits of UDL features results in a better level of engagement. This requires scaffolding and other forms of intervention to support students less technically and digitally savvy.

Factor Structure of UDL Implementation

A four factor structure of UDL (explaining 72.4% of the total variance) has emerged through exploratory factor analysis. Among all the UDL factors, Content Multimodality (23.1% of variance) was the most important factor followed by Interface Personalization (21.3%), Assessment Flexibility (15.8%), and Collaborative Support (12.2%). The results of the study indicate that in digital environments, all the UDL features may not be of equal importance in enhancing engagement, and representation and expression may have an immediate impact as compared to engagement.

Usage Patterns and Engagement Profiles

The results of cluster analysis indicate that about 28.8% of the students were high engagers. High engagers had a high diversity in modality and high participation in forums, low engagers and average engagers had low participation in forums. The use of UDL features was positively correlated with engagement metrics ($r = .234$ to $.523$), suggesting that those students who explored several learning pathways were highly engaged.

This study contributes significantly to theory in several key ways. First, it combines UDL and UTAUT to construct an integrative model to address the major research gap on technology acceptance in the educational field. The result demonstrates an excellent model fit and high explained variance, thus, representing a better understanding of educational technology acceptance than either framework in isolation.

The mediation results also contribute to technology acceptance theory by revealing the mechanisms through which design features affect user perceptions. Contrary to the literature which viewed usability and usefulness as separate constructs, our results showed that in the presence of design principles of inclusiveness, a positive feedback loop, or a spiral of increasing engagement and integration, is created.

Contributions to Self-Determination Theory in Digital Learning Contexts

Our results contributed to self-determination theory (Deci & Ryan, 2008) by demonstrating the use of UDL in educational technology to foster the psychological needs of learners, specifically in the areas of autonomy, competence and relatedness in digital learning environments. The high positive correlation between UDL and engagement ($r = .746$, $p < .001$) reinforces our conclusion that technology-based learning environments offer the potential to effectively foster students' intrinsic motivation when choice and flexibility are offered, as well as other means to gauge progress and achieve learning objectives.

The results of the factor analysis also support the needs for autonomy and competence as interface personalization and content multimodality

respectively. The emergence of collaborative supports as a third, distinct factor provides support for relatedness.

Shifting the Lens on Accessibility in Educational Technology

This study aims to support a paradigm shift on accessibility by presenting positive attitudes towards the application of UDL among learners with learning differences as evidence of effective proactive inclusive design.

That UDL features were related to higher levels of engagement among the whole sample, including the 82% of students with no declared specific learning needs, supports the universality of UDL principles beyond disability (Al-Azawei et al., 2016).

That UDL principles caused “curb-cut effects” among digital learning resources and created an inclusive learning environment for both “normal” and “special” learners, challenges the traditional duality of thinking, and supports the reality of learning differences as natural variation.

Application

Design Recommendations for Platforms

As improving the medium of instruction through multimodal content was related to expectancy ($\beta = .468$), designers should incorporate options for seamlessly integrating multiple modes, including text, audio, video and interactivity. The implicit cost-benefit analysis in R^2 values, indicates that investment in multimodal content created a positive impact on user engagement.

As the Personalization of interface impacted effort expectancy ($\beta = .447$), platforms should offer users options for control and customization including adjustment of fonts and colors, and preferences for layouts and navigational paths. A moderately steep learning curve justifies the incorporation of a default setting, and use of instructive aids for gradual introduction of the options.

Methodological Limitations

Several other limitations warrant acknowledgment. Though our sample

demonstrated adequate statistical power (observed power = .92), it predominately represented language and literature studies and may not be generalizable to other disciplines. Different patterns of UDL effectiveness may be observed in the STEM fields due to differences in the content types and assessment methods. For quantitative research, external validity is also reduced due to reliance on convenience sampling methods, researcher bias, and participants' limited exposure to or understanding of the fields being studied.

Because our program is just one semester long, we can't analyze how teaching with UDL may encourage students to vary their perception and engagement over longer periods of time. To gain insight into students' engagement over longer time periods, more longitudinal studies would be beneficial.

Measurement Considerations

Although our reliability coefficients were excellent (α range: .823-.913), the self-report nature of our measurement of engagement may have created a response bias. Future studies should incorporate other objective forms of assessment and validation, for example, learning analytics and/or physiological measures of engagement.

While the findings of our study are transferable to other cultures, they were conducted among a Moroccan university student sample; thus, cross-cultural validation would also be important.

Future Research Directions

There are a number of research opportunities based on the results of our study. Given the log data generated from the use of the online teaching platform, opportunities may exist for the application of machine learning to identify/recognize different student patterns and behaviors when interacting with different UDL features, as well as other potential personalization opportunities.

ETA in relation to UDL

One direction for future study is to investigate other emerging technologies associated with

UDL (i.e. artificial intelligence, virtual reality, and adaptive learning systems) and the potential benefits they may provide. Our finding that content multimodality plays a strong role in predicting engagement suggests that certain technologies may amplify UDL benefits and enhance engagement, and warrant further study.

There is potential for the growing availability of learning analytics data to make more sophisticated models of UDL and to create real time adaptability for learning environments to accommodate the needs and preferences of individual learners.

6. Conclusion

The findings from this study provide compelling evidence on the contribution of UDL to digital learner engagement. The strong quantitative evidence ($R^2 = .659$, and good SEM fit indices) points to substantial improvements in digital learner engagement when UDL is applied to e-learning platforms. Further, the extension of the UTAUT model to incorporate UDL principles provides a stronger foundation for understanding the behavior of digital learners and their engagement with e-learning platforms.

The mediation effects reveal that UDL's impact operates through enhanced perceptions of learning effectiveness, ease of use, social support, and resource availability—providing clear targets for intervention.

Paradigm Shift in Educational Technology Design

Beyond its academic contributions, this research supports a fundamental paradigm shift in educational technology design. The results support transitioning from reactive accommodation methods toward proactive inclusive design, which views diversity of learners as an asset rather than a problem to be solved.

Strong effect sizes for UDL variables across all engagement measures suggest that UDL principles benefit all, not just students with

identified needs. This universality of UDL implementation indicates that the implementation of UDL can be considered as "good practice" which benefits the whole population and not only minority populations.

Implications for Digital Equity

Our findings are particularly important given the growing role of digital access in shaping educational opportunity. The strong associations found between UDL features and engagement indicate that well-designed inclusive environments may act to "level the playing field" for students who vary in their learning needs, backgrounds, and preferences.

The moderating effect of technological experience suggests that UDL implementation should be accompanied by digital literacy training to ensure equal access to advanced learning programmes.

Final Reflection

Finally, this study illustrates how embedding UDL principles in educational technology is both a socially responsible issue to ensure accessibility and an approach that fosters engagement and learning for all students.

Our regression models (β coefficients ranging from .125 to .389) and our SEM analyses (RMSEA = .063, CFI = .946) provide important empirical evidence in support of the adoption of inclusive design.

While there are still a number of design, usability and accessibility challenges in the digital environments created by educators to expand their teaching, the frameworks and findings presented here point to ways of developing learning environments to best serve the entire spectrum of human diversity.

The future of educational technology lies not in one-size-fits-all solutions, but in flexible, inclusive platforms that adapt to learners rather than requiring learners to adapt to technology.

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8. Author declaration

The authors confirm that this manuscript is original, has not been published previously and is not under consideration for publication elsewhere.

The authors declare that they have no conflicts of interest.