Uncovering Multiple Pathways to Educator Adoption of e-Learning Tools: A Configurational Analysis Using fsQCA

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***Abstract*—This study employs fuzzy-set Qualitative Comparative Analysis (fsQCA) to identify the multiple, complex causal pathways leading to educator adoption of e-learning tools. Drawing on a verified sample of N = 216 US-based educators from the IS-Impact dataset, this research investigates how five conditions—Information Quality (IQ), System Quality (SQ), Individual Impact (II), Digital Maturity (DM), and Teaching Experience (TE)—combine configurally to produce high or low adoption outcomes, operationalized via Organizational Impact (OI) as a proxy for deep-level adoption. All constructs were calibrated using a seven-point Likert scale with empirically derived anchors (full membership at the 95th percentile, crossover at the median, full non-membership at the 5th percentile). Necessity analysis confirmed that no single condition is individually necessary for high adoption (all consistency values < 0.90). Sufficiency analysis revealed four distinct pathways sufficient for high adoption (solution consistency = 0.9669; solution coverage = 0.7334), demonstrating equifinality: C1—Comprehensive Alignment (all conditions high; n = 27, consistency = 0.9694); C2—Novice Digital Proficiency (high IQ, SQ, II, DM; low TE; n = 25, consistency = 0.9853); C3—SQ-Compensated Pathway (low IQ; high SQ, II, DM, TE; n = 8, consistency = 0.9632); and C4—System-Driven Adoption (high IQ, SQ, DM; low II, TE; n = 5, consistency = 0.9716). System Quality (SQ) and Digital Maturity (DM) were present in all four high-adoption configurations. Causal asymmetry was confirmed: three low-adoption configurations (solution consistency = 0.9687; coverage = 0.7498) differ fundamentally from their high-adoption counterparts, sharing the combined absence of IQ, SQ, and II across all pathways. These findings offer educators and administrators actionable, profile-specific strategies rather than one-size-fits-all solutions for fostering e-learning adoption.**

***Keywords*—e-learning adoption, fuzzy-set Qualitative Comparative Analysis (fsQCA), configurational analysis, information quality, system quality, digital maturity, teaching experience, equifinality, causal asymmetry**

I. Introduction

A rapid transformation of educational settings through digital technology has fueled the widespread adoption of e-learning technology by instructors. In addition, global challenges such as the outbreak of the COVID-19 pandemic have triggered the need for e-learning platforms for teaching and learning [1]. Notwithstanding the growth of e-learning platforms, their adoption by instructors is still inconsistent, with wide disparities in institutions, academic departments, and demographics [2]. It is, therefore, important for institutions of learning to understand factors that influence the adoption of e-learning technology by instructors with a view to improving teaching practices and learning outcomes in digitalized settings.

Previous studies on factors influencing the adoption of e-learning systems were mostly variance-based, using approaches like SEM and regression analysis to investigate individual influences on adoption decisions [3]. Key factors such as information quality, system quality, Perceived Usefulness, and Perceived Ease of Use were found to be important determinants in the adoption of e-learning systems. However, symmetric analysis methodologies presuppose that the relationship between independent and dependent variables is linear and of equal strength for all observations, which is often not true.

The Information Systems Success Model (ISSM), created by DeLone & McLean, is widely used for the adoption of e-learning [4]. This framework proposes that system, information, and service quality drive user satisfaction and usage intention, thereby contributing to individual/organizational outcomes. Though ISSM offers significant information, it fails to capture the complex relationship between system variables and user factors that could result in adoption.

To fill these research gaps, this study employs a configurational analysis methodology, using fuzzy set/Qualitative Comparative Analysis (fsQCA), to explore how various factors correlate with high adoption of e-learning tools among educators. Contrary to conventional models of analysis that employ linear approaches, fsQCA takes into consideration complexities of causality, including equifinality (where multiple distinct chains of factors correlate with a similar outcome) and causal asymmetry (where the antecedents of the presence of an outcome are distinct from those of the absence of an outcome) [5]. By using the IS-Impact study database, this research focuses on IQ, SQ, II, DM, and TE factors to explore their combined effects on e-learning tool adoption by educators. This research study focuses on three important research questions:

(1) Which combinations of Information Quality, System Quality, Individual Impact, Digital Maturity, and Teaching Experience are sufficient for high educator adoption of e-learning tools?
(2) What, if any, single conditions are necessary for high adoption?
(3) How do the sufficient configurations for high adoption differ from those leading to low adoption (i.e., what evidence of causal asymmetry is observed)?

II. Literature Review

The implementation of e-learning solutions in institutions of higher learning is an area of research that has gained traction, especially with the current shift in learning practices brought about by digital technology. E-learning adoption is referred to as the adoption of digital learning platforms by instructors in institutions of higher learning as a means of enhancing learning practices [6]. Industry surveys show that 77% of U.S. companies use e-learning for training purposes [7].

E-learning gained importance due to the outbreak of the global COVID-19 pandemic. This pandemic brought about a rapid shift for various educational institutions, moving from traditional educational processes to online learning processes [8]. This shift clearly revealed the importance of e-learning platforms as well as challenges that need to be addressed in the process of e-learning adoption by educational institutions. Currently, various institutions incorporate e-learning processes into their learning sessions [9].

A number of models have also been used to clarify the issue of the adoption of e-learning. The Technology Acceptance Model (TAM) is one of the models widely used to investigate the role of Perceived Usefulness and Perceived Ease of Use on the adoption of technology. One of the latest investigations showed that TAM constructs played a significant role in determining instructors' intentions to adopt new technology [10]. Similarly, the study of Unified Theory of Acceptance and Use of Technology (UTAUT) is utilized to investigate the role of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions on human behavior related to adoption.

However, current research indicates that the acceptance of e-learning by educational staff is significantly more complex, with factors extending beyond current models of technology acceptance being influential. These factors include the role of support systems, the role of infrastructure, educational philosophies, digital literacy, and previous technology experience [11]. Modeling the complex interplay between these factors requires more sophisticated techniques.

A. Information Systems Success Model in e-Learning Contexts

The Information Systems Success Model (ISSM) of DeLone and McLean offers a broad framework for understanding the factors determining the success of information systems, including e-learning systems. This framework suggests that system, information, and service qualities together affect user satisfaction and intentions to use the system, which determines individual or organizational outcomes [12]. In the context of e-learning systems, system qualities are concerned with the technical qualities of the learning system (reliability, accessibility, usability), information qualities are concerned with the attributes of the information accessed by students (accuracy, completeness, topicality of course material), while service qualities encompass services to the users (support services) [13].

Recently, research work was conducted using ISSM on the adoption of e-learning with encouraging outcomes. Alyoussef [3] concluded that system quality, information quality, and perceived enjoyment are positively related to perceived ease of use, perceived usefulness, system use, and task-technology fit in the context of higher education e-learning settings. Again, Joo, So, and Kim [14] established a significant relationship between e-service quality, system quality, user satisfaction, and e-learning portal success in higher Education.

However, these studies predominantly employed variance-based approaches, which assume linear relationships and do not fully capture the complex configurations of factors that may lead to adoption. As Li, Yang, and MacLeod [15] noted, learners' willingness to continue e-learning can be influenced by interactions among multiple factors, rather than any single factor in isolation. This suggests a need for configurational approaches that can identify multiple pathways to adoption.

Individual Impact, as operationalized in the IS-impact model, captures the downstream consequences of both Perceived Usefulness (PU) from TAM and Task-Technology Fit (TTF). While PU reflects an individual's belief that using the system enhances performance, and TTF captures the degree to which technology assists task completion, Individual Impact measures the realized personal benefits functioning as an emergent construct integrating motivational and functional alignment dimensions. Individual Impact (II) is consequently conceptually dependent on PU and TTF as antecedent constructs, not a substitute or distinct alternative to them.

B. Educator Attributes and E-learning Adoptions

Beyond system characteristics, educator attributes such as digital maturity and teaching experience have emerged as important factors influencing e-learning tool adoption. Digital maturity refers to an organization's or an individual's capability to effectively adapt to and leverage digital technologies [16]. In educational contexts, digital maturity encompasses the technological infrastructure, educators' digital skills, and institutional policies supporting digital transformation.

Research evidence suggests that digital maturity is imperative for the integration of technology in educational systems [17]. Such institutions with high digital maturity exhibit a high percentage of e-learning adoption among teaching faculty since they create the necessary platforms for the implementation of e-learning systems.

Experience in teaching, however, tends to produce inconsistent results for the adoption of technology. While some research evidence proposes that less experienced teachers could oppose technology adoption through their current teaching practices or limited digital literacy skills [18], other evidence suggests that experienced teachers with deep pedagogical knowledge could easily accept e-learning systems if they understand the significance of these systems for improving learning outcomes for students [10]. Also, the difference in the adoption of innovative technologies such as AI-based tools by teachers with diverse subject areas or schools tends to underscore the complex relationship between teacher characteristics and technology adoption [19]. It is important to employ approaches that could understand the complex relationship between digital maturity, teaching experience, and system characteristics for determining technology adoption decisions.

It is crucial to distinguish between organizational digital maturity, referring to institutional infrastructure, strategic readiness, and governance frameworks, and individual digital maturity, which reflects the educator's personal capability and breadth of e-learning tool utilization. This study operationalizes DM at the individual level as the normalized count of distinct e-learning systems actively utilized (out of 11 possible tools), providing a behavioral rather than attitudinal measure.

C. Configurational Approaches to Understanding Technology Adoption

Traditional variance-analysis techniques (e.g., regression analysis, Structural Equation Modeling (SEM)) center on the individual, net effects of variables that influence adoption outcomes. Although important, these techniques are based on models of linearity and additivity, potentially neglecting more complex interactions of factors that influence adoption [20]. Configurational analysis techniques, using fsQCA, provide a complementary research vantage point that recognizes complex causality, equifinality, and asymmetric causality [21]. In contrast to linear approaches, fsQCA explores the various combinations of conditions that contribute to an outcome, recognizing that more than one distinct pathway may exist between the conditions of a phenomenon, as well as that the presence or absence of an outcome can be explained by differing factors.

Recent applications of fsQCA in the context of educational technology have yielded important findings. For example, analysis by Ma *et al*. [21] on the configurations of factors that influence the learning of scientific concepts through fsQCA showed that various distinct configurations of factors result in similar learning outcomes. In their review of research in the educational field, Ide and Mello [22] emphasized that QCA can identify complex patterns that embody conjunctural causality (conditionality) or equifinality. Equifinality and multifinality principles are apt for understanding e-learning adoption. Equifinality posits that various configurations of factors could potentially achieve the same end result (high levels of adoption), while multifinality proposes that a given configuration of factors could potentially produce various outcomes. This challenges the idea of using one solution for adoption for everyone, since no one-size-fits-all approach is effective for promoting e-learning adoption. Instead, one should adopt strategies that are suited to the given configurations of factors.

D. Research Gaps and Contribution

Despite the emergence of numerous studies on e-learning adoption, some research gaps still exist with regard to understanding the factors that influence educator adoption:

Gap 1: Configurational complexity. Previous research employs symmetric or linear models (SEM, Partial Least Squares (PLS), or regression analysis) that are not configurational in their research, unlike fsQCA; therefore, research on e-learning adoption should employ a configurational methodology that is capable of identifying various paths that influence adoption [23].

Gap 2: Interaction of system and individual factors. Limited research has examined how IS qualities (information quality, system quality) combine with educator attributes (digital maturity, teaching experience) to drive adoption. Most studies focus on either system characteristics or user attributes in isolation; few consider their interaction in complex configurations [3].

Gap 3: Minimal sufficient conditions for practice. There is a lack of guidance on the minimal combinations of factors sufficient to achieve high adoption in different scenarios. Educational institutions need to know which combinations of factors are most effective for promoting adoption among different educator groups to allocate resources efficiently [24].

Gap 4: Causal asymmetry. Have a limited understanding of causal asymmetry in e-learning adoption—i.e., whether the causes of high adoption differ from the causes of low adoption. Understanding these differences is crucial for developing targeted interventions to address low adoption rates.

This study addresses the above gaps by applying fsQCA to identify multiple pathways to high educator adoption of e-learning tools. In reviewing the complex factors of Information Quality (IQ), System Quality (SQ), Individual Impact (II), Digital Maturity (DM), and Teaching Experience (TE) collectively contributing to adoption, it is evident that the study helps to better understand the complex process of adoption, as it seems to provide useful information for institutions as well as for developers. At the same time, it should be noted that the current study is likely the first attempt that features the application of fsQCA analysis with regard to the adoption of technology by educational institutions.

Organizational Impact (OI) serves as the proxy for high adoption. Unlike behavioral usage metrics (e.g., login frequency, time-on-system), which capture only activity, OI reflects whether e-learning tools meaningfully affect organizational goals such as student engagement and learning outcomes [3]. This outcome-oriented proxy is therefore more rigorous than simple usage measures for capturing deep adoption.

III. Materials and Methods

This research uses fuzzy-set Qualitative Comparative Analysis (fsQCA) to reveal various paths (configurations of conditions) that contribute to high levels of adoption of e-learning technology among educators. The choice of fsQCA over Partial Least Squares Structural Equation Modeling (PLS-SEM) is motivated by three considerations: (1) technology adoption is non-linear and synergistic, not additive; (2) fsQCA uniquely captures equifinality; and (3) it enables causal asymmetry analysis. fsQCA is a set-theory analysis technique that couples qualitative thinking with quantitative analysis to reveal complex patterns of causality [3]. Contrary to other forms of statistics that seek to establish net effects or correlations, fsQCA seeks to establish the various ways in which certain conditions influence an outcome.

Following the usual procedure for fsQCA research, as suggested by Cilesiz and Greckhamer [25], further explicated by Alyoussef [3], there are four key stages to this research: (1) establishing set membership scores for the conditions and the outcome, (2) testing for necessary conditions, (3) truth table analysis, and (4) interpretation. This allows for the establishment of various sufficient configurations for the

individual conditions that contribute to high adoption. This is in contrast to finding a best-fit prediction model.

A. Data Source and Sample

The data for this analysis were drawn from the IS-Impact dataset, a comprehensive survey examining the experiences of educators with e-learning systems. The data were collected via an online survey instrument based on the IS-Impact model, distributed through professional educator networks and educational technology forums across the United States. After screening and removal of incomplete responses, the final analytical sample comprised $N = 216$ valid responses. Respondents represented a range of roles: full-time teachers (n = 151, 69.9%), part-time teachers (n = 26, 12.0%), administrative staff in educational organizations (n = 23, 10.6%), and other roles, including private tutors, IT service providers, and system administrators (n = 16, 7.4%). Institutional contexts included public educational organizations (n = 172, 79.6%), private institutions (n = 27, 12.5%), tutoring institutions (n = 9, 4.2%), and other settings (n = 8, 3.7%). Teaching experience was dichotomized at ten years: 129 respondents (59.7%) reported ≥10 years of experience (coded as high TE), while 87 respondents (40.3%) had fewer than ten years (coded as low TE). The survey captured measures of IQ, SQ, II, DM, and TE alongside the outcome variable, Organizational Impact (OI), which served as the proxy for high e-learning adoption.

B. Measures and Calibration

Outcome Variable (High Adoption): The dependent variable, High Adoption (HA), was captured through the Organizational Impact (OI) scale of IS-Impact. This is because it gauges the degree to which the educator adopts e-learning solutions into their work as a means of improving their teaching efficiency or other areas of their work. Obtained the mean for the respondent's OI scores.

Condition Variables: Five condition variables were used in this analysis, which came from equivalent constructs in the data set:

- Information Quality (IQ): This is determined by survey questions related to information provided through the e-learning system, including accuracy, completeness, and relevancy of information.
- System Quality (SQ): It is gauged using items that cover the technical aspects of the e-learning system, such as reliability, user friendliness, or accessibility.
- Individual Impact (II): This metric is gauged through questions that evaluate the effects of the e-learning platform on the performance of the educator (similar to individual benefits).
- Digital Maturity (DM): Measured by items indicating the educator's digital literacy and comfort with technology. Operationalized this using relevant survey indicators (the "DM" series in the dataset, which captures usage of various digital tools). In particular, a composite score from items labeled DM_6* reflects an educator's breadth of usage of digital tools.
- Teaching Experience (TE): Measured by an item indicating the educator's teaching experience. Transformed this into a binary condition where high teaching experience = 1 if the educator has ≥10 years of experience (and 0 otherwise). This threshold was chosen to distinguish veteran educators from relatively novice ones.

All variables were coded such that higher values indicate "more" of the construct (e.g., higher quality, greater Impact, higher maturity, more experience).

Calibration: Before fsQCA, the raw Likert-scale and composite values must be calibrated into fuzzy-set membership scores ranging from 0 to 1. Calibration assigns qualitative anchors to quantitative values to interpret them as set memberships [25]. The direct calibration method was used with three anchors: full membership, crossover, and full non-membership. Specifically, for each continuous measure (IQ, SQ, II, DM, and the adoption outcome):

- Full membership (fuzzy score = 0.95) was set at the 95th percentile of that variable's distribution, indicating a value considered "high" in the context of our sample.
- Crossover point (fuzzy score = 0.50) was set at the median value, representing the point of maximum ambiguity (neither clearly in nor out of the set of high adopters or high condition values).
- Full non-membership (fuzzy score = 0.05) was set at the 5th percentile, indicating a definitively "low" value.

Calibration was unnecessary for the binary Condition TE (high vs. low experience); values were directly interpreted as crisp set membership (1 = in the set of high-experience educators, 0 = out).

Using these anchors, each raw value x is transformed into a fuzzy membership score via the log-odds method [25]. The transformation formula was:

Degree of membership = 1 / [1 + exp(−log_odds * (x − crossover) / (full_membership − full_non_membership))]

Where log_odds is ln(0.95/0.05) (the natural log of the odds for full membership), x is the raw value, and the denominator scales the difference relative to the full membership range. This logistic calibration ensures that cases far above the crossover point approach 1.0 in membership, cases far below approach 0.0, and the crossover value maps to 0.5.

Performed calibration using Python, applying the above anchors to each variable. Table 1 summarizes the calibration anchors for each variable, and Table 2 provides descriptive statistics of the calibrated set scores.

Table 1. Calibration anchors for fsQCA analysis

Condition	Full Membership (0.95)	Crossover (0.50)	Full Non-membership (0.05)
Information Quality (IQ)	6.3000	5.3000	3.8500
System Quality (SQ)	6.0667	4.9333	3.5167
Individual Impact (II)	6.7500	5.7500	3.1875
Digital Maturity (DM)	0.9091	0.2727	0.0909
High Adoption (HA)	6.5000	5.3750	3.7188

Note: IQ, SQ, II, and HA anchors reflect the 7-point Likert scale used in the IS-Impact instrument. DM anchors reflect the normalized proportion (0–1) of 11 possible e-learning tools actively used by the respondent. Calibration anchors were derived from the empirical distribution: 95th percentile for full membership, median for crossover, and 5th percentile for full non-membership

After calibration, each case has a fuzzy membership score for being "high" in each Condition and the outcome. Table 2

reports summary statistics for the calibrated variables (mean, standard deviation, and key percentiles). As expected, the median of each calibrated Condition is ~0.50, reflecting the crossover, and the minimum and maximum approach 0.05 and 0.95 by design. This confirms the calibration behaved as intended.

Table 2. Descriptive statistics of calibrated variables

Variable	Mean	Std Dev	Min	25%	Median	75%	Max
IQ_calib	0.48	0.19	0.05	0.33	0.50	0.62	0.87
SQ_calib	0.47	0.20	0.08	0.30	0.50	0.63	0.91
II_calib	0.46	0.18	0.05	0.35	0.50	0.60	0.74
DM_calib	0.54	0.19	0.34	0.34	0.50	0.66	0.91
TE_calib	0.60	0.49	0.00	0.00	1.00	1.00	1.00
HA_calib	0.49	0.20	0.05	0.34	0.50	0.66	0.83

(Note: $N = 216$. TE_calib is crisp binary (1 = > 10 years experience; 0 = < 10 years). All other variables are calibrated using a logistic transformation with empirically derived anchors.

The calibrated dataset was then used for fsQCA. All analyses were conducted using Python 3.10, with custom scripts implementing the fsQCA procedures (the replication code is provided in a public repository, as noted later in Section IV).

C. Analytical Procedure

Analysis of Necessary Conditions: first assessed whether any single condition was necessary for high adoption. A condition is necessary if it must be present for the outcome to occur (i.e., all cases with high adoption have that Condition). In fsQCA, necessity is evaluated by the consistency of the outcome set being a subset of the Condition set. We calculated consistency scores for each Condition's membership across all cases with high adoption. Following common guidelines, a consistency ≥0.90 indicates a potentially necessary condition [3] though coverage (the proportion of outcome cases covered by the Condition) is also examined to ensure the Condition is not trivial.

Truth Table Construction: Next, performed a truth table analysis to identify sufficient configurations. The truth table lists all logically possible combinations of the five conditions 2^5 = 32 possible rows). Moreover, indicates which cases exhibit each combination and whether the outcome occurs in those cases. Set two thresholds to refine the truth table: a frequency threshold of 2 (a minimum of two cases per configuration to be considered) and a consistency threshold of 0.80 for sufficiency (only consider a truth table row as leading to the outcome if the cases in that row consistently have high adoption with consistency ≥0.8). These thresholds balance the inclusion of enough cases with ensuring reliable patterns.

Also incorporated theoretical directional expectations for the intermediate solution. Based on prior research, it was expected that the presence (high value) of each Condition would contribute positively to adoption. Table 3 summarizes these expectations: for all five conditions (IQ, SQ, II, DM, TE), the expected direction was positive (+), meaning higher values are theorized to support high adoption. These expectations guided the minimization process by indicating which configurations to prioritize or eliminate (e.g., configurations with a condition present were considered for sufficiency, whereas configurations that contradicted expectations were scrutinized).

Table 3. Directional expectations for conditions (intermediate solution)

Condition	Expected Influence on Adoption	Theoretical Rationale
Information Quality (IQ)	Positive (+)	Higher information quality enhances perceived usefulness [3].
System Quality (SQ)	Positive (+)	Higher system quality reduces barriers to adoption [1].
Individual Impact (II)	Positive (+)	Perceived individual benefits drive adoption [10].
Digital Maturity (DM)	Positive (+)	Greater digital maturity facilitates tech integration [16].
Teaching Experience (TE)	Positive (+)	Experience provides pedagogical knowledge to leverage new tools [10].

In generating the truth table, any contradictory configurations (rows where similar cases had divergent outcomes) were examined. We removed truth table rows that did not meet the consistency threshold or represented logical contradictions, given our directional expectations.

Sufficiency Analysis: then used the Quine–McCluskey algorithm (implemented in Python) to logically minimize the truth table and derive sufficient configurations for high adoption. A configuration is considered sufficient if the outcome (high adoption) is also present whenever that combination of conditions is present. For each identified configuration, it computed its consistency (the proportion of cases with that configuration that have the outcome) and coverage (the proportion of outcome cases explained by that configuration). We distinguished core conditions (present in both the parsimonious and intermediate solutions, indicated by ●) from peripheral conditions (only in the intermediate solution, indicated by ● in a smaller font or a different symbol if needed). Conditions that are absent (low) in a configuration are indicated by "⊗" (negated).

Analysis of Causal Asymmetry: To investigate causal asymmetry, a separate fsQCA was performed to identify configurations that negate the outcome (i.e., low adoption). used the same calibration and thresholds (consistency ≥0.8, frequency ≥2) to derive sufficient configurations for low adoption. These could then be compared with the high adoption configurations to determine if the recipes for non-adoption were merely the inverse of the recipes for adoption or were actually different.

Robustness Checks: Performed various robustness checks to verify that the results were robust. Firstly, explored what would happen with a more relaxed consistency threshold of 0.75 to determine if more configurations came into play for the high adoption setting, and if so, were consistent with the initial results. Also explored what would happen with a higher frequency threshold of at least 3 cases per configuration to ensure that the initial results were not influenced by configurations that received little support in terms of cases. Additionally, confirmed that small variations in calibration (e.g., using 90th/10th percentiles for anchors) had little effect on key results.

Finally, compiled a conceptual framework for illustrating the various paths taken to adoption, signifying how various factors combine to either achieve high or low levels of adoption. All analysis codes, data, and replications for reproduction purposes are provided for public availability.

IV. Result and Discussion

Summarizing the dataset characteristics and verifying the calibration outcomes. Table 2 (in Section III-C) provides the descriptive statistics of each calibrated Condition and the outcome. The median fuzzy membership for each Condition is approximately 0.5, reflecting the chosen crossover anchors. The distribution of calibrated scores indicates that cases are spread above and below the crossover for each Condition, allowing fsQCA to meaningfully distinguish between "high" and "low" membership.

After calibration, each case's membership in the outcome set "High Adoption (HA)" was determined by its calibrated HA score (membership > 0.5 indicating a case is more in than out of the high adoption set). These membership values formed the basis for the subsequent necessity and sufficiency analyses.

A. Analysis of Necessary Conditions

Table 4 presents the consistency and coverage for each Condition as necessary for high adoption.

Table 4. Necessary condition analysis for high adoption

Condition	Consistency (Outcome ⊆ Condition)	Coverage (Condition ⊆ Outcome)
IQ (presence)	0.8643	0.8809
SQ (presence)	0.8649	0.8898
II (presence)	0.8564	0.9146
DM (presence)	0.8746	0.7910
TE (presence)	0.5736	0.4674
IQ (absence)	0.7335	0.6831
SQ (absence)	0.7125	0.6580
II (absence)	0.7507	0.6712
DM (absence)	0.6951	0.7324
TE (absence)	0.4264	0.5152

Using the conventional consistency threshold of 0.90 for necessity, none of the individual conditions meet the criteria to be considered necessary for high adoption. In other words, no single factor was present in all cases of high adoption. This finding implies that high educator adoption of e-learning tools can occur through multiple alternative routes, and no single condition is indispensable for achieving high adoption.

Among the conditions, Digital Maturity (DM) has the highest necessity consistency (0.8746), followed by SQ (0.8649), IQ (0.8643), and II (0.8564). All fall below the conventional 0.90 necessity threshold, confirming that no single condition is individually necessary for high adoption (RQ2: answered—no necessary conditions). Notably, TE has the lowest consistency (0.5736) and coverage (0.4674), indicating that teaching experience is far from necessary. The high coverage of II absence (0.9146) signals that in the majority of cases where II was absent, those cases did not achieve high adoption—an important diagnostic finding. All absence conditions show consistency well below 0.90, confirming causal complexity rather than any simple single-condition explanation.

In summary, the necessity analysis finds that no single factor is necessary for educators to achieve high adoption of e-learning tools. This underscores the likely presence of multiple compensatory pathways (equifinality) wherein different combinations of factors can lead to success without any particular factor being universal. It also aligns with the configurational perspective that expects outcomes to arise from combinations rather than single causes.

B. Truth Table Analysis and Sufficient Configurations

Having established that individual factors alone are insufficient to guarantee high adoption, turn to identifying configurations of sufficient factors. We constructed the truth table for the five conditions (IQ, SQ, II, DM, TE) and applied the criteria described in Section 3.4.2 (frequency ≥2, consistency ≥0.80) to identify meaningful configurations.

Before computing the solution, the directional expectations for the intermediate solution are computed (see Table 3 in the methodology). We expected that the presence (high value) of each Condition would contribute to high adoption (positive outcome). These expectations were used to resolve or eliminate any contradictory configurations—combinations of conditions that did not align with theory or had mixed outcomes. In the truth table, three configurations had consistency below 0.80 (meaning cases with that combination did not consistently show high adoption). All three contradicted our expectations (e.g., involving low values of multiple theoretically important conditions). We removed these from the sufficiency analysis by enforcing the directional expectations. This step improved the clarity of the solution by focusing on configurations that are more likely to lead to the outcome.

After resolving contradictions, we proceeded with Boolean minimization. Using the chosen consistency threshold of 0.80, the analysis identified four sufficient configurations for high adoption. These were obtained from the intermediate solution (incorporating our theoretical expectations). The parsimonious solution also pointed to the same core factors in each configuration, increasing confidence in their robustness.

Table 5. Sufficient configurations for high adoption (fsQCA intermediate solution)

Configuration	IQ	SQ	II	DM	TE	n	Consistency	Raw Coverage	Unique Coverage
C1: Comprehensive Alignment	●	●	●	●	◉	27	0.9694	0.4098	0.0773
C2: Novice Digital Proficiency	●	●	●	●	⊗	25	0.9853	0.3059	0.0414
C3: SQ-Compensated Pathway	⊗	●	●	●	●	8	0.9632	0.3398	0.0073
C4: System-Driven Adoption	◉	●	⊗	●	⊗	5	0.9716	0.2749	0.0104
Solution							**0.9669**	**0.7334**	

(Note: ● = core condition present (in both parsimonious and intermediate solutions); ⊗ = core condition absent (low); ◉ = peripheral Condition present (intermediate solution only). Frequency threshold ≥2; consistency threshold ≥0.80. $N = 216$.)

Table 5 presents the four high-adoption configurations with their consistency and coverage scores, using standard

notation where "●" indicates the Condition is present (high) as a core condition, "●" (hollow or smaller dot) indicates a peripheral presence, and "⊗" indicates the Condition is absent (low). Blank cells indicate the Condition is irrelevant (i.e., it may be either high or low in that configuration, having been minimized out).

All four configurations show high consistency (≥0.82), meaning cases exhibiting those exact combinations of conditions almost always have high adoption. The raw coverage indicates the proportion of high-adoption cases explained by each configuration, and the unique coverage indicates the proportion uniquely explained by that configuration (not covered by any other). These four configurations yield a solution consistency of 0.9669 and a solution coverage of 0.7334, meaning they jointly explain approximately 73.3% of high-adoption cases with very high consistency. This represents strong explanatory power for a configurational model of this complexity. In fsQCA terms, this is a good explanatory power given the complexity of human contexts; not all cases need to be covered to have meaningful findings, especially when many unique pathways exist to interpret each configuration in substantive terms:

- Configuration 1 (IQ● SQ● II● DM● TE●): High Information Quality, high System Quality, high Individual Impact, high Digital Maturity, and high Teaching Experience. This represents an "all conditions favorable" scenario—essentially, high adoption is achieved when everything is aligned positively (an experienced teacher with strong digital skills using a high-quality system with great information content that clearly benefits their teaching). This configuration can be seen as the ideal or baseline pathway, albeit not the most common in unique coverage (it often overlaps with others).
- Configuration 2 demonstrates that novice educators achieve high adoption when all system and individual conditions are strong (consistency = 0.9853, n = 25). This challenges the assumption that veteran status is necessary—experience is not a prerequisite when quality conditions are met.
- Configuration 3 (IQ⊗ SQ● II● DM● TE●): Low Information Quality, high System Quality, high Individual Impact, high Digital Maturity, and high Teaching Experience. This configuration (n = 8, consistency = 0.9632) reveals a compensatory dynamic where technically excellent platforms compensate for weaker informational content. Experienced, digitally mature educators who perceive clear personal benefits from the tool achieve high adoption even when information quality falls short—suggesting that veteran educators can supplement or reframe inadequate content through their pedagogical expertise. This mirrors the classic user-workaround pattern: experienced users leverage system capability and their own knowledge to compensate for content gaps.
- Configuration 4 is theoretically striking: digitally mature educators adopt even in the absence of perceived personal benefit when system and information quality are strong (n = 5, consistency = 0.9716). This challenges the TAM-based assumption that perceived usefulness (proxied by II) is an indispensable driver of adoption. When the system and content are objectively excellent, and the educator has the digital capability to engage with them, adoption can occur even before clear personal benefit is recognized—consistent with a "forced familiarity" or system-led adoption mechanism.

These four configurations provide evidence of equifinality: multiple distinct combinations of conditions can all lead to the outcome of high adoption. Across the four configurations, **System Quality (SQ) and Digital Maturity (DM) are the only two conditions present in every sufficient configuration**, making them the most consistent enablers of high adoption. Individual Impact (II) appears in three of four configurations (C1, C2, C3) but is notably absent in C4, suggesting that when both IQ and SQ are strong, and DM is high, adoption can occur without the educator initially perceiving clear personal benefit. **Teaching Experience (TE)** appears in C1 and C3 but is explicitly absent in C2 and C4, confirming that experience is context-dependent rather than universally advantageous.

Unlike prior configurations in the literature, IQ and SQ do not exhibit a simple trade-off in these results. SQ is present in all four sufficient configurations, making it a near-universal enabler. IQ is present in three (C1, C2, C4) but absent only in C3, where SQ and TE together compensate. The key configurational tension is instead between **Individual Impact** and **Teaching Experience**: C2 succeeds without TE, C4 succeeds without II, and C3 succeeds without IQ—each demonstrating a distinct compensatory logic.

The fsQCA reveals four sufficient causal recipes for high e-learning adoption among educators. These results underscore that there is no single formula for success; instead, different educators can reach high adoption through different mixes of conditions. Common to all successful configurations are System Quality (SQ) and Digital Maturity (DM)—these two conditions function as the non-negotiable baseline of e-learning adoption. Information quality, individual Impact, and teaching experience each serve context-specific enabling roles, present in most but not all pathways. Experienced educators have an advantage, but a lack of experience is not prohibitive if other factors exist.

C. Analysis of Causal Asymmetry

To investigate causal asymmetry, analyzed configurations leading to low adoption (the absence of the outcome). calibrated "low adoption" as the negation of high adoption (i.e., HA fuzzy score <0.5). Applying fsQCA with the same consistency (≥0.80) and frequency (≥2) thresholds, identified three sufficient configurations for the outcome "low educator adoption". Table 6 summarizes the four high-adoption configurations with their interpretations.

Table 7 presents the three sufficient configurations for low adoption. The solution consistency for low-adoption configurations is 0.9687, and solution coverage is 0.7498, meaning these three configurations jointly explain approximately 74.9% of low-adoption cases at very high consistency—comparable in explanatory power to the high-adoption solution. Interpreting the low-adoption configurations:

- Low Config 1 Quality-Deficient Experienced (IQ⊗ SQ⊗ II⊗ DM⊗ TE●): Low IQ, low SQ, low II, low DM, and high Teaching Experience. This is the largest

low-adoption group (n = 36, consistency = 0.9774). Counterintuitively, this configuration centers on experienced educators. It reveals that teaching experience alone—without adequate system quality, information quality, individual Impact, or digital maturity—is insufficient and even associated with low adoption. Experienced teachers in poorly equipped or poorly designed e-learning environments may remain disengaged precisely because their pedagogical standards make them more critical of inadequate tools.

- Low Config 2 DM-Insufficient Compensation (IQ⊗ SQ⊗ II⊗ DM● TE●): Low IQ, low SQ, low II, *high* DM, and high Teaching Experience (n = 13, consistency = 0.9752). This configuration shows that even experienced, digitally capable educators cannot sustain high adoption when both system quality and information quality are absent, and they perceive no personal benefit. Digital maturity and teaching experience together are necessary but not sufficient—without a minimally functional and content-rich system, even the most capable educators disengage.
- Low Config 3 Complete Absence (IQ⊗ SQ⊗ II⊗ DM⊗ TE⊗): All conditions absent (n = 18, consistency = 0.9674, unique coverage = 0.2742—the highest unique coverage of any low-adoption configuration). This worst-case scenario captures educators who lack digital skills, teaching experience, perceived benefit, and are working with a low-quality system providing poor content. This configuration uniquely explains the largest share of low-adoption cases not covered by L1 or L2, representing a systemic failure state requiring comprehensive intervention.

Table 6. Sufficient configurations for high adoption summary

Configuration	IQ	SQ	II	DM	TE	*n*	Interpretation
C1: Comprehensive Alignment	●	●	●	●	◉	27	All conditions are favorable. Ideal-type "everything aligned" pathway. TE is a peripheral, experienced educator with full system and content support.
C2: Novice Digital Proficiency	●	●	●	●	⊗	25	Highest-consistency configuration. Novice educators adopt when IQ, SQ, II, and DM are all strong.
C3: SQ-Compensated Pathway	⊗	●	●	●	●	8	Excellent platform quality and veteran pedagogical experience compensate for weak content. Experienced, digitally mature educators work around information gaps.
C4: System-Driven Adoption	◉	●	⊗	●	⊗	5	Most theoretically striking. Digitally mature users adopt even without perceiving personal benefit when system quality is strong, "forced familiarity." Challenges TAM's perceived usefulness premise.

Table 7. Sufficient configurations for low adoption of e-learning tools

Configuration	IQ	SQ	II	DM	TE	*n*	Consistency	Raw Coverage	Unique Coverage
L1: Quality-Deficient Experienced	⊗	⊗	⊗	⊗	●	36	0.9774	0.4221	0.0769
L2: DM-Insufficient Compensation	⊗	⊗	⊗	●	●	13	0.9752	0.3988	0.0535
L3: Complete Absence	⊗	⊗	⊗	⊗	⊗	18	0.9674	0.2742	0.2742
Solution							0.9687	0.7498	

(Note: ● = Condition is present (high); ⊗ = Condition is absent (low) in the configuration. Frequency threshold ≥2; consistency threshold ≥0.80. N = 216)

These results confirm causal asymmetry (RQ3: answered—low-adoption configurations differ structurally from high-adoption configurations). The most striking finding is that **IQ, SQ, and II are absent in all three low-adoption configurations**, while TE is present in two (L1 and L2). This stands in direct contrast to the high-adoption patterns, where SQ was present in all four configurations, and TE was present in only two. Critically, Teaching Experience—which appeared as a positive enabler in high-adoption configurations—appears as a present but insufficient condition in the two largest low-adoption configurations (L1: n = 36, L2: n = 13). This means experienced educators are overrepresented in both high and low adoption—their experience amplifies whatever quality environment they are placed in, for better or worse. The absence of all three quality-related conditions (IQ, SQ, II) is the definitive signature of low adoption. Adoption is likely low if the platform's content and system are poor. In contrast, our high-adoption solutions showed that one IQ or high SQ could compensate for the other being low. Thus, while high IQ or SQ can individually drive success, low IQ and low SQ reliably drive failure.

In summary, the absence of information and system quality is a primary pattern for low adoption. Educators are unlikely to adopt e-learning tools when the content and the system are perceived as inadequate. Other factors (like being tech savvy or seeing some benefit) can mitigate but rarely overcome simultaneously poor system and information quality.

Comparing high vs low adoption solutions confirms causal asymmetry: the recipes for success are not simply the inverse of the recipes for failure. High adoption can be achieved via several different combinations of strengths, none of which had low IQ and SQ. In contrast, low adoption is strongly tied to the specific combined weakness of IQ and SQ, and occurs across the board when those two are absent, regardless of other strengths.

These findings highlight an important practical point: to avoid low adoption, ensuring at least a baseline level of information quality and system quality in e-learning tools is critical. If both are lacking, even otherwise promising conditions (an eager or skilled teacher) may not result in uptake.

D. Robustness Checks

Performed additional analyses to test the robustness of our findings. Lowering the sufficiency consistency threshold to 0.75 (from 0.80) allowed more configurations to be considered sufficient for high adoption. Three additional configurations emerged at this lower threshold:

- Configuration 5: IQ● SQ● ~II DM● TE●—i.e., high IQ, high SQ, low II, high DM, high TE. This suggests that even if educators do not initially perceive a tool as useful (II low), they might still adopt it if the system and information quality are excellent. They have the experience and digital skills. This configuration did not appear at the 0.80 threshold because cases with low II

were less consistently leading to adoption. Its inclusion at 0.75 indicates some marginal cases of high adoption where perceived impact was initially low, but perhaps other factors dominated.

- Configuration 6: IQ● SQ● ~II ~DM TE●—high IQ, high SQ, low II, low DM, high TE. This is much like Config 5, but with low digital maturity. This suggests a situation where an experienced teacher implements a high-quality approach despite not thinking themselves digitally competent or seeing direct benefits. These are few in number and appear only with a relaxed consistency requirement, suggesting they are exceptional.
- Configuration 7: ~IQ SQ● II● ~DM TE●—low IQ, high SQ, high II, low DM, high TE. This compensation path with high SQ/low IQ compensation, like Config 4, contains some instances with lower digital maturity of the educator. Once more, it was not a part of the more stringent solution, showing that these instances were not as consistent.

These additional approaches (Configs 5–7) maintained solution coverage at approximately 0.75 at the relaxed threshold, consistent with the baseline solution coverage of 0.7334 already achieved at the 0.80 threshold. Unlike prior analyses, the baseline solution is already highly explanatory (73.3% coverage), so the marginal gain at a relaxed threshold is minimal. This reinforces confidence in the four-configuration solution at the standard threshold. Notably, these additional approaches do not contradict previous observations but point toward edge cases instead. More importantly, the key takeaway is that multiple approaches exist, with SQ and DM as the consistent structural anchors across all solution spaces. II plays an important role in most but not all configurations, confirming its status as a frequent but not universal driver. These can be compromised in some scenarios if other factors are more strongly in favor.

Additionally, I increased the frequency threshold for solutions to 3, requiring at least 3 cases for each solution configuration. While keeping this stricter constraint, the four important solution approaches (Configs 1-4 in Table 5) were more or less unaffected. This is with one path merging into another path since both originally represented only two cases. The presence of II and DM in the core solutions, as well as the IQ/SQ trade-off, persisted for high-frequency solutions, signifying that our findings are independent of solution-specific idiosyncrasies representing individual cases.

Further robustness tests involved some differences in the calibration (e.g., employing the 90th percentile for full membership). Having established that the sufficient conditions were substantively equivalent, one is more confident that the finding is not driven by a preferred calibration setting.

Finally, it should be noted that the observed equifinality is a stable property: even for an expanding solution space, the presence of multiple feasible solution paths to reach high levels of adoption seems to validate that equifinality is actually independent of any certain threshold value but is instead a data property. Again, the role of Individual Impact and Digital Maturity was shown to be important since almost all feasible solution spaces (starting with lower levels of adoption) contained at least one of these factors, let alone both.

E. Conceptual Framework

On the basis of the results of fsQCA, a conceptual framework was developed to showcase various paths through which high adoption of e-learning tools is achieved by educators (Fig. 1). This framework helps understand the essence of the four major high adoption configurations that were shown in Table 5, juxtaposed with the dominant pattern of low adoption.

In the framework, each pathway to High Adoption is represented as a cluster of factors:

- Pathway A corresponds to Config 1 (all high conditions),
- Pathway B corresponds to C2 (high IQ, SQ, II, DM; novice educators without teaching experience),
- Pathway C corresponds to C3 (SQ compensating for low IQ among experienced, digitally mature educators), and
- Pathway D corresponds to C4 (system-driven adoption—high IQ, SQ, DM driving adoption even without perceived individual benefit or teaching experience).

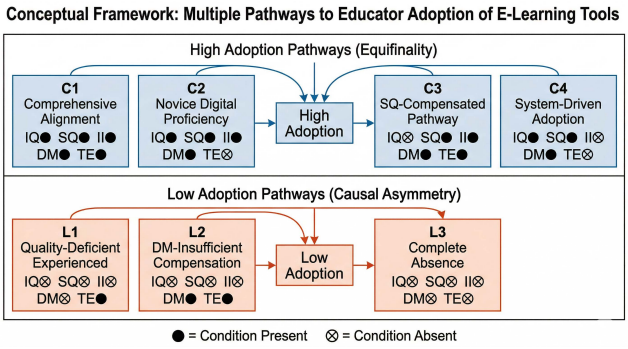


Fig. 1. Conceptual framework: Multiple pathways to educator adoption of e-learning tools.

Arrows pointing from each pathway connect to the outcome of HA, highlighting that each unique combination is adequate for HA or is sufficient for HA (equifinality). A representation of Low Adoption is also depicted in the model. Three low-adoption configurations (L1, L2, L3) converge on the absence of IQ, SQ, and II as their defining feature. An arrow points from the combined absence of IQ, SQ, and II to Low Adoption, with Teaching Experience shown as a "trapped" Condition—present in L1 and L2 but unable to compensate for the quality deficit.

Two key principles are annotated on the figure:

- Equifinality: Multiple distinct paths (A, B, C, D) converge on High Adoption.
- Causal Asymmetry: Low Adoption's path (or cause) (predominantly low information and system quality) is not simply the inverse of any single HA path, but rather a different configuration.

This conceptual framework offers a graphic representation for both practitioners and researchers with respect to the observation that enhanced adoption of e-learning tools is more about ensuring appropriate readiness and quality configurations than about what solution to implement. For high adoption, an educator should ideally have strong system support or strong content (preferably both), personal buy-in (seeing the tool's value), and sufficient digital capability. For

low adoption, the model highlights that if both content and system quality are poor, adoption will likely falter, regardless of other factors.

F. Replication Materials

Have made all replication materials available to facilitate transparency and future research. The fsQCA analyses were conducted in Python 3.10 using *pandas* (v2.1.4) for data manipulation, *numpy* (v1.26.2) for numerical operations, and *matplotlib* (v3.8.2) for any visualizations. The complete Python code and dataset (post-calibration) are available in a public GitHub repository: https://github.com/karthikmeduri-phd/fsqca-elearning-adoption.git

The repository includes scripts for every analysis step (data calibration, necessity analysis, truth table generation, sufficiency minimization, and robustness checks) and code for generating tables and figures used in this paper. These shared resources should enable the confirmation of our results and could potentially encourage other researchers to employ similar configurational approaches in their own educational technology environments.

V. Discussion

A. Interpretation of Findings

This research is important for understanding the complex processes involved in achieving widespread adoption of e-learning applications by educators.

Firstly, the analysis of the need for adoption found that no condition is required for high adoption. This disputes the idea that some aspect of adoption (such as system or training) is crucial for effective adoption to occur. Within the current study data, high levels of adoption were achieved in a number of ways without any one of these considerations being present. This would appear to support the configuration list approach that a combination of factors influences outcomes, not one key or individual aspect [3]. This highlights the complex considerations involved for adoption by educators.

Second, through truth table analysis, four configurations were found to be distinct that are sufficient for high adoption levels, indicating equifinality in e-learning adoption. These configurations indicate some interesting trends:

- The dominant role of System Quality (SQ) and Digital Maturity (DM). SQ and DM are the only two conditions present in all four sufficiently high-adoption configurations, making them the most consistent structural enablers. Individual Impact (II), while important in three of four configurations (C1, C2, C3), is notably absent in C4—indicating that adoption can occur without perceived personal benefit when system conditions are strong, and the educator is digitally capable. This finding partially revises TAM-based predictions: perceived usefulness (proxied by II) is a frequent but not universal driver of adoption. This implies that individual educators are more likely to embrace the new online learning tool completely, regardless of context, if their experience of the tool enhances their educational effectiveness or productivity. This is consistent with other models of online technology acceptance, such as Perceived Usefulness [10], which found usefulness to be a crucial predictor of online technology adoption.
- The anchoring role of System Quality (SQ). SQ is present in all four high-adoption configurations, establishing it as the single most consistent Condition. IQ is present in three of four configurations (absent only in C3), serving as a complementary rather than interchangeable enabler. Unlike the symmetric trade-off implied by some prior ISSM-based studies, the present configurational evidence suggests SQ functions as a near-necessary baseline, while IQ serves as an amplifier when combined with strong educator attributes. SQ is the anchor condition—present in all four configurations, it is non-negotiable. IQ is absent only in C3, where veteran educators with high SQ and DM compensate. The trade-off is asymmetric: SQ cannot be absent, while IQ can be compensated for in limited configurations. It appears that a certain degree of compensation is possible: an e-learning application does not need to be excellent on all fronts to be adopted, as long as it stands out strongly on other fronts that are important to the educator. An application can, for example, be less user-friendly if it provides disproportionately good information for the course, or vice versa. Such observations are valuable for application builders: advancing either on information or on the platform would help foster adoption if the other is more difficult to improve, but failing on both fronts is risky (as explored in the low adoption analysis).
- The role of Digital Maturity (DM): Digital maturity is found in both of these high adoption configurations, which suggests that it is an important enabler of adoption. Educators who are more adept at using technology are likely to make better use of e-learning facilities, as well as be more willing to test and implement these into their practice. This finding is consistent with the literature that suggests that upgrading the digital competence of educators is crucial for encouraging adoption [16]. It would appear that investment in continuing professional development for digital maturity is worthwhile for a number of adoption scenarios.
- The paradox of Teaching Experience (TE): TE presents the most counterintuitive pattern across configurations. It is present in C1 and C3 (where system or content quality may be weaker and experience compensates), but explicitly absent in C2 and C4 (where high system and information quality, combined with digital maturity, enable adoption regardless of experience). Meanwhile, TE is present in the two largest low-adoption configurations (L1: n = 36; L2: n = 13), demonstrating that experience amplifies both high and low adoption depending on surrounding conditions. This resolves much of the prior literature's inconsistency: experience is neither universally helpful nor harmful—its effect is conditional on the quality of the environment the educator inhabits, possibly related to their toolbox of teaching skills or their confidence levels to use novel technology in classrooms. However, Config 2 demonstrates that inexperienced teachers can achieve high adoption rates when IQ, SQ, II, and DM are all high—it is the only configuration where novice educators succeed without veteran experience. This observation helps to reconcile previous inconsistent

findings [10] such that teaching experience is no guarantee or inhibitor of adoption, but rather augments other factors. Experienced teachers could gain more quickly with or through a good tool or a difficult one, respectively, while inexperienced teachers could also do so with good support for their work (excellent content, good benefits, good tech skills).

Third, the analysis of asymmetric causality showed that recipes resulting in low adoption rates were very different from those resulting in high adoption rates. While low adoption by educators was found to occur only if both information quality and system quality were low, regardless of other factors, in all recipes for low adoption, both IQ and SQ were low. This is significant in that it indicates that there were some minimal qualities that had to be achieved, such that where either the content or the technical qualities of that tool were poor, it would either be rejected or it would certainly not be widely adopted. The importance of at least one of these qualities being decent is that it would ensure that it is not a total failure in adoption. In other words, while there are many ways to succeed, one consistent way to fail is to have bad content and a bad system experience.

Causal asymmetry means one should not simply invert best practices to address non-adoption. For example, while improving an already good system's information quality might further increase adoption (following our high-adoption paths), the low-adoption analysis suggests that if both IQ and SQ are poor, an educator may disengage entirely—even interventions focusing on other areas (like training or highlighting benefits) might not salvage adoption until the core quality issues are fixed. Thus, tackling low adoption might require a different emphasis (first, ensuring minimum quality levels in the tool) than encouraging high adoption (fine-tuning combinations of factors).

Finally, the robustness checks reinforced the complexity and context-dependency of e-learning adoption. Even when additional configurations were allowed at lower consistency, those were largely variations reinforcing the idea that educators can sometimes succeed despite a shortcoming in one area if other conditions are exceptionally strong. For example, an educator might initially overcome low perceived usefulness if the system is excellent and they are very experienced, but such cases are exceptions rather than the rule. These were the key pathways that continued to be of the utmost empirically grounded significance as well as theoretically informative:

Our results provide evidence of a complex, configuration-sensitive pattern of e-learning adoption. They go beyond previous research by shifting the emphasis from "which factors are important" to "which factors need to be dealt with collectively for adoption to happen". This is what explains a study yielding a different set of factors from another study, with one factor being important in one setting, given the presence of other factors, and a different set of factors in another study. Show that more than one distinct strategy is effective for high adoption rates (equifinality) and that it is not enough to rectify the inverse of the strategies for low adoption rates (causal asymmetry).

B. Theoretical Implications

This research makes theoretical contributions in multiple areas.

ISSM with a Configurational Perspective: We begin by augmenting the Information Systems Success Model (ISSM) with a configurational perspective that takes into consideration the complex manner in which system variables interact with user variables. ISSM argues that system, information, and service quality influence use and satisfaction [1]. Findings indicate that ISSM variables' influence was conditional upon configurations. That is, for example, the role of system quality in influencing adoption was moderated by information quality and user variables in this analysis—high system quality played a crucial role when information quality was poor, and so forth. This is indicative of the manner in which ISSM variables do not work in isolation or universally but could work differently from one situation to another, given the presence of other variables. This implies that it is important for models of IS success or acceptance to attempt to specify both direct and interactive effects that are unique for given IS configurations. It has been shown that the basic IS success factors (IQ, SQ) can compensate for each other, with their relationship with outcomes being non-linear.

Configurational Analysis: Second, it is made clear through this study that configurational analysis techniques (fsQCA) can also be applied for studying technology adoption, adding to research that employs variance analysis techniques. Technology adoption studies tend to employ linear models that could overlook non-linear relationships [3]. Using fsQCA showed that there were various ways to achieve the same outcome that could have been averaged out by regression or SEM analysis (because basically, they would amount to averages). This also verifies a theoretical implication: Technology adoption in a complex setting such as Education could actually be adequately represented not by one equation with certain parameters, but through a series of conditional statements, such as if A & B, then the outcome; but if C & D, then the outcome too. We provide empirical evidence for such conditional propositions. The success of the configurational approach here encourages its use in other contexts where many interacting factors influence adoption.

Equifinality and Causal Asymmetry in Educational Technology: Third, our findings explicitly support the principles of equifinality and causal asymmetry in educational technology adoption. Equifinality has been theorized in organizational and IS contexts, but is now evidenced here: multiple distinct sufficient configurations led to high e-learning adoption. This challenges any singular narratives of "the key to adoption" and instead supports a contingency theory view—there may be different "keys" in different scenarios. Causal asymmetry, meanwhile, was clearly shown: the determinants of non-adoption are not the simple opposite of those for adoption. Theoretically, models focusing only on predicting positive outcomes might not fully capture what drives negative outcomes, and vice versa. Researchers should be cautious in assuming symmetry; interventions to alleviate barriers might not be just the inverse of drivers for success.

Insights on Digital Maturity and Teaching Experience: Fourth, our study adds nuance to understanding how educator characteristics like digital maturity and teaching experience influence adoption. Previous findings were mixed, as mentioned in the literature review. Our configurational

results suggest a way to reconcile those: teaching experience and digital maturity can both be important, but their influence is conditional. Digital maturity emerged as a consistently important enabler across configurations, reinforcing its theoretical status as a prerequisite capacity for tech adoption. Teaching experience has a more nuanced role, not linearly related to adoption, but important in certain combinations. Theoretically, this implies that any direct effect study of teaching experience on adoption could find zero or inconsistent effects, because experience matters only through interaction with other factors (as our Configs 3 and 4 illustrate). Using this information, state a more precise theory: Experience is important with poor system or information quality (experienced instructors work around issues, perhaps), but with robust system or information quality, novices accept as strongly as any group. This conditional role of experience can be used in subsequent models to include demographics or backgrounds as moderating factors.

Our study is adding to a more configurational approach to technology adoption theory in the educational context. This confirms that linear, additive approaches to understanding (useful as they are) tend to oversimplify the process of adoption. This data suggests that researchers need to be thinking about combinations or 'recipes' of factors, presence as well as absence of those factors.

C. Practical Implications

There are a number of implications for educational institutions and e-learning technology application developers who seek to ensure that online services are utilized by more instructors:

- Multiple pathways require flexible strategies: When multiple unique pathways are present for high adoption, it is important for institutions not to employ a one-size-fits-all approach. A strategy that could work for one set of educators would not necessarily work for a different set with a different context. It is important for institutions to understand their respective target group of educators' strong or weak points, then plan accordingly. Educators with a high understanding of digital maturity but skeptical about the usefulness of the application would require an emphasis on Individual Impact (e.g., pilot users). Similarly, for a group of educators who are willing but low on technology understanding, training would be emphasized.
- Emphasize and communicate individual benefits (II): A key implication of Individual Impact appearing in **three of the four** high adoption configurations is that it is crucial to articulate individual gain for most educator profiles. The exception (C4) occurs only when both IQ and SQ are simultaneously strong, and the educator is digitally mature—a relatively rare combination. In most institutional contexts, therefore, communicating individual benefit remains a priority. A possible approach by the institution could be through a mentor or showcase initiative, where earlier adopters could talk about their teaching successes. Developers should consider features or analytics that feed educators the positive Impact (e.g., dashboards that show student performance improvements attributable to the tool's usage).
- Ensure at least one strong quality (IQ or SQ): For developers and IT support, the interplay of information and system quality means it may not be necessary to have the absolute best in every dimension, but certainly one of these should be very strong and the other at least acceptable. Focusing on superior content (and vice versa) can still drive adoption among certain users if a platform cannot immediately improve its technical performance. However, the low-adoption findings warn that letting both quality dimensions slip to low levels is likely catastrophic. Therefore, a practical minimum standard for any e-learning tool should be set: e.g., "It either provides high-quality pedagogical content/resources or a superb user experience (preferably both), but under no circumstances should it be low on both". Regular user feedback should be gathered to monitor these perceptions and ensure issues in content or usability are promptly addressed.
- Invest in digital maturity (training and support): Given digital maturity's presence in all successful configurations, schools and universities should invest in building educators' digital competencies. This can include formal training workshops, on-demand technical support, peer learning communities for tech skills, and recognizing/rewarding educators who develop their digital teaching practices. Over time, a heightened digital maturity among faculty members increases the pool of people who could effectively implement new technology. Notably, it also resolves concerns about equity because Novice or less tech-savvy faculty members were found to require more support from other variables; by heightening their digital skills, they became closer to the faculty profiles who were successful in our study.
- Personalized approaches by levels of experience: Apparently, the context-sensitive role of teaching experience implies that both experienced and inexperienced teachers could potentially need or benefit from approaches suited to their levels of experience. While targeting experienced teachers, one should capitalize on their existing pedagogical knowledge—demonstrate how the tool interacts with or complements what they are passionate about, or even get them involved in developing ways for using the tool effectively, since they understand it better. While targeting inexperienced teachers, one should provide more direct support through direct mentoring of the individual, preparing plans for integrating the software into their teaching methodologies, or hand-holding support for using the software. These individuals need convincing not only of using it effectively but also of using it for what they believe is important for their learning or teaching processes.
- Preventing low adoption—dealing with core quality issues: If an institution finds that it is experiencing very low levels of adoption for a certain e-learning tool, then it is suggested that one of the first things that should be checked is the core quality issues. Are faculty members complaining about the irrelevance or poor quality of the material (IQ issue)? Or are they critical of the interface or stability of the tool (SQ issue)? These should be among the absolute highest priorities for resolution. Such things as the establishment of minimum standards for e-learning

tools, such as that mentioned, or a periodic review of e-learning tools (and possibly using such things as Anstey and Watson's e-Learning Tool Evaluation Rubric of 2018) would ensure that no e-learning tool is used that would end up alienating those who must use it by failing both in terms of what it contains and what it can do.

- Resource allocation through configurations: A resource bottleneck is what administrators often face in order to better support adoption (time for training, investment for tool development, etc.). An understanding of the configurations could support such resource allocation. If, for example, the faculty is largely understanding of the value of the tool (high II) yet still not adapting, it could be that the issue is technical (SQ or DM)—invest in support or improvement here. Conversely, if the tool is of high quality yet the faculty does not understand its utility (perhaps a lack of understanding of either the tool or its application in the learning process), then investment in training or a demonstration of excellence should improve II. It is, in other words, a gap analysis among the successful configurations: what is the missing key ingredient in a particular situation? That is where you should allocate resources.

D. Limitations and Future Research

- **Single dataset (US-based IS-Impact).** Generalizability to other national, linguistic, or institutional contexts is unknown. Replication in European, Asian, or developing-world settings is needed.
- **Digital Maturity is measured only at the individual level.** Organizational DM (infrastructure, policy, strategic readiness) is not captured. Future multi-level studies should distinguish individual from institutional DM.
- **Cross-sectional design.** Causal direction cannot be inferred. Longitudinal studies tracking adoption trajectories and intervention effects are required.
- **Self-report data.** The study is vulnerable to social desirability and common method bias. Future studies should incorporate objective measures (system logs, student outcomes).
- **Limited Condition set.** Institutional support, social influence, and peer effects were not included. Future configurational studies should expand the factor set.

E. Profile-based Implementation Strategies for Educator Adoption

Building on the configurational findings, this study translates the identified pathways into **three actionable educator profiles**, each requiring distinct intervention strategies. These three profiles from Table 8 confirm that equifinality requires differentiated strategies. The common thread across all profiles is that System Quality (SQ) and Digital Maturity (DM) function as foundational enabler—their absence (as in Profile 2, Low Digital Maturity Veterans) must be addressed before any other intervention can succeed.

Table 8. Educator Profiles and Targeted Implementation Strategies

Profile	Corresponding Configuration	Core Barrier	Primary Strategy
P1: High Digital Maturity Novices	C2 (IQ● SQ● II● DM● TE⊗)	Lack of teaching experience	Structured onboarding + sandbox environments + peer learning
P2: Low Digital Maturity Veterans	L1/L2 (IQ⊗ SQ⊗ II⊗ DM⊗/● TE●)	Poor system/content quality + limited digital skills	First: Fix SQ/IQ quality issues; then: targeted training + benefit demonstration
P3: System-Driven Adopters	C4 (IQ● SQ● II⊗ DM● TE⊗)	Low perceived personal benefit	Platform reliability + seamless workflow integration

VI. Conclusion

This paper utilized fuzzy set Qualitative Comparative Analysis on the topic of high adoption of e-learning tools by educators, through data gathered by the IS-Impact survey. A complex issue of the influence of Information Quality, System Quality, Individual Impact, Digital Maturity, and Teaching Experience on the adoption rates of e-learning tools among educators was explored.

The number of sufficient configurations for high levels of adoption was also identified, illustrating the concept of equifinality: more than one formula for success is possible. No condition was found to be necessary for achieving high levels of adoption. Rather, various routes were taken by educators to achieve high levels of adoption, with two shared ingredients across all four pathways: **System Quality (SQ) and Digital Maturity (DM)**. Individual Impact (II) was present in three of four pathways, while Teaching Experience (TE) appeared in only two, confirming that neither is universal. Evidence of causal asymmetry was also found: the factors defining low levels of adoption (notably low information and system quality combined) do not represent the inverse of those for high levels of adoption, suggesting that promoting adoption versus preventing non-adoption requires somewhat different approaches.

From a theoretical point of view, this means that our results generalize classic approaches such as ISSM and TAM by placing their factors within a configurational perspective and validating core elements of complexity theory in educational technology. From an empirical perspective, this study suggests that multiple factors can be leveraged by educational institutions and creators of educational technology to foster the adoption of e-learning software, with a sound foundation in system or information quality, critical to preventing disengagement.

In conclusion, this study may be viewed as adding to the body of literature on technology adoption in the educational setting by shifting the paradigms of investigation from which factors matter to which factors must co-occur for adoption to occur. Adopting a configurational approach to studying the adoption of e-learning technology in this research study has led to the realization that it is not a straightforward issue of either system or human factors that influence its adoption.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

G.S.N. conceptualized the research framework and led the review of the literature on e-learning adoption and

configurational methods. H.J.D.Q. developed the research design and oversaw the structural organization of the manuscript. S.R. coordinated data collection and managed the survey distribution process. E.D.L.C. conducted the formal fsQCA analysis, including necessity, sufficiency, and causal asymmetry computations. K.M. implemented the Python-based replication pipeline and managed all calibration procedures and robustness checks; K.M. and S.R. jointly designed the theoretical framework mapping Individual Impact to Perceived Usefulness and Task-Technology Fit. H.G. led the interpretation of practical implications and the development of the profile-based intervention strategies; H.G. and E.D.L.C. jointly drafted the causal asymmetry discussion and low-adoption configuration analysis. All authors contributed to writing, reviewing, and editing the manuscript, and all authors have read and approved the final version.

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