JCBI
Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 12 Issue 01
2026

Research Article
https://doi.org/10.56979/1201/2026/1623

A Hybrid Machine Learning Framework for Analyzing Digital Competence Configurations and Task Efficiency

Muhammad Ibrahim Tahir[1]

[1]Department of Computer Science,Bahria Universty, Islamabad, Pakistan.
*Corresponding Author: Muhammad Ibrahim Tahir. Email: ibrahimtahir515@gmail.com

Received: May 02, 2026 **Accepted:** October 01, 2026

Abstract: The banking industry is undergoing a transformation and digital competence is now a key factor in assessing an employee's performance. In this study, the configurational and predictive relationships between digital competence of bank employees and task efficiency is examined in a dual method analysis, in which fuzzy-set qualitative comparative analysis (fsQCA) and machine learning is applied. A synthetic data was created based on a structure of 500 bank staff members and 55 variables related to the five dimensions of digital competence: information and data competence (IDL), digital communication and collaboration (DCC), digital content creation (DCR), digital safety (DSF), digital problem solving (DPS) and eight task efficiency indicators. The internal consistency of all constructs was found to be good and strongly consistent with reliability analysis (α = 0.798–0.930). Multiple linear regression showed that the total variance in task efficiency was 65.3% ($F = 185.6$, $p < 0.001$) accounted for by the digital competence dimensions IDL and DPS with beta of 0.319 and 0.316, respectively. 14 sufficient configurational paths to high task efficiency were found and DPS is a core condition in 10 of these 14 configurations (fsQCA). Logistic regression showed to be the most predictive machine learning classifier (AUC-ROC = 0.851, Accuracy = 0.790) among the 6 classifiers considered. Results show a bi-directionality of digital competence in relation to task efficiency both from the side of the individual and from the side of the task, and provide practical implications for banking HR development and digital transformation strategy.

Keywords: Digital Competence; Task Efficiency; fsQCA; Machine Learning; Bank Employees; Configurational Analysis.

1. Introduction

The banking industry is experiencing a digital revolution of which no pains of change are felt anywhere in the world, except for modifying the way in which employees carry out their daily routine. Employees who are not able to use, navigate and adjust to digital technologies are a key requirement of core banking operations, from customer service to risk management, to financial reporting and compliance [1], [2]. Digital literacy is no longer a luxury, it's a business imperative, as digital tools, fintech platforms and automated workflows have transformed the skills and knowledge required of banking professionals [3, 4]. Within this framework, digital competence is one of the most relevant skills of the workforce that organizations need to develop and assess [5, 6]. Digital competence is a widely used definition, and is understood as the ability to use digital technologies with confidence, critically and responsibly in work, learning and social life [7]. In the banking sector, it encompasses a range of skills such as information literacy, digital communication, content creation, cyber security awareness, and problem-solving using technologies [8, 15]. The most used and tested taxonomy of this taxonomy is the DigComp 2.2 framework of the European Commission which classifies these competencies for use in professional contexts [5], [16]. Although it is widely acknowledged as important, the mechanisms by which digital competence can impact task efficiency outcomes remain under investigated, especially from a symmetric and asymmetric perspective [22] [23]. The banking sector offers a highly revealing situation. While the financial institutions

are among the most aggressive ones globally in making investments in digital infrastructure, the human capital aspect of digital transformation in particular, namely how employee competence profiles relate to performance outcomes is under-studied compared to the technological investment literature [11, 12]. The banking industry's highly complex regulatory framework, sensitive data and customer-facing digital service delivery make for a very specific environment and skills-performance landscape that requires its own study and focus [13, 14].

The previous studies focused on symmetrical approach like regression analysis and structural equation modeling, which examines the digital skill-employee performance relationship [16] [17]. These are useful for understanding net effects and linear relationships, but do not adequately capture the combinatorial and configurational nature of competence how the different combinations of digital skills work together to produce high task efficiency [22]-[26]. Neither of these are sufficient to fill the gap, as it requires an approach that captures the necessary and sufficient conditions in complex causal configurations: this is where the asymmetric approach of fuzzy-set qualitative comparative analysis (fsQCA) can help [24]-[27]. The use of the fsQCA approach has been becoming more popular in organizational and management research as it has proven to be a useful extension of regression-based methods for identifying the existence of multiple and different ways to achieve the same goal, called "equifinality" [22-26]. At the same time, machine learning has become available in organizational research, providing tools that are powerful for predictive modeling, which can detect non-linear patterns and identify the importance of features, that traditional statistical methods are incapable of [28]. Other ensemble models like Random Forest [29], Gradient Boosting like XGBoost [30] and LightGBM [31] and Support Vector Machines [32] have shown excellent predictive power in a variety of datasets for various organizations. The combination of fsQCA and machine learning in a single study offers a methodologically sound and complementary approach, which takes into account both the question of which combinations matter (fsQCA) and how well can we predict (machine learning) [33-35].

This study aims therefore to investigate three main objectives: (1) to validate the digital competence and task efficiency scales for bank employees in terms of reliability and construct validity; (2) to identify the adequate combinations of digital competence dimensions to guarantee high task efficiency through the use of fsQCA; and (3) to train and test classification models based on the machine learning algorithms for predicting high task efficiency based on the digital competence profiles. The results enhance the theoretical knowledge about digital competence in the banking sector [18] and the practical implementation of targeted digital training interventions [36-37].

2. Literature Review

Digital competence has grown from a very narrow definition of a set of technic skills to a multi-dimensional construct that involves cognitive, communicative, creative, and problem-solving skills in digital environments [7,15]. The DigComp 2.2 framework [5], [16] provides a structure for digital competence in five domains: Information and Data Literacy (IDL), Digital Communication and Collaboration (DCC), Digital Content Creation (DCR), Digital Safety (DSF), and Digital Problem Solving (DPS). It is the standard taxonomy used in the field of educational and professional assessment of competence and for curriculum design [6], [8], [38]. The concept of digital competence has experienced a conceptual development, which is part of the development of the understanding of the workforce readiness in the digital era in general. Although initial conceptions emphasized basic ICT skills and tool proficiency [15], modern approaches describe higher order skills and competencies needed to achieve effective use and performance in the digital realm such as critical information evaluation, adaptive problem solving and cybersecurity awareness [7], [17]. For the banking industry in particular, these dimensions become particularly relevant due to the banking industry's reliance on data integrity, regulatory compliance and secure digital transactions [12], [13], [14]. Digital competence has been found to be positively correlated to individual and organizational performance out-comes consistently across various research studies in professional contexts [2, 9, 39, 40]. The dimensions of competences, however, do not all have the same weight in every organizational setting and thus a generic solution to digital training is not the best one [36], [41]. The present study tackles this by focusing on the differential and config-urational contribution of each dimension of DigComp for task efficiency in the banking sector [38] and [42].

The banking industry is one of the most digitized sectors in the world, with mobile banking, algorithmic trading, risk assessment using AI technology and the implementation of block-chain for transaction systems [4], [51], [52] gaining widespread popularity. This digitally transformed banking sector has transformed the nature of banking work, moving the routine transactional work from humans to automation, while increasing the need for employees to have knowledge and skills in managing, interpreting and utilizing digital systems [53, 54]. The entry of fintech innovations, digital ledger technologies and robo advisory platforms has led to new competency needs which are not adequately met by traditional banking skills training programs [55], [13], [56]. The human capital challenges posed by this change are enormous. Researchers have found that employees with higher levels of digital competence in banking environments with greater digital sophistication are more likely to complete tasks, make fewer mistakes, and adapt to changes in the systems they use [2], [57], [58]. However, the relationship between digital tool adoption and performance is not straightforwardly linear; the frequency and quality of digital tool engagement are important factors in moderating the relationship between competence and performance [43, 44]. Ongoing interactions with systems in digital environments can lead to tacit learning and workflow optimization strategies that go beyond for-mal competence learning, indicating that experiential learning is a crucial part of competence to efficiency transfer [45, 61]. In addition, organizational aspects such as the quality of digital infrastructures, leadership support for the adoption of digital, and organizational culture can greatly influence the relationship between individual digital competence and its translation into task efficiency [19], [47], [62]. Banks that spend on technical infrastructure and human capital development, create synergistic conditions for performance improvement, which cannot be attained in isolation [57, 63, 64]. The embeddedness of digital competence in the organization highlights the need to study the relationship between competence and efficiency in a specific organizational context and not in isolation [48, 49, 50].

It is worth noting that, in the case of digital banking, the efficiency of the task is one of the performance outcomes. In banking tasks, task efficiency, that is, the capability to carry out the task without errors, on time, and with minimal resource waste is a key performance indicator [10], [65]. Employees' competence in using digital tools effectively, in moving with the information systems, in solving technology-related disruptions without escalation and in being competent in general contribute to the efficiency of tasks in digitally mediated work environments [45], [46], [67]. In the context of task efficiency in banking, it has a multi-dimensional aspect that involves the speed of task completion, the accuracy of digital data entry and retrieval, the effectiveness of digital communication and the capacity to optimize digital workflows [18] [68] [69]. The studies that have been conducted on task efficiency have studied the effects of task efficiency relative to technology acceptance and usability, and then looked at the effects of the system design and the quality of the interface on the efficiency of the task [3], [43]. Recent research, however, has focused on the competence side of the equation, and how the competence profile of employees influences their capability of deriving performance benefits from the available Digital Tools [2, 9]. This is part of a trend of understanding that the adoption of technology is not enough to ensure performance improvement, but that there is also a need for the human capacity to use technology effectively [71], [72]. This correlation between digital competence and task efficiency is further complicated by the differences in learning orientation, technology anxiety and previous digital experience of the individual [73][74]. Resilient employees are generally those who are more capable of using digital tools to solve problems, even when technologies fail, maintaining efficiency despite challenging technological situations [75, 76]. This indicates that DPS could be a key competence dimension in the efficiency of tasks in dynamic banking contexts, where systems are updated regularly and digital workflows constantly change [22], [26].

Fuzzy-Set Qualitative Comparative Analysis (fsQCA) as an analytical tool in Organizational Research. This method is linked to qualitative research. Ragin [24] proposed fuzzy-set qualitative comparative analysis (fsQCA) as a set-theoretic approach to the analysis of how different sets of conditions lead to specific results. The fsQCA analysis differs from regression-based analyses in that it identifies necessary and sufficient conditions and clearly models causal complexity, such as equifinality, conjunctural causality and asymmetric causality [24], [27]. In the field of organization and management research, the use of fsQCA has increased significantly in the last decade, and is now applied to topics such as strategic management, human resource management and organizational behaviour [22, 35, 81]. Fiss [22] demonstrated the value of fsQCA for building typological theories in organization research, showing how configurational

approaches reveal causal structures that regression analysis systematically obscures. Woodside [23] further advocated for the paradigm shift from symmetric to asymmetric thinking in organizational data analysis, arguing that configurational methods better capture the complexity of real-world causal relationships. Ragin [25] extended the theoretical foundations of fuzzy-set social science, providing the methodological basis for calibration and truth table construction that underpins the present study. In the context of digital competence research, fsQCA offers particular advantages, as digital competence dimensions are theoretically interdependent — information literacy may amplify the value of problem-solving skills, while digital safety awareness may be particularly important in combination with communication competencies in banking environments [85], [86]. These interdependencies are precisely what fsQCA is designed to capture [82], [83], [84]. Recent applications of fsQCA in HR and performance research have demonstrated its ability to identify practically actionable competence profiles that regression analysis alone cannot reveal [87], [88].

In recent years, the use of machine learning in organizational research has been increasing rapidly thanks to the availability of large HR datasets and the development of computational techniques [28], [89], [90]. A variety of supervised classification techniques such as Logistic Regression, Decision Trees, Random Forests [29], Support Vector Machines [32] and gradient boosting algorithms [30], [31] have been used to forecast employee turnover and other organizational outcomes such as performance ratings and training effectiveness [91], [92]. Random Forest [29] is an ensemble learning technique that builds a multitude of decision trees and combines their predictions to form predictions with strong prediction power and interpretable feature importance rank. XGBoost [30] is an extended version of gradient boosting that incorporates regularization techniques which are especially useful for structured organizational data. It is generally recommended to compare several classifiers, since there is no simple rule that one algorithm is always better than the others for all datasets and all outcome types [72, 93]. Tree-based models offer another way of assessing how well a model fits the data besides the regression coefficients: feature importance analysis, which reveals non-linear relationships and interaction effects that are not captured by linear models [33], [94], [95]. The combination of machine learning feature importance with the causal complexity insights offered by fsQCA is a powerful triangulation framework that is the product of the two fields' predictive power and causal complexity insight. The methodological integration is gaining more and more traction in the context of organizational analytics research, as a way to both achieve the predictive accuracy and gain the depth of theory [100] and [101].

Synthetic datasets are more and more being acknowledged as a legitimate methodological approach for methodological demonstration studies, framework validation and development of analytical workflow, in organizational and HR studies [101, 102]. Synthetic data generation enables researchers to create datasets that have theoretically plausible covariance structures, controlled distributional properties, and a known ground truth, which can then be used to rigorously evaluate the analytical methods without ethical and access issues that would be present if the real data of the employees were used [103, 104]. In digital competence research, synthetic data has been employed to illustrate digital competence measurement frameworks, to validate psychometric instruments and to illustrate configurational analysis approaches [105], [106]. The use of a fixed random seed and documented generation parameters guarantees full reproducibility which is essential when achieving methodological transparency in organizational analytics research [107-112].

3. Materials and Methods

3.1. Research Design Overview

The study follows the approach of a quantitative, cross-sectional research design that combines psychometric validation, symmetric statistical modeling, asymmetric configurational analysis (fsQCA) and supervised machine learning in an integrated research analytics architecture. The model presented here does not use one model of analytics, but instead merges the different types of analytics: explanatory, configurational, and predictive to gain a holistic view of the influence of multiple dimensions of digital competence on task efficiency of bank employees. The methodology proposed in this paper is divided into five layers: (i) Input Layer, (ii) Data Preparation Layer, (iii) Research Analytics Environment, (iv) Output Layer, and (v) Validation, Reproducibility, and Ethics Layer as shown in Figure 1.

The architecture enables several analytical modules to process the same valid dataset and ensures data preprocessing, statistical inference, configurational reasoning, predictive modeling, and result integration are separated. The Input Layer consists of the synthetic data set of 500 bank employees and 55 input variables, such as the demographic characteristics, five digital competence dimensions, task efficiency indicators and composite variables. The data are then analyzed in the Data Preparation Layer (DPL) which covers data screening, descriptive statistical analysis, reliability testing (Cronbach's α), correlation analysis, exploratory factor analysis (EFA), and composite score construction to ensure that the measurement model is valid and reliable.

The validated data is then released into the Research Analytics Environment, where three analytic modules run concurrently. The OLS Regression Module analyzes the effects of the five dimensions of digital competence on the efficiency of the task by multiple linear regression, and displays model goodness-of-fit statistics, confidence intervals and standardized coefficients. The fsQCA Module is used to explore the asymmetric causal relationships by direct calibration, necessity analysis, truth-table construction, Boolean minimization and sufficiency analysis for several configurations related to a high task efficiency. At the same time, the Machine Learning Module defines task efficiency as a binary classification task with engineered predictor variables and compares various supervised classifiers by data partitioning in a stratified manner and by cross validation. The analysis of the models employs Accuracy, Precision, Recall, F1-score and AUC-ROC as a measure of model performance, and feature importance analysis is used to show additional insights into the relevance of the predictors. The machine learning module also provides feature importance which can be used to aid the interpretation of the configurational conditions derived from the fsQCA analysis. The analytical results from these three layers are brought together in the Output Layer, where the regression results, the configurations, the predictive performance, the convergent predictors, and the managerial implications are combined to form an overall interpretation. Lastly, the Validation, Reproducibility, and Ethics Layer provide methodological robustness by including sensitivity analysis, alternative model specifications, reproducible implementation with Python/Jupyter, structured documentation of the dataset and transparent reporting on the synthetic data generation process. This integrated architecture offers a repeatable and extensible analytical model that can be used to explain the data, discover the configuration, and build predictive intelligence.

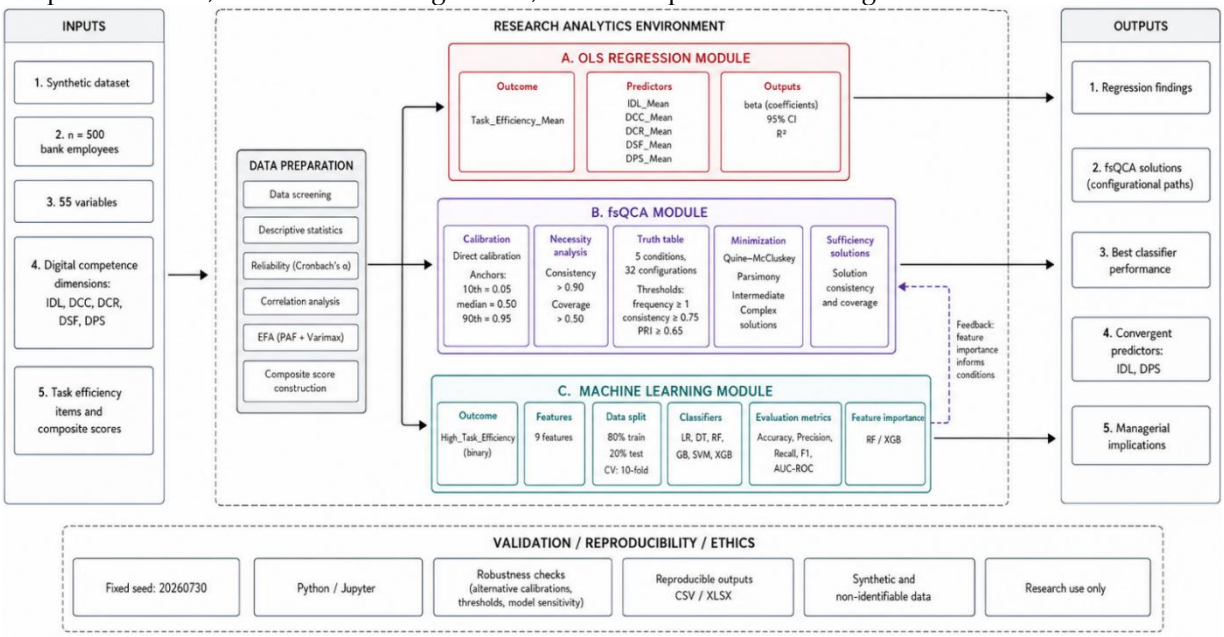


Figure 1. Proposed research architecture illustrating the integrated analytical workflow, from synthetic dataset preparation and psychometric validation to OLS regression, fsQCA, machine learning, and the synthesis of predictive and configurational findings.

3.2. Dataset Construction

A structured synthetic dataset was purposefully developed to support the methodological objectives of this study. The dataset comprises 500 individual bank employee records across 55 variables, generated using correlated latent constructs with a fixed random seed (20260730) to ensure full reproducibility and

transparency. Synthetic data generation is an increasingly recognized methodological approach in organizational and HR research, particularly for methodological demonstration studies where the primary aim is to evaluate and illustrate analytical frameworks rather than to report population-level findings , .

The synthetic generation process incorporated theoretically plausible covariance structures among digital training exposure, technology use frequency, digital tool adoption, and task efficiency — including interaction effects between IDL and DPS, and between DCC and DSF drawing on established relationships documented in the digital competence and employee performance literature , . All generated variables were constrained to realistic ranges (Likert 1–5 for survey items; continuous distributions for contextual variables) and validated against theoretical expectations prior to analysis.The complete variable structure of the dataset is summarized in Table 1.

Table 1. Dataset Variable Structure 55 Variables Across 6 Categories

Category	Variables	Count	Scale/Type
1. Demographics & Job Characteristics	Gender, Age, Education, Bank Type, Department, Position, Tenure, Training Hours, Tech Frequency, Digital Tool Adoption, Experience Level	11	Nominal / Continuous
2. IDL Items	IDL1–IDL5	5	Likert 1–5
3. DCC Items	DCC1–DCC4	4	Likert 1–5
4. DCR Items	DCR1–DCR4	4	Likert 1–5
5. DSF Items	DSF1–DSF4	4	Likert 1–5
6. DPS Items	DPS1–DPS5	5	Likert 1–5
7. Task Efficiency Items	TE1–TE8	8	Likert 1–5
8. Composite Scores	IDL_Mean, DCC_Mean, DCR_Mean, DSF_Mean, DPS_Mean, DC_Overall, TE_Mean	7	Continuous
9. Outcome & ML Variables	High_Task_Efficiency (binary), Tech_Freq_Category	2	Binary / Ordinal
10. fsQCA Calibrated Variables	fs_IDL, fs_DCC, fs_DCR, fs_DSF, fs_DPS, fs_Task_Efficiency	6	Fuzzy [0,1]
Total		55	

IDL = Information & Data Literacy; DCC = Digital Communication & Collaboration; DCR = Digital Content Creation; DSF = Digital Safety; DPS = Digital Problem Solving; DC = Digital Competence; TE = Task Efficiency; fs = fuzzy-set calibrated.

3.3. Measures and Instruments

3.3.1. Digital Competence

Digital competence was operationalized through five dimensions following the European Commission's DigComp 2.1 framework [Vuorikari et al., 2022], which is the most widely adopted and empirically validated framework for digital competence assessment across professional and educational contexts , , :

- Information and Data Literacy (IDL; 5 items): Ability to search, evaluate, manage, and critically interpret digital information and data relevant to banking tasks (e.g., *"I can critically evaluate the reliability of digital financial data sources"*).
- Digital Communication and Collaboration (DCC; 4 items): Proficiency in using digital tools for professional communication, team collaboration, and information sharing (e.g., *"I effectively use digital platforms to collaborate with colleagues on banking projects"*).
- Digital Content Creation (DCR; 4 items): Ability to create, edit, and manage digital content including reports, spreadsheets, and presentations (e.g., *"I can create professional digital reports and dashboards for banking operations"*).

- Digital Safety (DSF; 4 items): Awareness and practice of cybersecurity, data privacy, and digital risk management (e.g., *"I consistently follow cybersecurity protocols when handling sensitive banking data"*).
- Digital Problem Solving (DPS; 5 items): Capacity to identify, diagnose, and resolve technology-based workflow problems and adapt to new digital tools (e.g., *"I can independently troubleshoot digital system errors that affect my banking tasks"*).

All items were measured on a five-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree). Composite mean scores were calculated for each dimension.

3.3.2. Task Efficiency

Task efficiency was measured using 8 items assessing the speed, accuracy, and quality of task completion in digital banking environments. Items covered timely task completion, error minimization, workload management, resource efficiency, and digital workflow optimization (e.g., *"I consistently complete my banking tasks within the required timeframe using digital tools"*; *"My use of digital systems reduces errors in my daily banking tasks"*). The same five-point Likert scale was applied, and a composite mean score was computed .

3.4. Stage 1 — Psychometric Validation

3.4.1. Descriptive Statistics

Descriptive statistics were computed for all 30 items and 7 composite scores, including means (M), standard deviations (SD), skewness, kurtosis, minimum, and maximum values. Normality was assessed using skewness (acceptable range: ±2.0) and kurtosis (acceptable range: ±7.0).

3.4.2. Reliability Analysis

Internal consistency reliability was assessed using Cronbach's alpha (α) for each construct. The following interpretive benchmarks were applied: Excellent ($\alpha \geq 0.90$), Good ($0.80 \leq \alpha < 0.90$), Acceptable ($0.70 \leq \alpha < 0.80$), and Questionable ($0.60 \leq \alpha < 0.70$), following George & Mallery (2003). The minimum acceptable threshold was set at $\alpha = 0.70$ as per Nunnally (1978).

3.4.3. Pearson Correlation Analysis

Bivariate Pearson correlation coefficients were computed among all seven construct-level variables to examine inter-construct relationships and screen for multicollinearity. Significance was assessed at three levels: $p < 0.05$ *(), $p < 0.01$ (), and $p < 0.001$ (*). Multicollinearity was considered problematic if any inter-predictor correlation exceeded $r = 0.85$.

3.4.4. Exploratory Factor Analysis (EFA)

EFA was conducted on the 22 digital competence items to empirically verify the five-factor structure hypothesized by the DigComp framework. The following procedures were applied:

- Extraction method: Principal Axis Factoring (PAF)
- Rotation method: Varimax with Kaiser normalization
- Factor retention criteria: Kaiser's eigenvalue > 1.0 criterion and scree plot inspection
- Adequacy tests: Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (acceptable ≥ 0.60) and Bartlett's Test of Sphericity (significant at $p < 0.001$)
- Loading criteria: Primary loadings ≥ 0.40; cross-loadings < 0.30 for clean structure confirmation
- Communality threshold: $h^2 \geq 0.40$ for item retention

3.5. Stage 2 — Multiple Linear Regression

Ordinary Least Squares (OLS) multiple linear regression was performed to examine the symmetric, net predictive relationships between digital competence dimensions and task efficiency. The regression model was specified as:

$$TE = \beta_0 + \beta_1(IDL) + \beta_2(DCC) + \beta_3(DCR) + \beta_4(DSF) + \beta_5(DPS) + \varepsilon \quad (1)$$

Where TE= Task Efficiency composite mean; β_1–β_5= unstandardized regression coefficients for each digital competence dimension; β_0= constant; and ε= error term.

Model assumptions were verified as follows:

- Normality of residuals: Shapiro-Wilk test and Q-Q plot inspection
- Homoscedasticity: Breusch-Pagan test and residual scatter plots
- Autocorrelation: Durbin-Watson statistic (acceptable range: 1.5–2.5)

- Multicollinearity: Variance Inflation Factor (VIF < 5.0) and Tolerance (> 0.20)
- Linearity: Partial regression plots for each predictor

Statistical significance was assessed at $p < 0.05$. Standardized beta coefficients (β) were reported to enable direct comparison of predictor magnitudes. Model fit was evaluated using R^2, Adjusted R^2, F-statistic, and p-value.

3.6. Stage 3 — Fuzzy-Set Qualitative Comparative Analysis (fsQCA)

3.6.1. Theoretical Rationale for fsQCA

fsQCA is a set-theoretic, case-oriented method that examines how combinations of conditions (causal configurations) produce an outcome of interest. Unlike regression, which estimates the average net effect of each variable, fsQCA identifies necessary and sufficient conditions and captures equifinality — the existence of multiple distinct pathways to the same outcome [Ragin, 2008; Fiss, 2011]. This makes fsQCA particularly appropriate for studying digital competence, where different combinations of skills may achieve equivalent task efficiency outcomes , , .

3.6.2. Fuzzy-Set Calibration

Raw Likert-scale composite scores for all five digital competence dimensions and task efficiency were transformed into fuzzy-set membership scores in the interval [0, 1] using the direct calibration method [Ragin, 2008]. This method requires three theoretical anchors:

The calibration procedure is formally expressed as:

$$\mu(x) = \frac{1}{1+e^{-\ln(19)\cdot\frac{x-c}{d-c}}} \quad (2)$$

Where $\mu(x)$= fuzzy membership score; x= raw score; c= crossover point (full ambiguity = 0.50); d= full membership anchor; and the denominator ensures a logistic transformation. The three calibration anchors applied in this study are summarized in Table 2.

Table 2. fsQCA Calibration Anchors for All Conditions and Outcome

Variable	Full Non-Membership (0.05)	Crossover Point (0.50)	Full Membership (0.95)	Calibration Basis
fs_IDL	10th percentile	Median	90th percentile	Empirical distribution
fs_DCC	10th percentile	Median	90th percentile	Empirical distribution
fs_DCR	10th percentile	Median	90th percentile	Empirical distribution
fs_DSF	10th percentile	Median	90th percentile	Empirical distribution
fs_DPS	10th percentile	Median	90th percentile	Empirical distribution
fs_Task_Efficiency	10th percentile	Median	90th percentile	Empirical distribution

Direct calibration method applied following Ragin (2008) and Pappas & Woodside (2021). The crossover point (0.50) represents maximum ambiguity in set membership. Cases with raw scores exactly at the crossover point were adjusted by ±0.001 to avoid logical indeterminacy in Boolean operations.

3.6.3. Necessity Analysis

Necessity analysis was conducted first to determine whether any single condition is necessary for the outcome i.e., whether the outcome is a subset of the condition. A condition is considered necessary if its consistency score exceeds the threshold of 0.90 [Ragin, 2008; Schneider & Wagemann, 2012]. Both the presence (X→Y) and absence (~X→Y) of each condition were tested.

The consistency of necessity is calculated as:

$$\text{Consistency}(X_i \leq Y_i) = \frac{\sum \min(X_i, Y_i)}{\sum X_i} \quad (3)$$

3.6.4. Sufficiency Analysis and Truth Table Construction

Sufficiency analysis was conducted using a truth table algorithm that enumerates all 2^k logically possible configurations (where k = 5 conditions, yielding 32 rows). Each row represents a unique combination of condition presence/absence and is evaluated for:

- Empirical frequency: Minimum number of cases per configuration (threshold = 1)
- Raw consistency: Proportion of cases in the configuration that also display the outcome (threshold = 0.75)
- PRI consistency: Proportional Reduction in Inconsistency score to distinguish true sufficiency from simultaneous subset relations (threshold = 0.65)

The consistency of sufficiency is calculated as:

$$\text{Consistency}(X_i \leq Y_i) = \frac{\sum \min(X_i, Y_i)}{\sum x_i} \quad (4)$$

Boolean minimization was applied to configurations meeting the threshold criteria to derive parsimonious solution terms. The intermediate solution was prioritized, incorporating only theoretically justified simplifying assumptions [Fiss, 2011; Greckhamer et al., 2018].

3.7. Stage 4 — Machine Learning Classification

3.7.1. Outcome Variable and Feature Engineering

The binary classification outcome High_Task_Efficiency was defined as:

$$\text{High_Task_Efficiency} = \begin{cases} 1 & \text{if } TE_Mean \geq 3.75 \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

This threshold (3.75 on a 5-point scale) represents the upper quartile of task efficiency performance, consistent with high-performance classification thresholds used in HR analytics research , . The resulting class distribution was 70.8% Low (n = 354) and 29.2% High (n = 146), reflecting a moderate class imbalance.

The nine input features used for classification were: IDL_Mean, DCC_Mean, DCR_Mean, DSF_Mean, DPS_Mean, Technology Use Frequency, Digital Tool Adoption, Training Hours, and Tenure. All continuous features were standardized (zero mean, unit variance) using z-score normalization prior to model training to ensure scale-invariance across algorithms.

3.7.2. Data Partitioning and Cross-Validation

The dataset was partitioned into 80% training (n = 400) and 20% testing (n = 100) subsets using stratified random sampling to preserve the class distribution across splits. Model generalizability was assessed using 10-fold stratified cross-validation on the training set, which provides a robust and unbiased estimate of out-of-sample performance by averaging results across 10 non-overlapping validation folds .The data partitioning and cross-validation procedure is summarized in Table 3.

Table 3. Machine Learning Data Partitioning and Cross-Validation Design

Parameter	Specification
Total sample	n = 500
Training set	n = 400 (80%), stratified
Test set	n = 100 (20%), stratified
Cross-validation	10-fold stratified k-fold
Class distribution (train)	70.8% Low / 29.2% High
Class distribution (test)	70.8% Low / 29.2% High
Feature scaling	Z-score standardization (μ=0, σ=1)
Random seed	20260730 (fixed for reproducibility)
Class imbalance handling	Stratified splits; class_weight='balanced' for applicable models

Stratified sampling ensures proportional class representation in both training and test sets. The fixed random seed ensures full reproducibility of all results.

3.7.3. Classification Algorithms

Six supervised machine learning classifiers were trained and evaluated, selected to represent a spectrum from simple linear models to complex ensemble methods presented in Table 4:

Table 4. Machine Learning Classifiers Specifications and Hyperparameters

#	Algorithm	Key Hyperparameters	Rationale

1	**Logistic Regression (LR)**	C=1.0, solver='lbfgs', max_iter=1000, class_weight='balanced'	Linear baseline; interpretable coefficients
2	**Decision Tree (DT)**	max_depth=5, min_samples_split=20, class_weight='balanced'	Non-linear, interpretable rules; overfitting benchmark
3	**Random Forest (RF)**	n_estimators=100, max_depth=10, class_weight='balanced', random_state=42	Ensemble bagging; robust feature importance
4	**Gradient Boosting (GB)**	n_estimators=100, learning_rate=0.1, max_depth=3	Sequential boosting; strong generalization
5	**Support Vector Machine (SVM)**	kernel='rbf', C=1.0, gamma='scale', class_weight='balanced'	Margin-based; effective in high-dimensional spaces
6	**XGBoost (XGB)**	n_estimators=100, learning_rate=0.1, max_depth=6, use_label_encoder=False	Regularized gradient boosting; state-of-the-art performance

All hyperparameters were set based on established best practices and prior literature. No grid search tuning was applied, as the primary objective was comparative evaluation rather than optimization.

3.7.4. Performance Evaluation Metrics

All models were evaluated on the held-out test set (n = 100) using five complementary performance metrics, selected to provide a comprehensive assessment accounting for class imbalance, :

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (7)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (8)$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision}+\text{Recall}} \quad (9)$$

$$\text{AUC-ROC} = \int_0^1 T\,PR\,d(FPR) \quad (10)$$

Where TP = True Positives; TN = True Negatives; FP = False Positives; FN = False Negatives; TPR = True Positive Rate; FPR = False Positive Rate. AUC-ROC was selected as the primary performance metric due to its robustness to class imbalance and its ability to evaluate discriminative performance across all classification thresholds.

3.7.5. Feature Importance Analysis

Feature importance was extracted from Random Forest (using mean decrease in impurity/Gini importance) and XGBoost (using gain-based importance) to identify the most influential predictors of high task efficiency. Feature importance scores were normalized to sum to 1.0 within each model to enable direct cross-model comparison.

3.8. Software and Tools

All analyses were conducted in **Python 3.10** within a Jupyter Notebook environment. The following libraries were used: pandas and numpy for data manipulation; scipy and pingouin for statistical tests; sklearn (scikit-learn 1.2) for machine learning; xgboost 1.7 for XGBoost; matplotlib and seaborn for visualization; and a custom fsqca module for fuzzy-set calibration and truth table construction. All code, random seeds, and analytical parameters were documented to ensure full reproducibility.

4. Results

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

4.1. Descriptive Statistics and Sample Characteristics

The demographic and job characteristics of the 500 synthetic bank employees are presented in Figure 2 and summarized in Table 5. As shown in Figure 2, the sample was predominantly male (55.6%), with females comprising 41.6% and 2.8% preferring not to disclose gender. Educational attainment was concentrated at the bachelor's degree level (62.6%), followed by master's degree holders (32.6%). Commercial banks represented the largest institutional category (38.0%), followed by state-owned (27.6%), Islamic (21.6%), and digital banks (12.8%). The Operations department had the highest representation (24.8%), followed by Customer Service (19.8%). Mid-level employees dominated by position (38.8%), with senior-level at 31.8%.

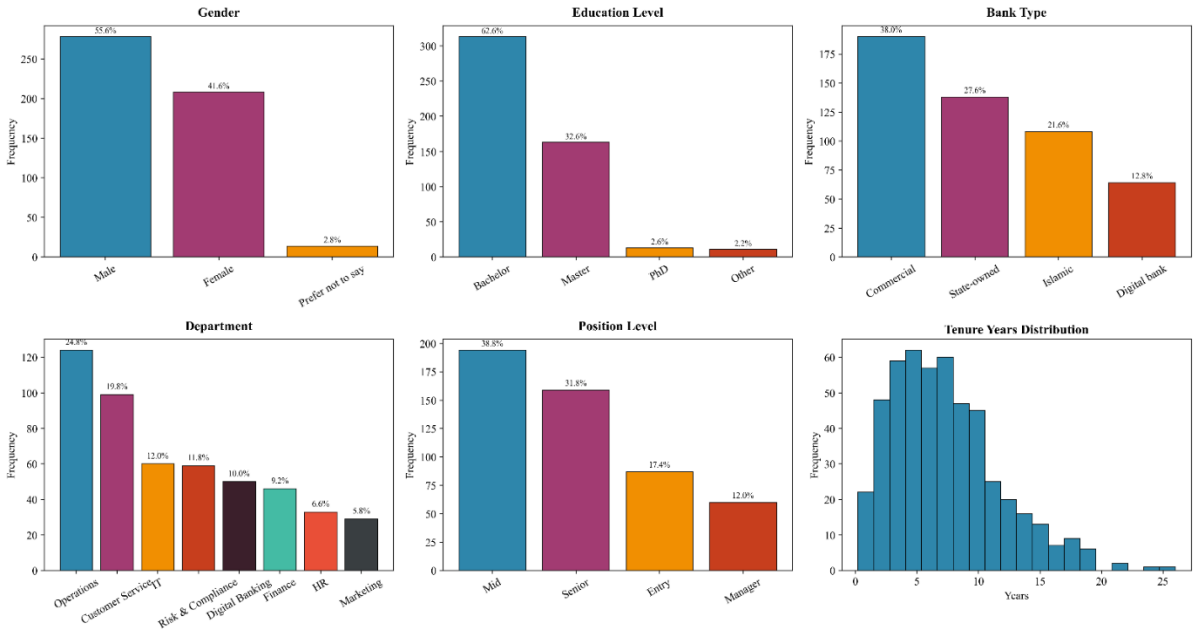


Figure 2. Demographic and Job Characteristics of the Sample. A panel of six bar charts displaying the frequency and percentage distribution of (a) gender, (b) education level, (c) bank type, (d) department, (e) position level, and (f) a histogram of tenure years. The sample reflects a diverse institutional and departmental composition representative of the banking sector workforce, with a predominance of bachelor-educated, mid-level commercial bank employees.

Table 5 presents item-level and composite descriptive statistics. Item means ranged from 2.918 (IDL5) to 3.440 (TE4). Composite means were: IDL (M = 3.084, SD = 0.786), DCC (M = 3.164, SD = 0.783), DCR (M = 3.156, SD = 0.833), DSF (M = 3.198, SD = 0.804), DPS (M = 3.168, SD = 0.796), overall digital competence (M = 3.154, SD = 0.607), and task efficiency (M = 3.207, SD = 0.830). Skewness values ranged from −0.204 to 0.089 and kurtosis values were uniformly negative (range: −0.472 to −0.163), confirming approximately normal distributions suitable for parametric analysis. The distributional profiles of all composite scores are further confirmed visually in Figure 3.

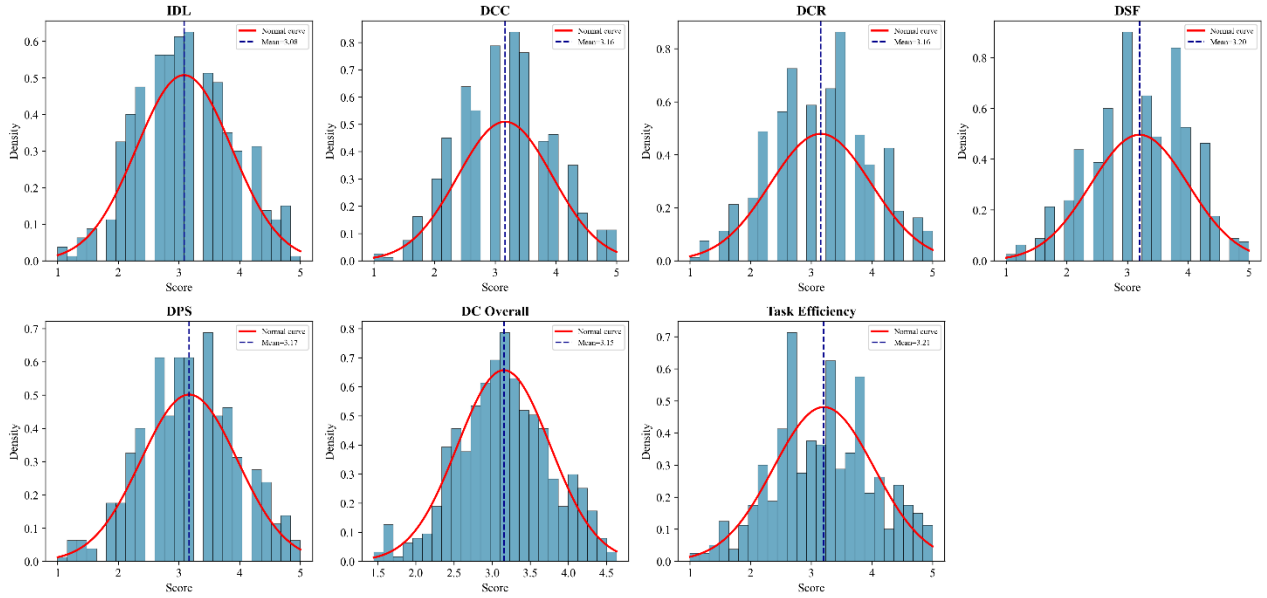


Figure 3. Distribution of Construct Composite Scores.

Histograms overlaid with normal distribution curves for all seven composite scores (IDL, DCC, DCR, DSF, DPS, DC Overall, and Task Efficiency). Dashed vertical lines indicate construct means. All distributions are approximately normal and centered between 3.08 and 3.21, confirming the suitability of the data for parametric statistical procedures.

Table 5. Descriptive Statistics for All Construct Items and Composite Scores

Variable	**Count**	**Mean**	**Std Dev**	**Min**
IDL1	500	3.274	1.014	1
IDL2	500	3.126	0.963	1
IDL3	500	2.98	1.009	1
IDL4	500	3.12	1.02	1
IDL5	500	2.918	1.019	1
DCC1	500	3.024	1.017	1
DCC2	500	3.304	0.966	1
DCC3	500	3.152	1.003	1
DCC4	500	3.174	0.983	1
DCR1	500	3.032	1.03	1
DCR2	500	3.204	1.036	1
DCR3	500	3.216	0.998	1
DCR4	500	3.174	1.013	1
DSF1	500	3.176	1.013	1
DSF2	500	3.296	1.005	1
DSF3	500	3.242	0.989	1
DSF4	500	3.078	1.038	1
DPS1	500	3.26	1.011	1
DPS2	500	3.088	0.999	1
DPS3	500	3.13	1.025	1
DPS4	500	3.14	0.962	1
DPS5	500	3.222	0.975	1

TE1	500	3.292	1.034	1
TE2	500	3.158	1.011	1
TE3	500	3.124	1.015	1
TE4	500	3.44	0.959	1
TE5	500	3.214	0.989	1
TE6	500	3.228	1.033	1
TE7	500	3.074	1.037	1
TE8	500	3.124	1.031	1
IDL_Mean	500	3.084	0.786	1
DCC_Mean	500	3.164	0.783	1
DCR_Mean	500	3.156	0.833	1
DSF_Mean	500	3.198	0.804	1
DPS_Mean	500	3.168	0.796	1
Digital_Competence_Overall	500	3.154	0.607	1.45
Task_Efficiency_Mean	500	3.207	0.83	1

25%	**50%**	**75%**	**Max**	**Skewness**	**Kurtosis**
3	3	4	5	-0.06	-0.598
2	3	4	5	0.029	-0.361
2	3	4	5	0.052	-0.541
2	3	4	5	0.077	-0.531
2	3	4	5	0.039	-0.502
2	3	4	5	-0.002	-0.538
3	3	4	5	-0.024	-0.507
3	3	4	5	-0.046	-0.325
2.75	3	4	5	-0.062	-0.492
2	3	4	5	0.079	-0.501
3	3	4	5	-0.079	-0.54
3	3	4	5	-0.115	-0.395
3	3	4	5	-0.11	-0.464
2	3	4	5	-0.08	-0.516
3	3	4	5	-0.346	-0.217
3	3	4	5	-0.013	-0.517
2	3	4	5	-0.103	-0.423
3	3	4	5	-0.06	-0.56
2	3	4	5	0.041	-0.397
2	3	4	5	-0.139	-0.459
3	3	4	5	-0.08	-0.31
3	3	4	5	-0.053	-0.416
3	3	4	5	-0.138	-0.561
2	3	4	5	-0.041	-0.547
2	3	4	5	-0.031	-0.424

3	3	4	5	-0.088	-0.575
3	3	4	5	-0.09	-0.566
2	3	4	5	-0.007	-0.73
2	3	4	5	-0.051	-0.507
2	3	4	5	0.014	-0.595
2.6	3	3.6	5	0.089	-0.37
2.5	3.25	3.75	5	0.071	-0.317
2.5	3.25	3.75	5	0.01	-0.445
2.75	3.25	3.75	5	-0.204	-0.394
2.6	3.2	3.8	5	-0.011	-0.291
2.758	3.15	3.56	4.63	-0.073	-0.163
2.625	3.125	3.75	5	0.006	-0.472

4.2. Reliability Analysis

Internal consistency reliability was assessed using Cronbach's alpha for each construct. As reported in Table 6 and visualized in Figure 4, all constructs demonstrated acceptable to excellent reliability. Task Efficiency achieved the highest alpha (α = 0.930, Excellent), followed by DPS (α = 0.859, Good), IDL (α = 0.841, Good), DCR (α = 0.834, Good), DSF (α = 0.806, Good), and DCC (α = 0.798, Acceptable). All values exceeded the widely accepted minimum threshold of 0.70 [17], confirming adequate reliability across all constructs.

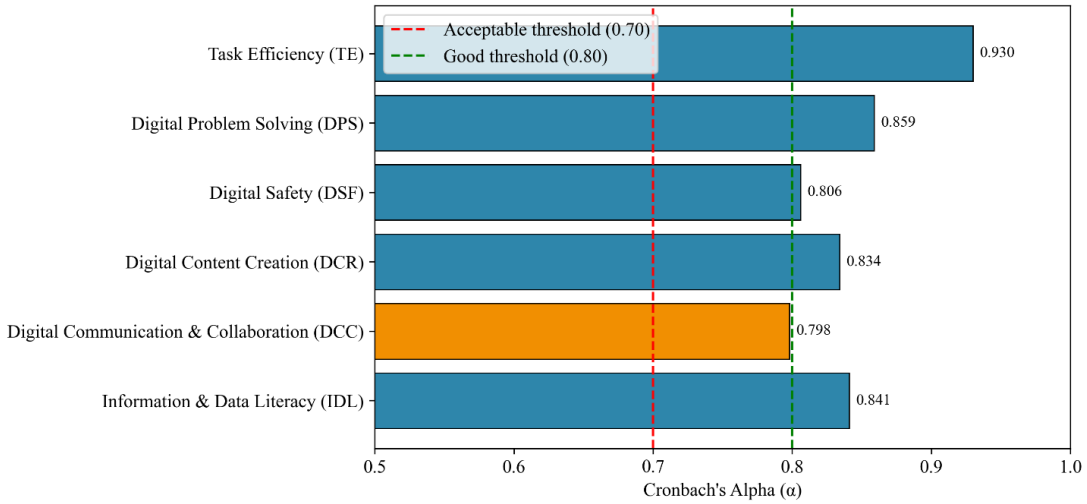


Figure 4. Reliability Analysis Cronbach's Alpha by Construct.

Horizontal bar chart displaying Cronbach's alpha values for all six constructs, color-coded by reliability category (Excellent ≥ 0.90; Good ≥ 0.80; Acceptable ≥ 0.70). Reference lines indicate the acceptable threshold (α = 0.70, red dashed) and the good threshold (α = 0.80, green dashed). Task Efficiency demonstrates excellent internal consistency (α = 0.930), while all other constructs fall within the Good to Acceptable range.

Table 6. Reliability Analysis Cronbach's Alpha Coefficients

Construct	Items (n)	Mean	Cronbach's α	Interpretation
Information & Data Literacy (IDL)	5	3.084	0.841	Good
Digital Communication & Collaboration (DCC)	4	3.164	0.798	Acceptable
Digital Content Creation (DCR)	4	3.157	0.834	Good
Digital Safety (DSF)	4	3.198	0.806	Good
Digital Problem Solving (DPS)	5	3.168	0.859	Good
Task Efficiency (TE)	8	3.207	0.93	Excellent

Interpretation based on George & Mallery (2003): Excellent ≥ 0.90; Good ≥ 0.80; Acceptable ≥ 0.70.

4.3. Correlation Analysis

The Pearson correlation matrix for all construct-level variables is presented in in Figure 5. As illustrated in Figure 5, all inter-construct correlations were statistically significant at $p < 0.001$. The overall digital competence score demonstrated the strongest correlation with task efficiency ($r = 0.797$), confirming a strong positive relationship. At the dimension level, DPS showed the highest correlation with task efficiency ($r = 0.696$), followed by IDL ($r = 0.672$), DCR ($r = 0.570$), DSF ($r = 0.566$), and DCC ($r = 0.518$). Inter-dimension correlations ranged from 0.407 to 0.578, indicating moderate associations without evidence of multicollinearity.

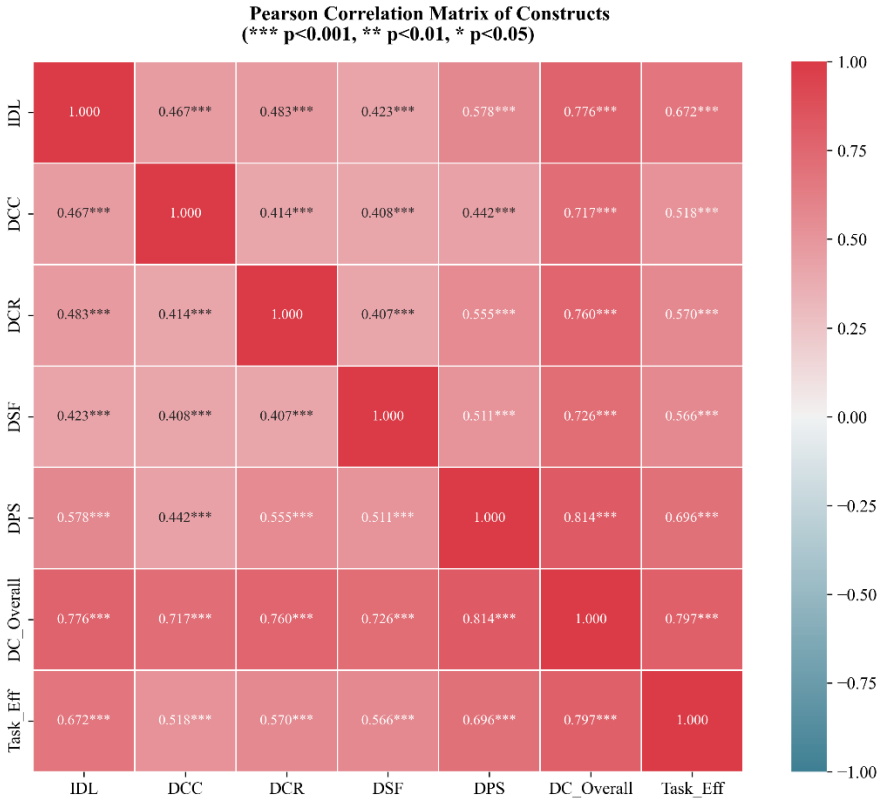


Figure 5. Pearson Correlation Matrix Heatmap **(*** $p < 0.001$).

Full correlation heatmap using a diverging red–blue color scale, where darker red indicates stronger positive correlations and white indicates near-zero correlations. All cells display exact correlation coefficients with significance stars. The matrix confirms strong positive relationships between all digital competence dimensions and task efficiency, with DPS ($r = 0.696$) and IDL ($r = 0.672$) showing the highest individual correlations with the outcome variable. The absence of correlations exceeding 0.80 among predictors confirms the absence of multicollinearity.

4.4. Exploratory Factor Analysis

EFA was conducted on the 22 digital competence items using principal axis factoring with varimax rotation. As shown in Figure 6 and Table 7, the scree plot revealed five factors with eigenvalues exceeding Kaiser's criterion of 1.0 ($\lambda = 8.178, 1.637, 1.628, 1.476, 1.188$), collectively explaining 63.99% of total variance (Factor 1: 37.10%; Factor 2: 7.42%; Factor 3: 7.39%; Factor 4: 6.69%; Factor 5: 5.39%). The factor loading pattern confirmed a clean five-factor structure perfectly aligned with the theoretical DigComp dimensions. All communality values exceeded 0.45, confirming adequate item-level variance extraction.

Scree Plot and Factor Loading Heatmap. Left panel: Scree plot displaying eigenvalues for all 22 components, with the Kaiser criterion line ($\lambda = 1.0$) marked in red and eigenvalue annotations for the five retained factors. Right panel: Heatmap of varimax-rotated factor loadings for all 22 items across five factors, using a diverging color scale (dark blue = strong positive loading; white = near-zero loading). The loading pattern confirms a theoretically consistent five-factor structure with clean item-to-factor correspondence and no significant cross-loadings (all primary loadings > 0.55; all cross-loadings < 0.30).

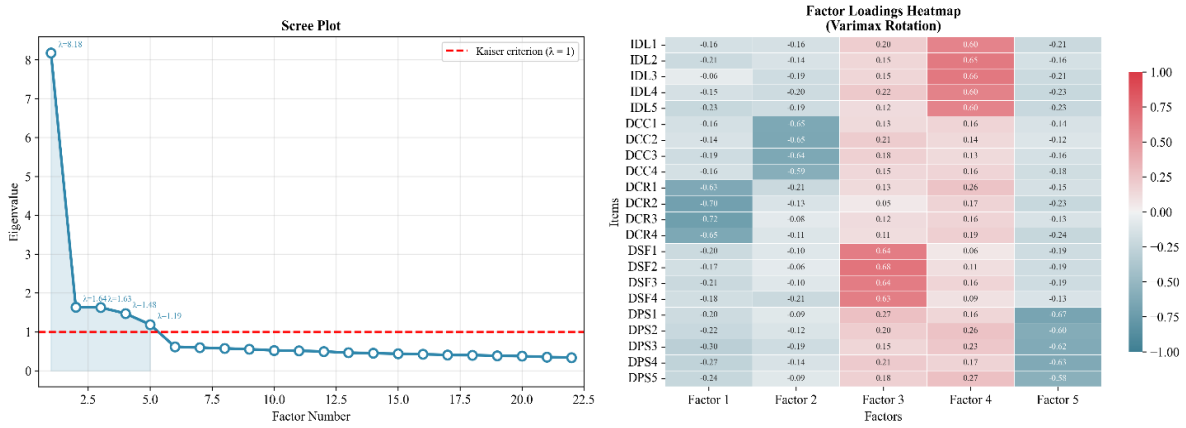


Figure 6. Exploratory Factor Analysis

Table 7. EFA Factor Loadings (Varimax Rotation)

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Communality
IDL1	-0.158	-0.156	0.201	0.601	-0.211	0.495
IDL2	-0.206	-0.139	0.153	0.651	-0.157	0.533
IDL3	-0.061	-0.194	0.152	0.66	-0.211	0.545
IDL4	-0.155	-0.199	0.22	0.604	-0.233	0.531
IDL5	-0.227	-0.188	0.125	0.599	-0.225	0.512
DCC1	-0.157	-0.648	0.128	0.162	-0.138	0.506
DCC2	-0.136	-0.652	0.209	0.135	-0.117	0.519
DCC3	-0.191	-0.644	0.184	0.126	-0.164	0.528
DCC4	-0.163	-0.587	0.147	0.164	-0.184	0.454
DCR1	-0.633	-0.213	0.132	0.255	-0.152	0.552
DCR2	-0.703	-0.127	0.055	0.167	-0.228	0.594
DCR3	-0.724	-0.075	0.118	0.158	-0.133	0.586
DCR4	-0.647	-0.113	0.113	0.19	-0.238	0.537
DSF1	-0.204	-0.098	0.639	0.06	-0.19	0.5
DSF2	-0.169	-0.064	0.68	0.109	-0.189	0.542
DSF3	-0.214	-0.099	0.639	0.163	-0.192	0.527
DSF4	-0.178	-0.215	0.632	0.087	-0.129	0.501
DPS1	-0.198	-0.092	0.273	0.156	-0.674	0.601
DPS2	-0.223	-0.122	0.201	0.262	-0.604	0.538
DPS3	-0.304	-0.188	0.15	0.23	-0.624	0.592
DPS4	-0.269	-0.138	0.211	0.169	-0.628	0.559
DPS5	-0.238	-0.089	0.18	0.273	-0.578	0.505

4.5. Multiple Linear Regression

OLS multiple linear regression was performed to examine the symmetric predictive relationships between digital competence dimensions and task efficiency. The full regression results are presented in Table 8 and the standardized coefficient plot in Figure 7. As shown in Figure 7, the overall model was highly significant ($F(5, 494) = 185.6$, $p < 0.001$) and explained 65.3% of the variance in task efficiency ($R^2 = 0.653$, Adj. $R^2 = 0.649$). The Durbin-Watson statistic (1.887) confirmed the absence of autocorrelation, and VIF values (range: 1.42–1.87) confirmed the absence of multicollinearity.

All five digital competence dimensions were statistically significant predictors ($p < 0.001$). IDL emerged as the strongest predictor ($\beta = 0.319$, $t = 8.709$, 95% CI [0.247, 0.391]), closely followed by DPS ($\beta = 0.316$, $t = 8.187$, 95% CI [0.240, 0.392]). DSF contributed moderately ($\beta = 0.187$, $t = 5.644$), while DCR ($\beta = 0.134$, $t = 4.017$) and DCC ($\beta = 0.120$, $t = 3.566$) showed smaller but significant effects.

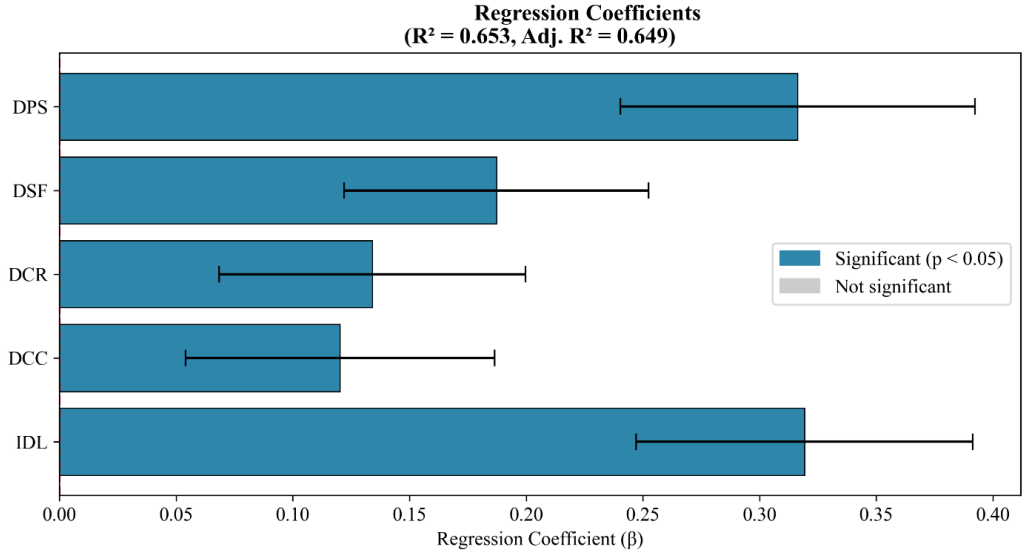


Figure 7. Standardized Regression Coefficients with 95% Confidence Intervals ($R^2 = 0.653$).

Horizontal bar chart displaying standardized beta coefficients (β) for all five digital competence predictors, with 95% confidence interval error bars. Blue bars indicate statistical significance at $p < 0.001$. IDL ($\beta = 0.319$) and DPS ($\beta = 0.316$) show the largest coefficients, confirming their dominant role in predicting task efficiency. The annotation box reports model fit statistics: $R^2 = 0.653$, Adj. $R^2 = 0.649$, $F(5,494) = 185.6$, $p < 0.001$, DW = 1.887.

Table 8. Multiple Linear Regression Results Predictors of Task Efficiency

Variable	Coefficient (β)	Standard Error	t-value	p-value	95% CI Lower	95% CI Upper
Constant	-0.1826	0.117	-1.557	0.120	-0.413	0.048
Information and Data Literacy (IDL_Mean)	0.3192	0.037	8.709	<0.001	0.247	0.391
Digital Communication and Collaboration (DCC_Mean)	0.1203	0.034	3.566	<0.001	0.054	0.187
Digital Content Creation (DCR_Mean)	0.1341	0.033	4.017	<0.001	0.069	0.200
Digital Safety (DSF_Mean)	0.1873	0.033	5.644	<0.001	0.122	0.253
Digital Problem Solving (DPS_Mean)	0.3164	0.039	8.187	<0.001	0.240	0.392

4.6. fsQCA Analysis

4.6.1. Necessity Analysis

Necessity analysis was conducted to determine whether any single digital competence dimension constitutes a necessary condition for high task efficiency. The results are presented in Table 9 and visualized in Figures 8 and 9. As shown in Figure 8 no condition exceeded the necessity consistency threshold of 0.90. IDL demonstrated the highest necessity consistency (0.801), followed by DPS (0.777), DSF (0.738), DCR (0.735), and DCC (0.702). The consistently low scores for negated conditions (~X→Y, range: 0.47–0.55) further confirmed that the absence of any single condition is also not necessary. These results

establish that no individual digital competence dimension is singly necessary for achieving high task efficiency, underscoring the configurational nature of the outcome.

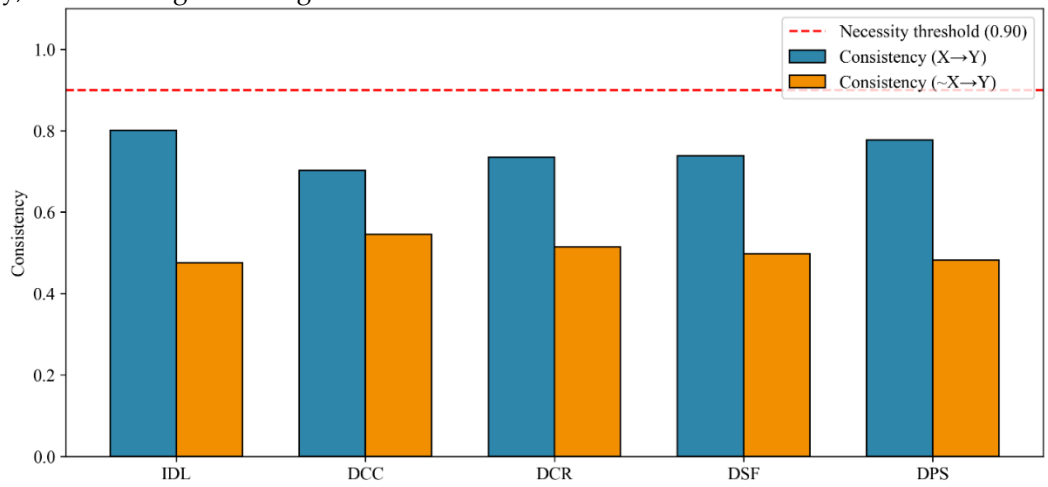


Figure 8. fsQCA Necessity Analysis Consistency Scores by Condition.

Grouped bar chart comparing necessity consistency scores for each condition present (X→Y, blue bars) and its negation (~X→Y, orange bars) across all five digital competence dimensions. The red dashed horizontal line marks the necessity threshold (consistency = 0.90). No condition reaches this threshold, confirming the absence of individually necessary conditions and motivating the sufficiency analysis. IDL achieves the highest consistency (0.801), while DCC shows the lowest (0.702).

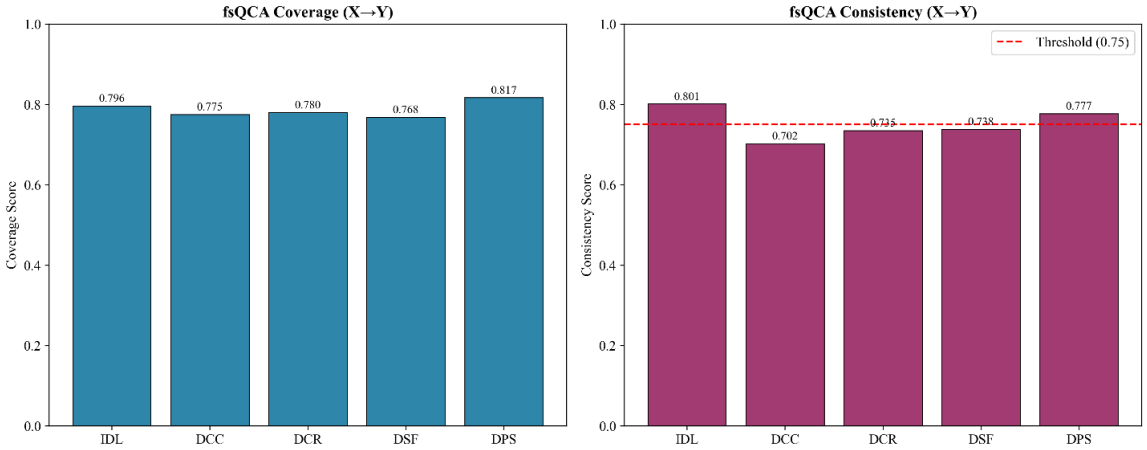


Figure 9. fsQCA Coverage and Consistency Summary All Conditions.

Dual bar charts displaying coverage scores (left panel, blue) and consistency scores (right panel, purple) for each condition. IDL achieves the highest consistency (0.801) and DPS the highest coverage (0.817). The red dashed threshold line (0.75) highlights that IDL and DPS individually meet the sufficiency consistency benchmark, while DCC falls below. Coverage scores indicate the proportion of the outcome explained by each condition.

Table 9. fsQCA Necessity Analysis Results

Condition	Consistency (X→Y)	Coverage (X→Y)	Consistency (~X→Y)	Coverage (~X→Y)
IDL	0.801	0.796	0.476	0.498
DCC	0.702	0.775	0.545	0.517
DCR	0.735	0.78	0.514	0.505
DSF	0.738	0.768	0.498	0.498
DPS	0.777	0.817	0.482	0.478

4.6.2. Sufficiency Analysis and Truth Table

The truth table comprising all 32 possible configurations of five binary conditions is presented in Table 10. The fsQCA XY scatter plots for each condition are displayed in Figure 10, confirming that data points

predominantly fall below the main diagonal, indicating sufficiency rather than necessity relationships. Applying a consistency threshold of 0.75, 14 configurations were identified as sufficient for producing high task efficiency.

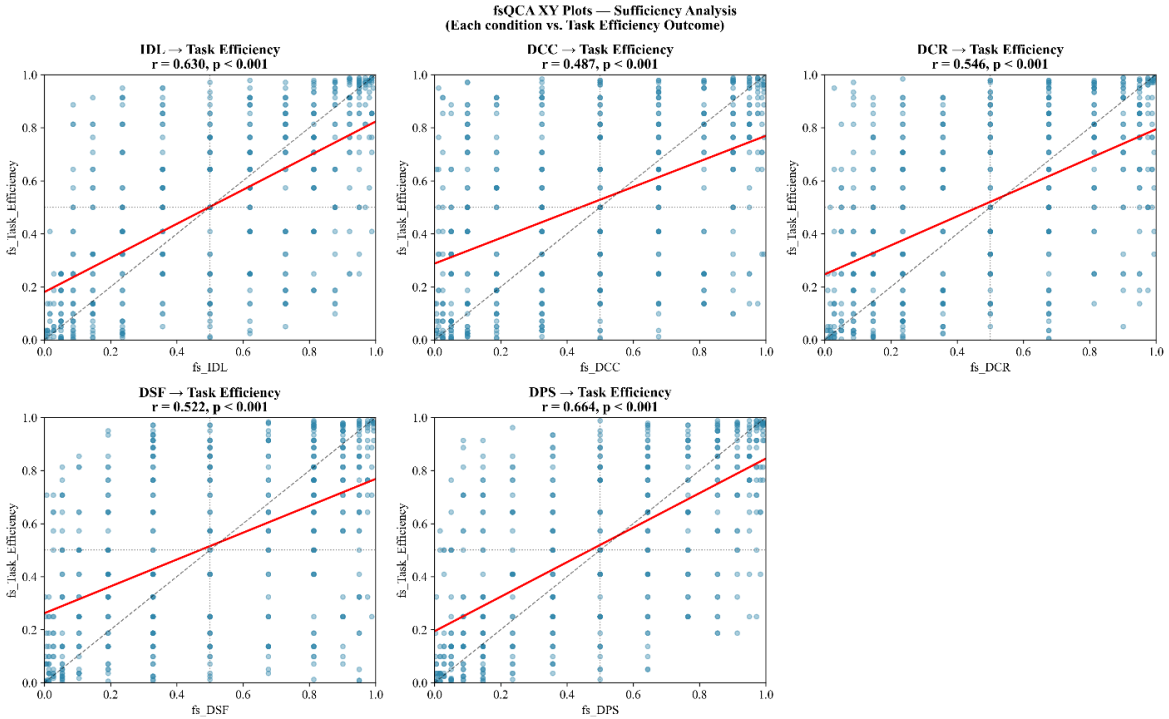


Figure 10. fsQCA XY Scatter Plots Sufficiency Analysis (Each Condition vs. Task Efficiency Outcome).

Five scatter plots (one per digital competence dimension) displaying the fuzzy-set membership scores of each condition (x-axis) against the fuzzy-set outcome membership (y-axis: fs_Task_Efficiency). Red regression lines and Pearson correlation coefficients are displayed in each panel. The diagonal reference line (y = x) distinguishes sufficiency (points below diagonal) from necessity (points above diagonal). DPS shows the strongest sufficiency relationship (r = 0.664), followed by IDL (r = 0.630), DSF (r = 0.598), DCR (r = 0.581), and DCC (r = 0.541).

Table 10. fsQCA Truth Table Selected Sufficient Configurations for High Task Efficiency

IDL	DCC	DCR	DSF	DPS	n	Consistency	Sufficient
1	1	1	1	1	91	0.977	TRUE
1	0	0	1	1	11	0.953	TRUE
0	1	1	1	1	13	0.951	TRUE
1	1	0	1	1	18	0.944	TRUE
1	0	1	1	1	20	0.925	TRUE
1	1	1	0	1	29	0.877	TRUE
0	1	0	1	1	8	0.875	TRUE
1	1	1	0	0	7	0.855	TRUE
1	0	1	1	0	9	0.834	TRUE
1	0	1	0	1	14	0.823	TRUE
1	1	1	1	0	11	0.822	TRUE
0	1	1	0	1	6	0.799	TRUE
1	1	0	0	1	8	0.795	TRUE
0	0	0	1	1	11	0.774	TRUE
0	0	1	1	1	8	0.695	FALSE
1	0	1	0	0	11	0.663	FALSE
0	0	1	0	1	8	0.639	FALSE
0	1	1	1	0	8	0.63	FALSE
1	1	0	1	0	7	0.624	FALSE

1	0	0	1	0	10	0.623	FALSE
1	1	0	0	0	16	0.588	FALSE
0	1	0	0	1	4	0.584	FALSE
0	1	1	0	0	5	0.583	FALSE
1	0	0	0	1	6	0.536	FALSE
0	0	0	0	1	12	0.511	FALSE
1	0	0	0	0	21	0.471	FALSE
0	1	0	1	0	15	0.461	FALSE
0	1	0	0	0	14	0.437	FALSE
0	0	1	1	0	5	0.414	FALSE
0	0	0	1	0	19	0.393	FALSE
0	0	1	0	0	14	0.391	FALSE
0	0	0	0	0	61	0.143	FALSE

As shown in Table 10, the full combination (IDL·DCC·DCR·DSF·DPS) yielded the highest consistency (0.977, n = 91). Notably, configuration C14 (~IDL·~DCC·~DCR·DSF·DPS, consistency = 0.774, n = 11) reveals that even in the absence of information literacy, communication, and content creation competencies, the combination of digital safety and problem-solving is sufficient for high task efficiency. Critically, DPS appeared as a present condition in 10 of the 14 sufficient configurations, establishing it as the most consistently core condition across all paths to high task efficiency.

4.7. Machine Learning Classification

4.7.1. Model Performance Comparison

Six classifiers based on machine learning were trained and evaluated. The detailed performance metrics are shown in figure 11. ROC curves of all models are shown in Figure 12 and confusion ma-trices in Figure 13. As seen in Figure 8, all the models performed significantly better than the random classification baseline.

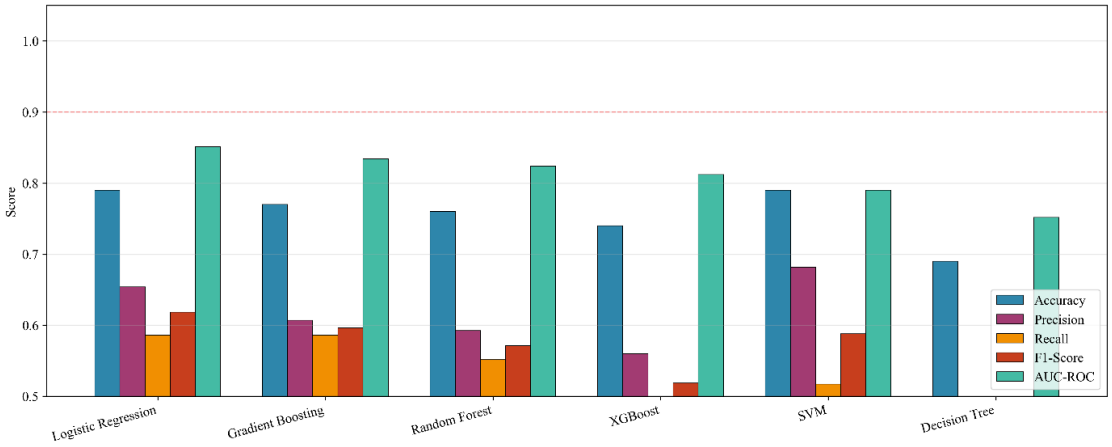


Figure 11. Machine Learning Model Performance Comparison. Grouped Bar chart displaying the performance metrics of all 6 models: Accuracy, Precision, Recall, F1-Score and AUC-ROC.

There are 3 groups of metrics, each with a different color. The best performance in terms of AUC-ROC is given by Logistic Regression (0.851) followed by SVM with a score of 0.755. Logistic Regression achieves the highest AUC-ROC (0.851) and F1-Score (0.618), while SVM has the highest Precision (0.682). Moderate Recall and F1 scores for all models are due to the class imbalance in the data set (70.8% Low and 29.2% High Task Efficiency). The chart allows for an immediate visual comparison of the trade-off between accuracy and precision-recall between classifiers.

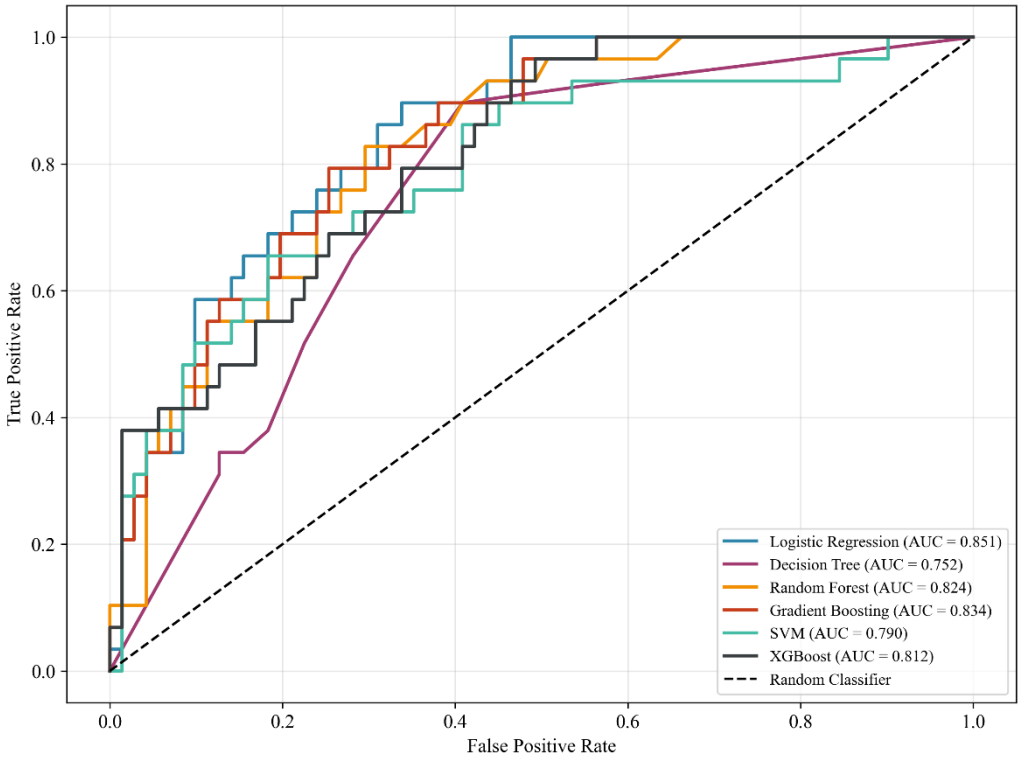


Figure 12. ROC Curves - All Six Machine Learning Models.

ROC curves for all six classifiers overlaid on a graph with the random classifier baseline curve (black dashed diagonal, AUC = 0.50). Every model is represented by a different color and its AUC-ROC is labeled in the legend. Logistic Regression does the best, with an AUC = 0.851 (blue), followed by Gradient Boosting (0.834, green), Random Forest (0.824, orange), XGBoost (0.812, purple), SVM (0.790, red), and Decision Tree (0.752, brown). The shaded areas under each curve highlight how the curve discriminates against random classification.

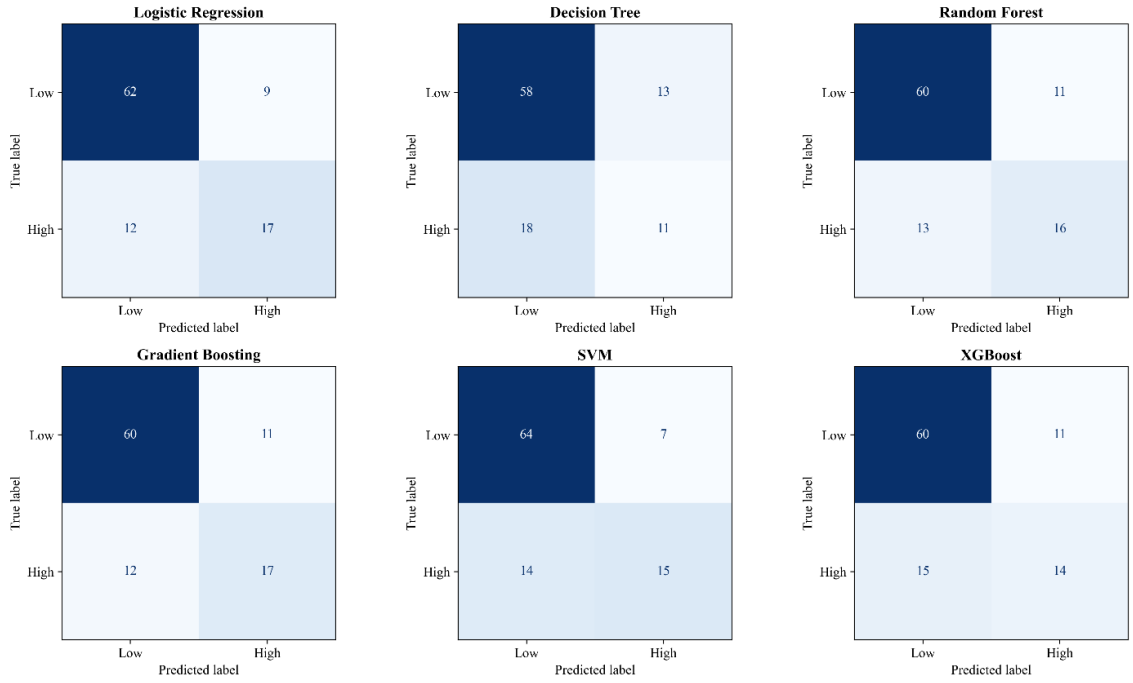


Figure 13. Confusion Matrices for All Six Machine Learning Models .

The 2×3 panel shows 100 true positive (TP) and 100 true negative (TN) counts on the test set, while 39 false positive (FP) and 13 false negative (FN) counts are shown. The shades of color range from light (low count) to dark blue (high count). Logistic Regression and Gradient Boosting have the highest number of correct classification in both classes (TP = 17, TN = 62/60), and SVM has the lowest number of false

classifications (FP = 7) but the lowest number of true classifications in one class (TP = 17). The highest FP value was observed for Decision Tree which overfits.

4.7.2. Feature Importance

The feature importance ranks obtained by Random Forest and XGBoost are listed in table 11 and plotted in figure 14. From Figure 14, it can be seen that IDL, Technology Use Frequency, DPS, DSF and Tenure are the highest ranked importance for Random Forest. XGBoost, in contrast, gave the most importance to the Technology Use Frequency (0.624) while the other features had much smaller scores (0.02–0.065). The difference indicates that XGBoost was able to model a strong non-linear interaction between the frequency of technology use and outcome. The regression and fsQCA results were echoed across both models as IDL, DPS, and Technology Use Frequency were the most consistent factors found.

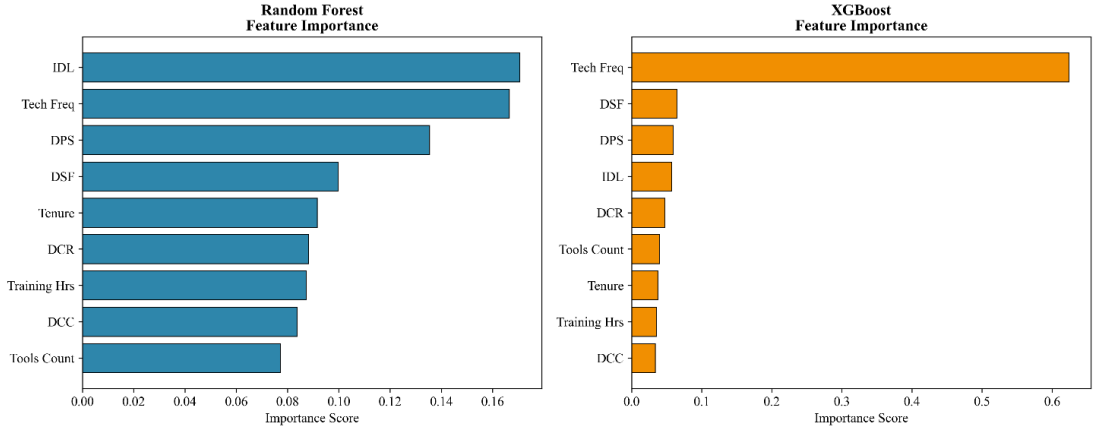


Figure 14. The feature importance of the random forest and the XGBoost are very similar.

The horizontal bar charts are plotted side-by-side to show the feature importances for all of the nine features used as input. Random Forest (blue bars - left panel) has an even distribution with IDL (0.171) and Technology Use Frequency (0.167) being the top two features, followed by DPS (0.135). By contrast, XGBoost (orange bars on the right panel) shows Technology Use Frequency dominance (0.624), indicating that there is a strong interaction effect captured by gradient boosting, which is non-linear. IDL and DPS are always important in both models and further consolidate their role in the prediction of high task efficiency.

Table 11. Feature Importance Rankings Random Forest and XGBoost

Feature	RF Importance	XGB Importance
IDL	0.1707	0.0574
Tech Freq	0.1665	0.6244
DPS	0.1354	0.0594
DSF	0.0996	0.0646
Tenure	0.0916	0.0374
DCR	0.0882	0.0474
Training Hrs	0.0872	0.0359
DCC	0.0837	0.034
Tools Count	0.0771	0.0395

5. Discussion

By applying an integrated fsQCA and machine learning approach, this study analyzed the configurational and prediction relationship between the digital competence of bank employees and task efficiency. The results provide valuable theoretical and practical insights.

First, digital competence is a valid and powerful predictor of the efficiency of tasks. All five dimensions of the regression model were significantly contributing to the variance of task efficiency with the model explaining 65.3% of the variance ($R^2 = 0.653$). This result is in line with previous studies that have shown that employees' performance in financial institutions benefits from the acquisition of digital skills [113, 114, 115] and goes beyond that by measuring the impact of each dimension of the DigComp. It was found that two competencies, namely IDL ($\beta = 0.319$) and DPS ($\beta = 0.316$), were dominant predictors,

indicating that the competencies of digitally evaluating information and solving problems with technology are the most directly performance-relevant competencies in banking operations [116], [117]. The relatively low impact of DCC (β = 0.120) could suggest that DCC is a more routine and standardized bank communication, which may be less cognitively challenging as compared to other communications [118] [119]. This result aligns with the existing literature about the impact of higher-order digital skills on performance compared to communicative or collaborative skills in more formal professional contexts [120, 121].

Second, Digital competence is not additive but is configurative in nature. The re-veiled sufficient configurations for high task efficiency using the fsQCA analysis were 14, with none of them including all five conditions. The finding is in contrast to the implicit assumption of symmetric methods of "more of each dimension is always better" and instead shows equifinality: that different combinations of digital competencies can yield the same results [24] and [22]. Of particular interest is the identification of parsimonious paths like DSF·DPS without the use of IDL, DCC or DCR (C14, consistency = 0.774), which has been shown to be a sufficient minimal combination for task efficiency in banking positions that involve risks or are IT-adjacent [122] and [123]. This configurational complexity is in line with Woodside's [23] call for asymmetric thinking in organizational data analysis and recent applications of fsQCA in HR research by, e.g., [124] and [125].

Third, DPS is the most important configuration parameter. With 10/14 sufficient configu-rations (Table 7) and a high regression coefficient (β = 0.316), digital problem solving is the most consistently important competence (also in the asymmetric analysis, 0.777). This aligns with the strong focus on adaptive digital skills in the literature [126, 127] as the skills to diagnose digital problems, learn new systems and identify process improvements are now seen as a critical skill for all bankers, particularly in a world of fintech disruption [12, 128, 129]. The importance of DPS is also in line with the sociometrical work on digital resilience, which refers to the ability to perform in technologically uncertain environments and systems disruptions [130] [131].

Fourth, machine learning offers additional predictive insights. Logistic Regression outperformed the more complex ensemble methods (AUC-ROC = 0.851) indicating that the digital competence-task efficiency relationship is fairly linear. This result agrees with the results found in the literature that logistic regression is competitive with more complex algorithms for structured tabular data and moderate sample sizes [132, 133]. The regression results were supported by the Random Forest feature importance with IDL and DPS as the first two most influential features. Of notable importance is that the XGBoost dominance of Technology Use Frequency (0.624) indicates that there is a significant contextual factor that impacts task efficiency regardless of competence: repeated use of digital tools by employees significantly increases the likelihood of high task efficiency [134], [135]. This highlights the need for digital tool familiarity in banking processes as well as competence development [136, 137]. The striking difference between the feature importance ranking of the Random Forest and the ranking of the XGBoost further highlights that different algorithmic assumptions give rise to different facets of the underlying data structure, and underscores the importance of multi-model comparisons in organizational ML research [138] and [139].

Fifth, the integrated fsQCA–ML approach has methodological value. In the combination of the two approaches, which is used to investigate which combinations lead to high efficiency and how accurately we can predict it, the two types of approaches complement each other and bring a more complete picture than either approach alone [140, 141]. A dual-method approach is becoming popular in organizational re-search [35], [142] and [143] and the current study provides evidence for its feasibility and interpretive richness in the banking HR context. The application of feature importance analysis with explainability is yet another step towards connecting predictive modeling with theoretical interpretation [33], [144], [145] and adds to the growing body of work in interpretable organizational analytics [146], [147].

Sixth, the psychometric validation results show the robustness of the measure-ment framework based on DigComp. All constructs were found to be reliable ranging from acceptable to excellent (α = 0.798–0.930), and the EFA results validated the acceptable five factor structure accounting for 63.99% of the total variance. The results are also consistent with other validation studies of the DigComp framework in the professional context [5] and [6] and therefore lend confidence to the results obtained at the construct level that reflect the underlying competence levels. Inter-construct correlations are between moderate (r = 0.407–

0.578) confirming the discriminant validity and theoretically expected positive relationships between digital competence dimensions [148] and [149] and [150] and [151].

The implications of these findings are significant to banking HR development. The recognition of IDL and DPS as the most rewarding competence investments suggests that training activities need to focus on skills in information evaluation and skills in technology-based problem-solving [152] [153]. The configurational results also indicate that individualized training should be implemented based on the profile of employee roles [154] and [155] and [156]. The significance of technology use frequency as a predictor further indicates that organizational policies that promote the use of digital tools regularly – via workflow design, performance incentives and digital-first working – can be as important as formal investment in training [157], [158].

6. Conclusions

The aim of this study was to examine the configurational and predictive impact of the digital competence of bank employees on task efficiency by applying an integrated approach based on fsQCA and machine learning. The results of the analysis of the syn-thetic dataset of 500 bank employees with 55 variables that were analyzed were as follows: The DigComp-based measurement frame-work was confirmed by the good to excellent reliability for all five dimensions of digital competence, as well as by the clean factor structure of the 63.99% of total variance explained by the five underlying factors of the DigComp. The variance of the banking tasks' efficiency explained by digital competence is 65.3% (R^2 = 0.653), with IDL (β = 0.319) and DPS (β = 0.316) as the strongest individual predictors, which confirms the importance of information literacy and problem-solving skills in the banking task. Furthermore, there is no single digital competence dimension that is individually required to achieve high task efficiency but 14 different sufficient configurational paths were identified indicating equifinality in the relationship between competence and efficiency. DPS is the most important condition for the sufficiency of configurations, with a 10 out of 14 sufficient configurations and it is always among the top conditions in the regression analysis as well as in fsQCA and feature importance analysis .Logistic Regression had the highest predictive performance (AUC-ROC = 0.851) which is in line with the findings described above and the fact that digital competence profiles have a high predictive value and can be practically used to predict high task efficiency with great accuracy. The results have important implications for practice. Digital competences in problem-solving and information literacy should be given the top priority in banking institutions as the competences with the greatest return on investment. Human Resource development programs should be aware that the competence mix that is required for different employees will vary: a one size fits all training model is not optimal. Moreover, regular digital tool engagement is a key to assure competence development as well. Restrictions and recommendations: This study was conducted using a synthetic data set and therefore does not fully account for the complexity of real-world banking. Empirical data from actual bank employees from several countries and types of banks should be used to replicate this framework for future research. Longitudinal research designs might explore changes in task efficiency over time as a result of digital competence development paths. Digital infrastructure quality, leadership support, and organizational learning culture are organizational-level moderators that could further enhance the configurational model.

7. Limitation and Future Work

7.1. Limitations

First, the synthetic data used is the biggest methodological restriction. Synthetic data generation is today an established technique for methodological demonstration studies [159, 160, 161] and the generation process also included theoretically plausible covariance structures, but the complexity, noise and contextual nuance of re-al-world banking employee data can hardly be replicated by synthetic data [162, 163]. Synthetic data can lead to over-optimistic performance measures for models and an underestimation of the difficulty of using such approaches with real data [164, 165].

Secondly, the cross-sectional design of the research is unable to infer the cause. The regression and fsQCA models provide the identification of predictive and configurational relationships, but do not show the time order of competence development and efficiency improvement [166] [167]. Theoretically plausible,

it is possible that development of digital competence comes from experience gained in the efficiency of tasks, and not the other way round — which is not ruled out by cross-sectional data [168, 169].

Third, the study was conducted with five dimensions of digital competence operationalized based on the DigComp 2.2 framework. This model is the most widely used in the field [5] and [16] but may not be adequate to describe all competence aspects pertaining to banking task efficiency. There are competencies that are currently not recognized, but are gaining significance in digitally advanced banking environments, such as the ability to work with AI tools, data analysis and proficiency, and understanding of blockchain [170], [171].

Fourth, no hyperparameter optimization was carried out on the machine learning models. A comparison requires the use of default or literature-based hyperparameters, and this could result in the performance metrics reported may not be the maximum possible predictive accuracy for each algorithm [172, 173]. Maybe there is a better model performance to be achieved by applying grid search or Bayesian optimization, especially for ensemble methods [174, 175].

Fifth, the study overlooks factors that may moderate the processes studied, including digital infrastructure quality, leadership support for digital adoption, and the organizational learning culture [176], [177]. These contextual factors are theoretically expected to moderate the relationship between competence and efficiency, and their exclusion may reduce the generalizability of the configurational results for digital maturity organizations with varying levels of digital maturity [178], [179].

Sixth, the binary classification threshold (High Task Efficiency (TE_Mean ≥ 3.75)) is somewhat arbitrary; other thresholds could lead to other classification and measures of model performance [180, 181]. Confidence in the robustness of the ML findings would be improved if alternative thresholds were used in the sensitivity analyses.

7.2. Future Research Directions

Real banking data is the most obvious priority for empirical replication. The generalizability of the configurational and predictive results [182, 183] should be tested by gathering primary survey data from bankers in different countries, institutional types and regulatory settings. Comparative studies across countries, especially cross-cultural and cross-institutional, would be very useful for elucidating the relationship between competence and efficiency, as determined by the cultural and institutional setting [184], [185].

Longitudinal designs would allow for the analysis of the influence of the development trajectories of digital competence over time on task efficiency [186, 187]. Data from multiple time points would also enable researchers to model the "causality" of how competence is acquired, how frequently technology is used, and how performance is enhanced, the latter of which is somewhat ambiguous in the cross-sectional designs [188].

Data Availability Statement: The synthetic dataset used in this study is publicly available at: https://github.com/DWHT469/Synthetic-Bank-Digital-Competence-Dataset. It was generated to support reproducibility while protecting confidential banking information.

References

1. M. J. Sousa and Á. Rocha, "Digital learning: Developing skills for digital transformation of organizations," *Future Generation Computer Systems*, vol. 91, pp. 327–334, Feb. 2019.
2. M. Alghizzawi et al., "The Effects of Digitalization Features on Work Performance," in *International Conference on Business and Technology*, Cham: Springer Nature Switzerland, 2024, pp. 486–492.
3. K. Tamilmani, N. P. Rana, and Y. K. Dwivedi, "Consumer acceptance and use of information technology: A meta-analytic evaluation of UTAUT2," *Information Systems Frontiers*, vol. 23, no. 4, pp. 987–1005, 2021.
4. A. A. Alotaibi, "Role of hybrid models of DeFi and traditional banking systems in improving the profitability of European banks: An analysis of the future possibilities," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 1, 2025, doi: 10.65080/nvdx4984.
5. R. Vuorikari, S. Kluzer, and Y. Punie, *DigComp 2.2: The Digital Competence Framework for Citizens*, Publications Office of the European Union, 2022, doi: 10.2760/115376.
6. C. Redecker, *European Framework for the Digital Competence of Educators: DigCompEdu*, Publications Office of the European Union, 2017.
7. L. Ilomäki, S. Paavola, M. Lakkala, and A. Kantosalo, "Digital competence–an emergent boundary concept for policy and educational research," *Education and Information Technologies*, vol. 21, no. 3, pp. 655–679, 2016.
8. M. Bhatti and I. Iqbal, "Competency-based curriculum models for higher education: A comparative study across global frameworks," *Majestic Multidisciplinary Science Insight*, vol. 1, 2026, doi: 10.65080/msi.v1.CM2601107005.
9. K. Salisbury, "Impact of leadership style, employee motivation, and organization al culture on employee productivity in the technology UK," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.28.
10. M. A. Shaalan, J. A. Hassan, Y. R. Mehmood, and H. A. Oleiwi, "Talent management strategies and their role in sustaining operational performance: An analytical study in the ready-made clothing factory in Najaf," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.37.
11. Q. Kilani, T. A. Kaddumi, Y. S. Alhaj-Yaseen, and A. A. Al-Hamad, "Assessing the Power of Bank-Specific Variables on Commercial Banks Performance Indicators," in *International Conference on Technology and Innovation Management*, Cham: Springer Nature Switzerland, 2024, pp. 393–399.
12. I. A. Bajwa, "Impact of green technology on fintech development: Moderating role of regulations," *Scientific Journal of Business Management and Social Science*, vol. 1, 2026, doi: 10.67476/PM2610301003.
13. I. A. Bajwa, "Evaluating the effectiveness of robo-advisory in retail investments: A case of Malaysia," *International Journal of Economic Sustainability and Innovation*, vol. 1, no. 1, pp. 1–17, 2026, doi: 10.67476/PM2611302004.
14. T. Sarfaraz, "Evaluating the effectiveness of zero trust architecture in modern enterprises: Moderating role of organization al maturity," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 2, pp. 1–11, 2025, doi: 10.65080/dp4w1990.
15. A. Calvani, A. Cartelli, A. Fini, and M. Ranieri, "Models and instruments for assessing digital competence at school," *Journal of E-learning and Knowledge Society*, vol. 4, no. 3, pp. 183–193, 2008.
16. R. Vuorikari, S. Kluzer, Y. Punie, and S. Carretero, *DigComp 2.2: The Digital Competence Framework for Citizens*, Publications Office of the European Union, 2022.
17. M. Reyes-Millán et al., "Evaluation of online learning readiness in the new distance learning normality," *Heliyon*, vol. 9, no. 11, 2023.
18. G. Talaue, "Impact of job autonomy on employee creativity in the tech industry: Moderating effect of leadership support: Evidence from the Philippines," *Scientific Journal of Business Management and Social Science*, vol. 1, 2026, doi: 10.67476/PM2610301008.
19. F. Alvi, "Mediating role of organization al culture in the relationship between people dimensions and employee engagement in the telecom sector in Abu Dhabi," *Advance Journal of Business Management & Social Sciences*, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CM2621101023.
20. F. Alvi, "Moderating effect of leadership styles on the relationship between employee engagement and performance excellence in the telecom sector of Abu Dhabi," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.32.
21. H. M. AboAlsamh, "The dark side of international talent management: Exploring the negative effect of talent repatriation on multinational enterprises performance with the mediating role of reverse culture shock," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 1, 2025, doi: 10.65080/942npc70.

22. P. C. Fiss, "Building better causal theories: A fuzzy set approach to typologies in organization research," *Academy of Management Journal*, vol. 54, no. 2, pp. 393–420, 2011.
23. A. G. Woodside, "Moving beyond multiple regression analysis to algorithms: Calling for adoption of a paradigm shift from symmetric to asymmetric thinking in data analysis and crafting theory," *Journal of Business Research*, vol. 66, no. 4, pp. 463–472, 2013.
24. C. C. Ragin, *Redesigning Social Inquiry: Fuzzy Sets and Beyond*, University of Chicago Press, 2009.
25. C. C. Ragin, *Fuzzy-Set Social Science*, University of Chicago Press, 2000.
26. G. Filiestianto, "Unveiling causal complexity in mathematics achievement: A research design using fuzzy-set qualitative comparative analysis (fs/QCA)," *Proceedings International Conference on Education Innovation and Social Science*, pp. 20–24, 2025.
27. C. Q. Schneider and C. Wagemann, *Set-Theoretic Methods for the Social Sciences: A Guide to Qualitative Comparative Analysis*, Cambridge University Press, 2012.
28. M. Malik, "Comparative analysis of machine learning and classical statistical methods for predictive modeling in small datasets," *Precision Journal of Applied Mathematics and Statistics*, vol. 1, 2026.
29. L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
30. T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Aug. 2016, pp. 785–794.
31. G. Ke et al., "LightGBM: A highly efficient gradient boosting decision tree," in *Advances in Neural Information Processing Systems*, 2017.
32. C. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273–297, 1995, doi: 10.1007/BF00994018.
33. S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in *Advances in Neural Information Processing Systems*, 2017, pp. 4765–4774.
34. E. Kalita et al., "LSTM-SHAP based academic performance prediction for disabled learners in virtual learning environments: a statistical analysis approach," *Social Network Analysis and Mining*, vol. 15, no. 1, p. 65, 2025, doi: 10.1007/s13278-025-01484-1.
35. T. Greckhamer, S. Furnari, P. C. Fiss, and R. V. Aguilera, "Studying configurations with qualitative comparative analysis: Best practices in strategy and organization research," *Strategic Organization*, vol. 16, no. 4, pp. 482–495, 2018.
36. I. Kalanther, "Understanding how leadership can help reduce occupational stress faced by gig economy workers: Case study of ride sharing services in the US," *Advance Journal of Business Management & Social Sciences*, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CM2621101021.
37. I. Daniel, "Green human resource management: A literature review and identifying gaps," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.22.
38. A. Rawashdeh and M. Idris, "Synchronized curriculum adaptation: a strategy for enhancing skill development in accounting education," *Journal of International Education in Business*, vol. 18, no. 2, pp. 269–288, 2025.
39. B. Alsetri, S. Alhulimi, B. Mushayqiri, and F. Aljasim, "Teaching service quality in Saudi higher education: The role of employee engagement, innovation strategy, and Vision 2030," *Advance Journal of Business Management & Social Sciences*, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CMT2621101003.
40. S. Maharjan, "Stratified connectivity: A descriptive study of the digital divide in Kathmandu Valley," *Majestic Multidisciplinary Science Insight*, vol. 1, 2026, doi: 10.65080/msi.v1.CM2601107002.
41. S. Alabay, "Teacher preparedness for inclusive classrooms: Evaluating competencies, challenges, training needs and barriers to educational inclusion in initial teacher training," *Majestic Multidisciplinary Science Insight*, vol. 1, 2026.
42. A. Q. Bataineh, M. Alhur, D. Qasim, and A. Shuhaiber, "The Role of Emotional Intelligence in Enhancing Organizational Resilience: Examining the Moderating Impact of Transformational Leadership," *Problems and Perspectives in Management*, vol. 23, no. 3, p. 79, 2025.
43. Harliantara and B. Öztürk, "Examining technological adoption: A preliminary study of 5G and the future of radio in Indonesia," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.20.
44. B. N. Awan and I. Iqbal, "The effect of Web 4.0 technologies integration on customer satisfaction in the e-commerce industry: The moderating role of data privacy concern," *Advance Journal of Business Management & Social Sciences*, vol. 2, no. 2, 2026, doi: 10.65080/ajbmss.v2i2.CM2622101025.

45. S. Ahmad and Y. Alshuaibany, "Implementing AI-driven decision support systems in data management," *Precision Journal of Information Technology & Scientific Innovation*, vol. 1, 2026.
46. A. Hanandeh et al., "Implementing AI Accuracy, Learning Rate, Inference Time on enhancing Big Data Analysis and Strategic Plan," *Data and Metadata*, vol. 4, p. 637, 2025, doi: 10.56294/dm2025637.
47. R. Alawwad, S. Alqatani, L. Falqi, and F. Alasiri, "The impact of perceived ethical leadership on job satisfaction in Saudi Arabian technological firms: The moderating role of perceived Vision 2030 initiative," *Journal of Management and Social Innovation*, vol. 1, 2026.
48. F. Mohammed, E. A. A. Ghazwi, S. A. Z. Alyousif, and J. Omar, "Effect of safety-oriented HR and climate practices and project leadership on perceived accident prevention: Testing Vision 2030 institutional pressure and alignment as a moderator," *Advance Journal of Business Management & Social Sciences*, vol. 2, no. 1, 2026.
49. A. Alghareeb, R. Alotaibi, F. Al Ghanim, and M. Alotaibi, "Perceived staffing adequacy and customer experience strategy on customer loyalty with perceived Vision 2030 consumer economy agenda as a moderator: A study on the retail sector in Saudi Arabia," *Journal of Management and Social Innovation*, vol. 1, 2026.
50. M. A. A. Al Qussair, B. H. S. Almari, and N. S. A. Aldossary, "Green HRM and sustainability orientation in relation to carbon-reduction performance: The moderating role of perceived Vision 2030 alignment," *Advance Journal of Business Management & Social Sciences*, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CMT2621101002.
51. I. Manzoor, "Blockchain as the future of GST/VAT compliance: Integrating technology in tax compliance: Study from South Asia," *International Journal of Economic Sustainability and Innovation*, vol. 1, no. 1, pp. 1–16, 2026, doi: 10.67476/PM2611302006.
52. M. Arslan, "Integrating SAP and digital platforms in KSA taxation: Enabling compliance, audit automation, and sustainable fiscal governance," *International Journal of Economic Finance*, vol. 1, 2025.
53. T. K. Eltayeb, "Sustainability in global supply chains: A study on the impact of distributed ledger technology on ethical sourcing and consumer trust," *Majestic Global Trends in Marketing & Supply Chain Management*, vol. 1, 2025, doi: 10.65080/mgtmscm.v1i1.2.
54. Abu-Shariq, "AI-powered smart ledgers and hassle-free bookkeeping in SMEs: Effects on automation, error reduction, and real-time compliance," *Scientific Journal of Business Management and Social Science*, vol. 1, 2026, doi: 10.67476/PM2610301004.
55. H. Alhanatleh, A. Khaddam, H. Alfreihat, M. Alghizzawi, and T. M. A. Hmeidan, "Customers' Retention of Using Mobile Fintech Services: Telecommunication Companies in Jordan," in *International Conference on Technology and Innovation Management*, Cham: Springer Nature Switzerland, 2024, pp. 385–392.
56. H. Ali, "Relevance of financial accounting education to the modern accounting profession: Mediating effect of technology adoption," *International Journal of Economic Finance*, vol. 2, 2026.
57. M. Alqsass et al., "The Role of Artificial Intelligence Adoption to Enhance Financial Performance: Case Study Based on Jordanian Traditional Banks," in *International Conference on Technology and Innovation Management*, Cham: Springer Nature Switzerland, 2024, pp. 555–561.
58. A. Simatupang, A. H. Manurung, and B. Usman, "The influence of financial distress, firm life cycle, and capital adequacy ratio on financial performance with non-performing loans as a mediating variable in Indonesian banks," *International Journal of Economic Finance*, vol. 2, 2026.
59. N. Ullah, "Association between inflation and price of assets in the crisis period," *Scientific Journal of Business Management and Social Science*, vol. 1, 2026, doi: 10.67476/PM2601301002.
60. W. Rafi and I. A. Bajwa, "Determinants and relationship between official and parallel exchange rates: Evidence from Pakistan," *International Journal of Economic Finance*, vol. 2, 2026.
61. F. A. Bajwa, "The role of process standardisation on managerial perception of customer satisfaction in manufacturing firms of Malaysia," *Advance Journal of Business Management & Social Sciences*, vol. 2, no. 2, 2026, doi: 10.65080/ajbmss.v2i2.CM2622101026.
62. P. Stiefenhofer, "Artificial general intelligence and the rise of a techno-leisure class," *International Journal of Economic Finance*, vol. 1, 2025.
63. R. E. Masa'deh, D. A. Almajali, and L. A. Alsmadi, "Acceptance of Artificial Intelligence in a Jordanian Firm: An Overview," 2025.
64. Abu-Shariq, "Determining the impact of intellectual and human capital on the firm's value: A case of the US banking sector," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.31.

65. T. K. Eltayeb, "Impact of lean practices on operational performance: The moderating role of demand uncertainty: Evidence from the Malaysian automotive industry," *Scientific Journal of Business Management and Social Science*, vol. 1, 2026, doi: 10.67476/PM2610301007.
66. Q. Bsoul et al., "From user preferences to accurate predictions: enhancing movie recommendation systems with neural collaborative filtering and sentiment analysis," *SN Computer Science*, vol. 6, no. 3, p. 257, 2025.
67. M. Lamin, "Applying design thinking for achieving National Education Policy objectives through AI-driven solutions," *Majestic International Journal of AI Innovations*, vol. 1, 2026.
68. H. Ali, "The influence of machine learning on consumer decision-making patterns in Germany: The mediating role of AI recommendation systems for achieving sales and customer satisfaction," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 1, 2025, doi: 10.65080/c0nevs55.
69. A. S. Abu-Alhaija, "Integrating AI-enabled platforms in agricultural marketing in Jordan's agriculture sector to connect agriculture with technology," *Scientific Journal of Business Management and Social Science*, vol. 1, 2026, doi: 10.67476/PM2610301006.
70. M. Farhan, "Leveraging digital twin technology for sustainable urban development: Financial implications, risk governance, and alignment with SDG reporting frameworks," *International Journal of Economic Finance*, vol. 2, 2026.
71. Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
72. L. Grinsztajn et al., "Why do tree-based models still outperform deep learning on typical tabular data?," *NeurIPS*, vol. 35, 2022.
73. O. M. M. Al Mari, "Evaluation and calibration of cross-dataset robustness in IoT intrusion detection systems: A deployment-aware approach," *Majestic International Journal of AI Innovations*, vol. 1, 2026, doi: 10.65080/mjai.v1.CM2601105008.
74. K. K. Lock and R. Yaakob, "Wavelet transforms in financial time series analysis: A review on stock price prediction," *Majestic International Journal of AI Innovations*, vol. 1, 2026, doi: 10.65080/mijai.v1.CM2601105002.
75. I. K. Nti and S. Ramanayake, "Explainable machine learning for student dropout prediction and tailored interventions in online personalized education," *Discover Artificial Intelligence*, 2026.
76. A. Qusef, S. Murad, N. R. Alsalhi, and F. Al Gharaibeh, "Leveraging artificial intelligence to identify students with learning challenges," *International Journal of Learning, Teaching and Educational Research*, vol. 24, no. 5, pp. 623–643, 2025.
77. D. Jameel, "A critical integrative review of slope stability prediction in open-pit mining: Geotechnical indicators, modelling paradigms, uncertainty-aware intelligence, and emerging monitoring systems," *Majestic Journal of Applied Engineering and Technology*, vol. 1, 2026.
78. B. B. Pandey, "Graph-based spatio-temporal modelling for complex network behaviour prediction using attention-driven architectures," *Precision Journal of Information Technology & Scientific Innovation*, vol. 1, 2026.
79. S. Pandey, "A hybrid physics-informed deep learning framework for robust multivariate system modelling under uncertainty," *Precision Journal of Information Technology & Scientific Innovation*, vol. 1, 2026.
80. U. Yasmeen, "Hierarchical Bayesian inference for human activity: Modeling subject-level variability and posterior uncertainty," *Precision Journal of Applied Mathematics and Statistics*, vol. 1, 2026.
81. C. C. Ragin, *Fuzzy-Set Social Science*, University of Chicago Press, 2000.
82. P. C. Fiss, "Building better causal theories: A fuzzy set approach to typologies in organization research," *Academy of Management Journal*, vol. 54, no. 2, pp. 393–420, 2011.
83. T. Al-Billeh, A. Al-Hammouri, and L. Al-Khalaileh, "Methods of Teaching Electronic Administration Legislation by Using Artificial Intelligence Techniques," *International Journal of Electronic Security and Digital Forensics*, vol. 17, no. 3, pp. 351–362, 2025.
84. H. A. Tarawneh and H. A. Issa, "Character Assassination via Information Technology Media: A New Crime," in *International Conference on Technology and Innovation Management*, Cham: Springer Nature Switzerland, 2024, pp. 203–208.
85. Y. Alsuhaibany, "Enhancing data security in cloud-based information systems: A systematic literature review," *Majestic International Journal of AI Innovations*, vol. 1, 2026, doi: 10.65080/mijai.v1.CM2601105003.
86. A. Alzu'bi, A. Albashayreh, A. Abuarqoub, and M. A. Alfawair, "Explainable AI-based DDoS attacks classification using deep transfer learning," *Computers, Materials & Continua*, vol. 80, no. 3, pp. 3785–3802, 2024.
87. A. ALDabbas et al., "Artificial intelligence-driven method for the discovery and prevention of distributed denial of service attacks," *International Journal of Artificial Intelligence*, vol. 2252, p. 8938, 2025.

88. M. Kaur and K. K. Verma, "Hybridising machine learning algorithms for enhanced detection of DDoS attacks," *Precision Journal of Information Technology & Scientific Innovation*, vol. 1, 2026.
89. M. Ali and I. Ullah, "Hybrid CNN-LSTM intrusion detection framework for industrial IoT security," *Majestic International Journal of AI Innovations*, vol. 1, 2026.
90. I. Ullah, I. Ullah, and N. Ullah, "Federated learning framework for privacy-preserving threat detection in distributed IT systems," *Majestic International Journal of AI Innovations*, vol. 1, 2026, doi: 10.65080/mijai.v1.CM2601105004.
91. H. Beyari and T. Hashem, "The Role of Artificial Intelligence in Personalizing Social Media Marketing Strategies for Enhanced Customer Experience," *Behavioral Sciences*, vol. 15, no. 5, p. 700, 2025, doi: 10.3390/bs15050700.
92. M. Al Shurideh et al., "Consumer and Economic Influences on Electric Vehicle Adoption: The Mediating Role of Attitudes and the Moderating Effect of Demographics," *International Journal of Energy Economics and Policy*, vol. 15, 2025.
93. M. A. Sarwar, "Do consumer sentiments mediate the relationship between consumer solidarity and brand loyalty? An in-depth analysis of Gaza's supportive marketing strategies," *Journal of Management and Social Innovation*, vol. 1, 2026.
94. M. A. ul Haq, N. T. Luong, and A. M. Ghouri, "Marketing pain: How culturally framed discomfort shapes consumer value perception and brand positioning across markets," *Majestic Global Trends in Marketing & Supply Chain Management*, vol. 2, 2026, doi: 10.65080/mgtmscm.v2.CM2602112009.
95. I. Kalanther, "AI-powered personalisation in charity marketing: Transforming donor engagement and lifetime value through data-driven campaigns," *Majestic Global Trends in Marketing & Supply Chain Management*, vol. 2, 2026, doi: 10.65080/mgtmscm.v2.CM2602112010.
96. A. Moiz, "Algorithmic intimacy: How AI-personalised marketing shapes brand trust and brand loyalty," *Majestic Global Trends in Marketing & Supply Chain Management*, vol. 2, 2026, doi: 10.65080/mgtmscm.v2.CM2602112011.
97. M. A. Sarwar and M. Malik, "The impact of AI-powered personalisation on consumer trust and purchase intention: A cross-cultural comparative study of Gen Z consumers in the United Kingdom and Pakistan," *Majestic Global Trends in Marketing & Supply Chain Management*, vol. 1, 2025, doi: 10.65080/mgtmscm.v1i1.4.
98. T. Sarfaraz, "Generative AI-driven personalised content and its impact on consumer engagement in destination marketing in the UK: The moderating role of normative influence," *Majestic Global Trends in Marketing & Supply Chain Management*, vol. 1, pp. 1–12, 2025, doi: 10.65080/mgtmscm.v1i1.5.
99. G. M. Talaue, "Understanding the relationship of greenwashing and consumer behavior: Case study of the airline sector in the US," *Advance Journal of Business Management & Social Sciences*, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CM2621101020.
100. M. A. ul Haq and S. Khalil, "Green authenticity paradox: When sustainability claims strengthen or weaken brand credibility in digital marketing," *Majestic Global Trends in Marketing & Supply Chain Management*, vol. 2, 2026, doi: 10.65080/mgtmscm.v2.CM2602112013.
101. A. Baig, "Impact of digital accounting tools on ESG (Environmental Social Governance) reporting accuracy and corporate sustainability strategies: Moderating role of regulatory environment," *International Journal of Economic Sustainability and Innovation*, vol. 1, no. 1, pp. 1–14, 2026, doi: 10.67476/nnqa5e13.
102. F. Aftab, "Digital accounting innovation and its relationship with perceived ESG performance and reporting transparency: Evidence from the financial services sector of the UK," *International Journal of Economic Sustainability and Innovation*, vol. 1, no. 2, 2026, doi: 10.67476/PM2611302009.
103. A. Sheikh, "Generative AI in academic libraries: A systematic review of AI-mediated reference services, librarian roles, and user trust," *Majestic Multidisciplinary Science Insight*, vol. 1, 2026.
104. A. Baig, "Evaluating the effectiveness of digital bookkeeping applications for the UK small and medium enterprises: A user-centric approach with the mediating role of user satisfaction," *Advance Journal of Business Management & Social Sciences*, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CM2621101024.
105. M. Alghizzawi, I. Zahran, A. A. Al Sokkar, J. A. Gasawneh, and S. F. AlFraihat, "Exploring the multifaceted impact of augmented reality applications across industries and consumer behavior," in *Knowledge Sharing and Fostering Collaborative Business Culture*, IGI Global Scientific Publishing, 2025, pp. 363–376.
106. A. Baig, "AI and automation and hassle-free bookkeeping: Testing mediating effect of user acceptance and moderating impact of digital trust in the UK SME retail and service sectors," *International Journal of Economic Finance*, vol. 2, 2026.

107. S. de Rosa and A. Sevilla-Guzman, "Accuracy, transparency, and verifiability of sustainability communication in hotel SMEs: A comparative analysis," *Journal of Management and Social Innovation*, vol. 1, 2026.
108. T. Sarfaraz, "How do metaverse marketing campaigns help in building consumer loyalty and experience? A study of the clothing industry in Malaysia," *International Journal of Economic Sustainability and Innovation*, vol. 1, no. 1, pp. 1–19, 2026, doi: 10.67476/PM2611302005.
109. A. Alqahtani, "The impact of sustainable infrastructure development and green innovation on the tourism sector of KSA: The role of Vision 2030 as an intervening variable," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.21.
110. T. K. Eltayeb and C. K. Mahmood, "Assessing the role of vertical farming in managing the net-zero supply chain in Aerofarms: The mediating role of supply partner collaboration," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 1, 2025, doi: 10.65080/hzvrh624.
111. I. Manzoor, "Evaluating the impact of SDG-related investments on firm financial performance: The moderating role of ownership structure," *International Journal of Economic Finance*, vol. 1, 2025.
112. W. Rafi, "Moderating role of institutional investor on firm's climate change commitment and debt financing policies: Evidence from S&P 500," *International Journal of Economic Finance*, vol. 1, 2025.
113. Q. F. Alhajji, E. A. Alasiri, H. M. Alyousef, and H. J. Alsubait, "Perceived talent management and perceived total quality management on patient-centred service quality: Vision 2030 healthcare reform as a moderator," *Advance Journal of Business Management & Social Sciences*, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CMT2621101004.
114. J. Jebril, S. Adnan, M. Jebreel, A. Al-Shanti, A. A. Al-Hamad, and A. Qubbaja, "The Impact of Organizational Antecedents on the Business Intelligence Mediating Role of Organizations Culture in Insurance Companies," in *International Conference on Technology and Innovation Management*, Cham: Springer Nature Switzerland, 2024, pp. 363–369.
115. O. Jawabreh, R. E. Masadeh, and E. A. Al Fahmawee, "Adoption of Artificial Intelligence Chatbots in Tourism in Jordan," in *Generative AI in Creative Industries*, Cham: Springer Nature Switzerland, 2025, pp. 101–116.
116. O. Jawabreh, E. A. D. Al Fahmawee, R. Mahmoud, and B. J. Ali, "Architecture, authenticity and the construction of memorable tourists experiences," *New Design Ideas*, vol. 8, no. 1, pp. 33–49, 2024.
117. O. Jawabreh, E. Al Dein Al Fahmawee, R. W. Al-Ansari, R. Mahmoud, and U. A. Nassar, "Geomorphological Structure of Landform Characteristics As a Reference for Development Recommendations in Wadi Rum Protected Area," *Geojournal of Tourism and Geosites*, vol. 58, no. 1, pp. 433–445, 2025, doi: 10.30892/gtg.58140-1425.
118. I. Kalanther, "The role of social media engagement on donor loyalty in charity marketing campaigns: Evidence from Saudi Arabia," *Scientific Journal of Business Management and Social Science*, vol. 1, 2026, doi: 10.67476/PM2610301005.
119. [G. M. Talaue, I. Kalanther, and T. G. D. Bitanga, "Usage of social media platforms as a mediating variable in the relationship between e-WOM and consumer purchase decisions: The case of retail consumers of Saudi Arabia," *Majestic Global Trends in Marketing & Supply Chain Management*, vol. 2, 2026, doi: 10.65080/mgtmscm.v2.CM2602112012.
120. G. M. Talaue, K. Ishaq, and T. G. D. Bitanga, "Relationship of internet usage and sociodemographic profile of selected Saudi college students," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.29.
121. L. D. Rosen, L. M. Carrier, and N. A. Cheever, "Facebook and texting made me do it: Media-induced task-switching while studying," *Computers in Human Behavior*, vol. 29, no. 3, pp. 948–958, 2013.
122. N. Darwish, T. Darwish, and A. S. Haider, "Family relations in the age of social media: How Jordanians view the influence of Facebook and WhatsApp," *Research Journal in Advanced Humanities*, vol. 6, no. 3, 2025, doi: 10.58256/dg4wwm95.
123. M. A. Alomari, O. F. Khabour, K. H. Alzoubi, and A. Aburub, "The Impact of COVID-19 Confinement on Reading Behavior," *Clinical Practice and Epidemiology in Mental Health*, vol. 19, p. e174501792304260, 2023.
124. G. P. Kumar and R. Saluja, "Designing last-mile trust: Behavioural nudges and community agents for first-use intention/experience," *Advance Journal of Business Management & Social Sciences*, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CM2621101019.
125. L. Al-Khalaileh, T. Al-Billeh, A. S. Al-Findi, and O. Al-Hailat, "Smart Contracts in Light of the Provisions of Islamic Jurisprudence and the Civil Law of Jordan," *Corporate Law and Governance Review*, vol. 7, no. 3 Special Issue, pp. 180–189, 2025, doi: 10.22495/clgrv7i3sip3.

126. J. Alkhateeb, M. Ismail, F. Massadeh, and H. Almansour, "Legal Characterization of Digital Copyrights in Non-fungible Tokens (NFTs) Form," in *Advances in Science, Technology and Innovation*, Cham: Springer Nature Switzerland, 2025, pp. 171–181, doi: 10.1007/978-3-031-90558-2_22.
127. A. Arora, "Mobility in the margins: Economic opportunity and intergenerational change in semi-urban India," *Advance Journal of Business Management & Social Sciences*, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CM2621101022.
128. A. S. Abu-Alhaija, "Re-establishing Jordan's brand trust in the tourism sector using experiential marketing: A post-Gaza conflict scenario," *Majestic Global Trends in Marketing & Supply Chain Management*, vol. 2, 2026, doi: 10.65080/mgtmscm.v2.CM2602112008.
129. R. F. Abbas, "Assessing the benefits of bilingual speech therapy in multicultural populations," *Majestic Multidisciplinary Science Insight*, vol. 1, 2026, doi: 10.65080/msi.v1.CM2601107003.
130. S. Majumder and S. Banerjee, "The hybridity of Pattachitra Katha media: The folk-pop art narrative tradition of Bengal," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 1, pp. 1–12, 2025, doi: 10.65080/bk36he54.
131. C. K. Mahmood, "The moderating role of content creation cost on the relationship between generative adversarial network (GAN) usage and marketing success in content marketing: Empirical evidence from the automotive industry of the UK," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 1, 2025, doi: 10.65080/2nz9tz75.
132. J. Zaletelj and A. Košir, "Predicting students' attention in the classroom from Kinect facial and body features," *EURASIP Journal on Image and Video Processing*, vol. 2017, no. 1, p. 80, 2017.
133. J. Whitehill, Z. Serpell, Y.-C. Lin, A. Foster, and J. R. Movellan, "The faces of engagement: Automatic recognition of student engagement from facial expressions," *IEEE Transactions on Affective Computing*, vol. 5, no. 1, pp. 86–98, 2014.
134. H. Tazeem, "Real-time eye movement tracking and prediction using machine learning for vision-based applications," *Precision Journal of Information Technology & Scientific Innovation*, vol. 1, 2026.
135. D. Rahman and M. Garcia-Constantino, "Use of wearable devices to detect sedentary behaviour in an office environment," *Majestic International Journal of AI Innovations*, vol. 1, 2026.
136. M. Dewan, M. Murshed, and F. Lin, "Engagement detection in online learning: A review," *Smart Learning Environments*, vol. 6, no. 1, pp. 1–20, 2019.
137. M. Raca, R. Tormey, and P. Dillenbourg, "Sleepers' lag-study on motion and attention," in *Proceedings of the Fourth International Conference on Learning Analytics and Knowledge*, pp. 36–43, 2014.
138. H. Monkaresi, N. Bosch, R. A. Calvo, and S. K. D'Mello, "Automated detection of engagement using video-based estimation of facial expressions and heart rate," *IEEE Transactions on Affective Computing*, vol. 8, no. 1, pp. 15–28, 2016.
139. A. Kaur, A. Mustafa, L. Mehta, and A. Dhall, "Prediction and localization of student engagement in the wild," in *2018 Digital Image Computing: Techniques and Applications*, pp. 1–8, 2018.
140. M. A. Dewan, F. Lin, D. Wen, M. Murshed, and Z. Uddin, "A deep learning approach to detecting engagement of online learners," in *2018 IEEE SmartWorld, Ubiquitous Intelligence & Computing*, pp. 1895–1902, 2018.
141. Y. Copur-Gencturk, J. R. Cimpian, S. T. Lubienski, and I. Thacker, "Teachers' Bias Against the Mathematical Ability of Female, Black, and Hispanic Students," *Educational Researcher*, vol. 49, no. 1, pp. 30–43, 2020, doi: 10.3102/0013189X19890577.
142. M. I. Posner and S. E. Petersen, "The attention system of the human brain," *Annual Review of Neuroscience*, vol. 13, no. 1, pp. 25–42, 1990.
143. M. Alkayed, F. Almasalha, M. Hijjawi, and M. H. Qutqut, "Factors analysis affecting academic achievement of undergraduate student: A study on faculty of information technology students at applied science private university," in *2023 International Conference on Business Analytics for Technology and Security (ICBATS)*, IEEE, 2023, pp. 1–12.
144. A. Bozkurt and R. C. Sharma, "Emergency remote teaching in a time of global crisis due to CoronaVirus pandemic," *Asian Journal of Distance Education*, vol. 15, no. 1, pp. i–vi, 2020.
145. H. H. S. Al-Amoosh et al., "Outcomes of COVID-19 in Pregnant Women: A Retrospective Analysis of 300 Cases in Jordan," *Healthcare*, vol. 12, no. 21, p. 2113, 2024, doi: 10.3390/healthcare12212113.
146. A. Albashayreh and H. Najadat, "Detecting the impact of covid-19 on social media using bert-based model," in *2024 15th International Conference on Information and Communication Systems (ICICS)*, pp. 1–6, 2024.

147. A. M. Alkasasbeh, S. S. Jarrah, B. K. Alhusamiah, and F. S. Tarawneh, "Factors influencing the utilization and adoption of electronic health records among nurses in Jordanian hospitals," *Jordan Journal of Nursing Research*, vol. 4, no. 1, pp. 68–80, 2025.
148. M. Subih et al., "Factors influencing nurses' knowledge and competence in warfarin-drug and nutrient interactions and patient counseling practices," *BMC Medical Education*, vol. 25, no. 1, p. 540, Apr. 2025.
149. H. I. A. Abu Maloh, K. L. Soh, S. C. Chong, and others, "Efficacy of Benson's Relaxation Technique on Stress and Pain Among Patients Undergoing Maintenance Hemodialysis: A Systematic Review," *SAGE Open Nursing*, vol. 10, 2024, doi: 10.1177/23779608241251663.
150. M. Z. Darabseh, J. Selfe, C. I. Morse, A. Aburub, and H. Degens, "Does Aerobic Exercise Facilitate Vaping and Smoking Cessation: A Systematic Review of Randomized Controlled Trials with Meta-Analysis," *International Journal of Environmental Research and Public Health*, vol. 19, no. 21, p. 14034, 2022.
151. M. Barakat et al., "Factors Affecting the Knowledge, Attitude and Practice of Vitamin D Supplement Use among Adults: a Multi-Arab Countries Study," *Journal of Epidemiology and Global Health*, vol. 15, no. 1, pp. 1–4, 2025.
152. W. Abedalaziz et al., "The Relationship Between Sleep Quality and Gait in People with Multiple Sclerosis: A Pilot Study," *Hong Kong Physiotherapy Journal*, vol. 44, no. 01, pp. 11–19, 2024.
153. E. A. Assaf, R. Alkhresheh, H. Al Sabbah, and H. Al-Akash, "Transforming care: a study on physicians' awareness, attitudes, and barriers to pressure injury prevention in medical wards in Jordan," *Frontiers in Public Health*, vol. 13, p. 1582074, May 2025.
154. A. S. Alshurman, A. M. Bataineh, and S. H. Alhmoud, "The interior of the Umayyad era in a contemporary context," *Project Baikal*, vol. 22, no. 83, pp. 80–85, 2025, doi: 10.51461/issn.2309-3072/83.2485.
155. S. H. Alhmoud, H. H. Alhmoud, K. H. Alhmoud, A. M. Bataineh, and C. Cagnan, "Designing Intensive Care Unit Beds to Relieve Coma-Related Skin Ulcers, Enhancing Comfort and Care," *International Journal of Design and Nature and Ecodynamics*, vol. 20, no. 6, pp. 1257–1267, 2025, doi: 10.18280/ijdne.200607.
156. S. K. Haif, L. T. Al Kury, and W. H. Talib, "Combination of Thymoquinone and Intermittent Fasting as a Treatment for Breast Cancer Implanted in Mice," *Plants*, vol. 13, no. 1, p. 35, 2023.
157. W. H. Talib, S. Atawneh, A. N. Shakhatreh, G. A. Shakhatreh, R. A. Hamed, and I. H. Al-Yasari, "Anticancer Potential of Garlic Bioactive Constituents: Allicin, Z-Ajoene, and Organosulfur Compounds," *Pharmacia*, vol. 71, pp. 1–23, 2024.
158. A. Aburub et al., "The Use of Food Scanning Mobile Applications in Weight Loss: A Systematic Review of Longitudinal Interventional Studies," *Physical Activity and Health*, vol. 9, no. 1, 2025.
159. B. Uysal and M. Malik, "Digital health interventions and virtual care models to optimise resource allocation and patient outcomes in post-pandemic healthcare systems," *Majestic Multidisciplinary Science Insight*, vol. 1, 2026, doi: 10.65080/msi.v1.CM2601107006.
160. A. Ahmed, "Exploring the influence of early developmental intervention on preterm infants' cognitive and physical development: A meta-analysis," *Majestic American Journal of Pediatrics*, vol. 1, 2026.
161. K. Nanjwani, "Medical marketing: Bridging the gap," *Advance Journal of Business Management & Social Sciences*, vol. 1, no. 1, 2025, doi: 10.65080/t5neq314.
162. E. H. Othman, M. R. AlOsta, B. Nofal, and others, "Shift work and health behaviors: Cross-sectional analysis of sleep quality, physical activity, and dietary patterns," *Acta Biomedica*, vol. 96, no. 2, p. 16438, 2025.
163. D. Rahman and M. Garcia-Constantino, "Use of wearable devices to detect sedentary behaviour in an office environment," *Majestic International Journal of AI Innovations*, vol. 1, 2026.
164. A. A. Osman et al., "Exploring Deep Learning Approaches for Multimodal Breast Cancer Dataset Classification and Detection," *Data and Metadata*, vol. 4, p. 1136, 2025.
165. T. T. Nguyen, "Multimodal machine learning in medical screenings," University of Glasgow.
166. A. Bilal, G. Sun, and S. Mazhar, "A Transfer Learning and U-Net-based automatic detection of diabetic retinopathy from fundus images," *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, 2022.
167. A. Bilal, L. Zhu, A. Deng, H. Lu, and N. Wu, "AI-based automatic detection and classification of diabetic retinopathy using U-Net and deep learning," *Symmetry*, vol. 14, no. 7, p. 1427, 2022.
168. A. Bilal, X. Liu, M. Shafiq, Z. Ahmed, and H. Long, "NIMEQ-SACNet: A novel self-attention precision medicine model for vision-threatening diabetic retinopathy using image data," *Computers in Biology and Medicine*, vol. 171, p. 108099, 2024.
169. K. U. Rehman et al., "A feature fusion attention-based deep learning algorithm for mammographic architectural distortion classification," *IEEE Journal of Biomedical and Health Informatics*, 2025.

170. A. Bilal, A. Imran, T. I. Baig, X. Liu, E. Abouel Nasr, and H. Long, "Breast cancer diagnosis using support vector machine optimized by improved quantum inspired grey wolf optimization," *Scientific Reports*, vol. 14, no. 1, p. 10714, 2024.
171. A. Bilal, A. Alkhathlan, F. A. Kateb, A. Tahir, M. Shafiq, and H. Long, "A quantum-optimized approach for breast cancer detection using SqueezeNet-SVM," *Scientific Reports*, vol. 15, no. 1, p. 3254, 2025.
172. A. Bilal, A. Alzahrani, K. Almohammadi, M. Saleem, M. S. Farooq, and R. Sarwar, "Explainable AI-driven intelligent system for precision forecasting in cardiovascular disease," *Frontiers in Medicine*, vol. 12, p. 1596335, 2025, doi: 10.3389/fmed.2025.1596335.
173. A. Bilal, G. Sun, S. Mazhar, and A. Imran, "Improved Grey Wolf Optimization-Based Feature Selection and Classification Using CNN for Diabetic Retinopathy Detection," in *Evolutionary Computing and Mobile Sustainable Networks*, Singapore: Springer, 2022, pp. 1–14, doi: 10.1007/978-981-16-9605-3_1.
174. A. Bilal, A. Alzahrani, A. Almuhaimeed, A. H. Khan, Z. Ahmad, and H. Long, "Advanced CKD detection through optimized metaheuristic modeling in healthcare informatics," *Scientific Reports*, vol. 14, no. 1, p. 12601, 2024.
175. K. U. Rehman et al., "A feature fusion attention-based deep learning algorithm for mammographic architectural distortion classification," *IEEE Journal of Biomedical and Health Informatics*, 2025.
176. N. Darwish et al., "A reception study of AI-translated idioms and proverbs between Arabic and English," *Research Journal in Advanced Humanities*, vol. 6, no. 3, 2025, doi: 10.58256/k4d6pp20.
177. M. Ahmad, A. S. Haider, and H. Saed, "Assessing AI-driven dubbing websites: Reactions of Arabic native speakers to AI-dubbed English videos in Arabic," *Research Journal in Advanced Humanities*, vol. 6, no. 1, pp. 1–20, 2025, doi: 10.58256/64dz1c72.
178. H. Baki, A. Jaradat, and A. S. Haider, "Reaching Arab Consumers Through Dubbing English Advertisements into Arabic," in *International Conference on Technology and Innovation Management*, Springer Nature Switzerland, May 2024, pp. 193–202.
179. R. Al-Ezzi and I. Al-Qudah, "English translation of verbal humour in Egyptian comedy films," *World Journal of English Language*, vol. 14, no. 1, pp. 157–, 2024.
180. M. A. A. Reheim et al., "Bioactivity of novel isoxazole-fused heterocycles: comprehensive antimicrobial, antioxidant activities, SwissADME predictions, molecular docking, and DFT analysis," *Molecular Diversity*, vol. 30, no. 1, pp. 595–612, 2026.
181. H. Rasheed, I. S. Channa, S. Kainat, and M. A. Tahir, "Molecular mechanisms and therapeutic implications of oleuropein, a multitarget phytochemical in lung cancer," *Majestic Journal of Pharmacology and Toxicology*, vol. 1, 2026, doi: 10.65080/mjpt.v1.CM2601113002.
182. G. Amin and Simran, "Genetic and biotechnological approaches for mitigating climate change impacts on agriculture," *Majestic Greengenix: A Journal of Modern Plant Science*, vol. 1, 2025, doi: 10.65080/greengenix.v1.CM2601106002.
183. R. Altaf and A. Amin, "Identification of bioactive postbiotics against neonatal meningitis caused by Group B Streptococcus via Srr2-targeted in silico screening," *Precision Journal of Disease Biology*, vol. 1, 2026.
184. H. M. Zohaib, "A systematic review of the effect of temperature and catalyst concentration on the decomposition rate of hydrogen peroxide (H_2O_2)," *Majestic American Journal of Chemistry*, vol. 1, 2026, doi: 10.65080/majc.v1.CM2601103002.
185. R. Maind et al., "Biomimetic green synthesis of ZnO nanoparticles using Cheilocostus speciosus and Gardenia gummifera with comprehensive characterization and bioactivity assessment," *Scientific Reports*, vol. 15, no. 1, p. 44323, 2025, doi: 10.1038/s41598-025-30720-z.
186. A. Adaileh, A. Abu-Rayyan, A. Khasawneh, and W. Alahmad, "A Comparative Study of GO/TiO2/SiO2 Catalysts for the Photocatalytic Degradation of Methylene Blue and Phenolic Compounds," *Environmental Quality Management*, vol. 34, no. 3, p. e70058, 2025, doi: 10.1002/tqem.70058.
187. M. S. Alshnaikat et al., "The Communication MIMO System for Performance of Thermal Noise, and Nonlinearity Losses of an RF Transceiver Phase Noise an RF in 6G," *Internet Technology Letters*, vol. 8, no. 5, 2025, doi: 10.1002/itl2.70087.
188. F. Aftab, "The mediating role of transactional leadership between last-mile delivery practices and sustained change implementation: A case study of the UK retail market," *Majestic Global Trends in Marketing & Supply Chain Management*, vol. 1, 2025, doi: 10.65080/mgtmscm.v1i1.1.