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Business Intelligence Capabilities and Workforce Agility in Emerging Banking Systems: A Cross-Sectional Study of Jordan and Malaysia with Moderation and Sensitivity Analysis

Maryam Khalid Obeidat
Lecturer, Department of Computer Information Systems, King Abdullah II School for Information Technology, University of Jordan, Amman 11942 Jordan, E-mail: mk5918183@gmail.com

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Abstract: This study examines how three Business Intelligence (BI), data mining speed, simulation usage, and analytics usage, relate to workforce agility in the banking sectors of Jordan and Malaysia. Using a cross-sectional survey of 412 employees and Partial Least Squares Structural Equation Modeling (PLS-SEM) with bootstrapping (5,000 resamples), the study tests direct associations, cross-country differences, bank type moderation, and sensitivity to unmeasured confounding (E-value). Results show that all BI dimensions are positively associated with workforce agility, with analytics usage exerting the strongest effect ($\beta = 0.46$), followed by simulation usage ($\beta = 0.31$) and data mining speed ($\beta = 0.24$). The model explains 69% of the variance in workforce agility. Multi-group analysis indicates no significant differences between Jordan and Malaysia, and bank type (commercial vs. Islamic) does not moderate the relationships. The E-value (2.43) suggests moderate robustness to unmeasured confounding. The findings indicate that analytical and simulation capabilities are more strongly linked to workforce agility than data speed alone, supporting Data Driven Decision-Making (DDDM) theory over Information Systems Success perspectives. The study provides comparative evidence from underrepresented, emerging banking contexts and highlights the importance of BI capability differentiation in explaining employee agility, while acknowledging the correlational nature of the evidence and the limitations of self-reported data.

Keywords: Business intelligence; workforce agility; analytics usage; data mining speed; simulation usage; banking sector; cross-sectional study; Jordan; Malaysia.

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1. Introduction

The banking industry has adopted advanced technological processes to meet customer demands and comply with competitive and regulatory pressures (Tripathi et al., 2020). One tool used for this purpose is a Business Intelligence (BI) system, which collects, processes, and analyzes data within an organization to support decision-making (Dresner, 1989). Business intelligence systems are responsible for data processing, analysis, and decision-making within organizations (Monfared and Akbari, 2019). Advanced analytical capabilities contribute to better organizational responsiveness and performance (Wamba et al., 2017; Mikalef et al., 2020).

Workforce agility is an important organizational capability within digital banking environments. While past literature has demonstrated the connection between BI and organizational performance/competitiveness (Mikalef et al., 2020; Cheng et al., 2020). There is insufficient literature on the relationship between individual BI attributes and workforce agility from an employee perspective, particularly in developing banking systems. Moreover, little research has assessed BI as a capability across its dimensions. Thus, this research will investigate the effect of three BI dimensions, including data mining speed, simulation usage, and analytics usage, on workforce agility among banking employees in Jordan and Malaysia. This study will adopt the Data-Driven Decision-Making (DDDM) theory and the Information Systems Success Theory as complementary yet competing theoretical perspectives to explain the relationship between BI and workforce agility. According to DDDM theory, the capability of analytics will be the most influential variable, as it contributes to interpretation, prediction, and decision-making under uncertainty. On the other hand, IS Success Theory considers system quality as an important determinant and expects data mining speed to have the highest effect (DeLone and McLean, 2003). Analyzing these contrasting perspectives contributes to the body of knowledge aimed at determining the extent to which BI capabilities are linked to workforce agility in the current banking sector.

These two countries were chosen because they both have dual banking systems but differ in their digital maturity and analytics capability development (Al Zyadat et al., 2022; Mikalef and Gupta, 2021). The comparative case study between Jordan and Malaysia thus serves as a platform for analysis of whether there is consistency in the relationship between BI capabilities and workforce agility across other emerging banking sectors with varying levels of technological advancement.

This study makes many contributions to the existing literature. Firstly, the scope of BI research has expanded from the organizational level to workforce agility. Secondly, this research focuses on testing the significance of different BI dimensions rather than analyzing BI as a single entity. Thirdly, there is an analysis of the relationships among these variables in two emerging banking systems, both of which have both types of banks operating in their financial sectors.

The study addresses the following research questions:

1. What is the association between data mining speed and workforce agility?
2. What is the association between simulation usage and workforce agility?
3. What is the association between analytics usage and workforce agility?
4. Which BI dimension demonstrates the strongest association with workforce agility?
5. Does bank type moderate these associations?
6. Are the observed relationships robust to unmeasured confounding?

The following hypotheses were tested: H1a proposed that data mining speed is positively associated with workforce agility. H1b proposed that simulation usage is positively associated with workforce agility. H1c proposed that the use of analytics is positively associated with workforce agility. H2 proposed that bank type moderates the relationships between BI dimensions and workforce agility.

2. Literature Review

2.1. Business Intelligence and Workforce Agility

The use of agility within the workforce in the BI concept is important for providing an approach that enables employees to address changing technology, customer demands and regulations governing business operations (Nyamrunda and Freeman, 2021; Seyadi and Elali, 2021). Workforce agility is about how well an organization can respond to changing organizational conditions through employee adaptability (learning, flexibility, anticipation, and quick response). With rapidly evolving technology in Digital Banking and constantly changing customer expectations, workforce agility will be the key factor driving future success. Recent studies suggest that cloud-based BI increases employees ability to respond to changing conditions, improves an organization's ability to adjust, and improves a banking firm's performance by increasing access to data, improving knowledge sharing, and developing the analysis skills of an organization's staff members (Alomari and Al Tall, 2026; Al-Maaitah et al., 2026). Agility has been widely studied at the organizational level (Doz, 2020), but research on the relationship between workforce agility and Business Intelligence capabilities remains limited.

BI offers technology support to help organizations adapt; workforce agility is contingent on employees being responsive and flexible in their behavior. The literature has shown that advanced analytics capability and availability of information are positively related to an employee's ability to exhibit adaptive behaviors (Cheng et al., 2020; Ramakrishnan et al., 2018), but as such research shows the relationship, very little research has investigated if all BI capabilities will contribute similarly to workforce agility or if some capabilities contribute more significantly than others to enhance employee adaptability in the emergent banking system.

2.2. Theoretical Perspectives and Competing Predictions

These theories offer competing predictions about which BI element will show the strongest relationship with workforce agility. According to DDDM theory, organizations relying on data-driven decision-making demonstrate greater adaptive capability under uncertainty (Sharda et al., 2020). Accordingly, analytics usage is expected to demonstrate the strongest association with workforce agility because it supports interpretation, prediction, and adaptive decision-making (Mikalef et al., 2020; Cheng et al., 2020). According to DDDM, value addition occurs not only in having relevant information available but also in converting that information into insights that inform appropriate responses. This means that the use of analytics should have the strongest connection to employee agility.

On the other hand, according to Information Systems Success Theory, system quality, information quality, and timely access to information are important factors influencing organizational performance (DeLone and McLean, 2003). In this regard, improving data mining procedures can increase employees flexibility, making them more responsive and prompt in decision-making (Monfared and Akbari, 2019). Based on this understanding, the quick availability of information is an important organizational asset, since delays in receiving information could hinder employees responsiveness to organizational needs. Therefore, data mining speed could be strongly associated with organizational agility. The use of simulations falls between the two approaches discussed above because simulation capabilities depend on both the availability of timely information and the ability to interpret alternative scenarios.

The Dynamic Capabilities Perspective provides a broader explanatory lens emphasizing organizational sensing, adaptation, and resource reconfiguration under changing conditions (Teece, 2007; Schoemaker et al., 2018). However, because the theory does not specify which BI dimension should exert the strongest influence, the study primarily relies on DDDM and IS Success Theory to derive testable expectations. However, Dynamic Capabilities Theory can still help in understanding how BI systems might support adaptive employee behaviors through an organization's sensing, learning, and response capabilities.

2.3. BI Dimensions and Workforce Agility

Data Mining Speed**:** Data mining speed is related to how quickly an organization can obtain, process, and deliver data to support operational decision-making (Cheng et al., 2020). Rapid data retrieval may improve organizational responsiveness and decision speed. Research has shown that faster data retrieval leads to better decision quality and higher levels of organizational responsiveness (Ramakrishnan et al., 2018; Monfared and Akbari, 2019). Rapid data retrieval alone does not guarantee workforce agility without an analytical interpretation skill set among employees operating in an agile culture (Nyamrunda and Freeman, 2021). Excessive information speed may overwhelm employees and reduce decision quality (Doz, 2020). Data mining speed is therefore expected to demonstrate a weaker association with workforce agility than interpretive BI capabilities.

H1a: Data mining speed is positively associated with workforce agility.

Simulation Usage: Simulation usage involves modeling operational scenarios to forecast outcomes and support decision-making (Sharda et al., 2020). Within banking systems, simulation tools support stress testing, forecasting, and operational preparedness. The literature has suggested that simulation tools will increase preparedness, reduce uncertainty, and provide greater operational flexibility (Alolayyan et al., 2022; Sharda et al., 2020), but also that simulation effectiveness is highly dependent upon both the quality of models and the users' analytical skills (Bregar, 2022). Users who lack sufficient skills or have poorly developed calibration may develop false confidence in their simulation results rather than real-time adaptability (Doz, 2020). Overall, simulation use is expected to be positively associated with workforce agility, as it enhances preparedness and facilitates responses to alternative operational scenarios.

H1b: Simulation usage is positively associated with workforce agility.

Analytics Usage: The use of statistical, predictive, and prescriptive analytical tools by an organization in order to derive insights and inform business decisions (Tripathi et al., 2020). Within banking systems, analytics capabilities support predictive decision-making and operational responsiveness. Analytics has been shown through prior research to improve responsiveness (Mikalef et al., 2020), strategic flexibility (English and Hoffmann, 2018) and organizational adaptation (Mikalef et al., 2020). Cheng et al. (2020) also found that analytics facilitates organizational responsiveness. Additionally, Ebril et al. (2023) report that organizations utilizing strategic intelligence systems had higher levels of competitive responsiveness.

Overreliance on analytics may delay decision-making and reduce experiential judgment (Seyadi and Elali, 2021; Nyamrunda and Freeman, 2021). Analytics usage is expected to demonstrate the strongest association with workforce agility because it supports interpretation, prediction, and adaptive decision-making under conditions of uncertainty, which are central mechanisms within the DDDM framework.

H1c: Analytics usage is positively associated with workforce agility.

2.4. Bank Type as a Moderator

There is limited knowledge about how the form of the banking institution will affect the relationship between BI capability and workforce agility. Commercial and Islamic banks have significant differences as far as organizational structure, process of operation and regulatory environment. For example, because Islamic banks are required to function according to Shariah principles, they could be affected by the way decisions are made, the way risk assessments are done, and the way that data (information) is used. These differences in institutions, therefore, can also determine the degree to which BI capabilities will lead to increased workforce agility.

Both Jordan and Malaysia operate on a dual banking system, which includes commercial and Islamic banks, but their levels of technological sophistication and the availability of online banking services vary. However, there is an insufficiency in empirical research to determine if the association between BI capabilities and employee agility varies based on the type of bank. For this reason, bank type is being investigated as a potential moderator for the association between BI dimensions and Employee Agility.

H2: Bank type moderates the relationships between BI dimensions and workforce agility.

2.5. Research Positioning and Conceptual Framework

While the current study focuses on the relationships between the capabilities associated with BI and the agility of the organization's workforce, previous research has identified potential mediators that include decision quality, role clarity, psychological empowerment, and organizational learning (Nyamrunda and Freeman, 2021; Eisenhardt and Martin, 2000). Unfortunately, these factors have not been empirically studied and require longitudinal analysis in future research.

The majority of studies examining workforce agility have been conducted in industrialized nations or manufacturing settings (Nyamrunda and Freeman, 2021; Doz, 2020). The most recent systematic review of literature shows that business intelligence capabilities significantly contribute to organizational adaptability and improve performance in dynamic conditions (Saputra et al., 2024). Nevertheless, the level of technological advancement, digital readiness, and regulatory development varies across emerging banking systems (Al Zyadat et al., 2022).

In previous studies, the concept of BI is considered to be a multidimensional construct, but the emphasis has been placed on the impact of BI at the organizational level. Previous studies have paid little attention to workforce agility or to the comparative importance of BI dimensions in emerging banking systems. Moreover, in previous studies, the role of bank type as a moderator in the BI-agility relationship has received little attention. Additionally, cross-sectional studies of BI remain subject to unobservable confounders; hence, the current study employs E-value sensitivity analysis.

Therefore, the present study addresses four interrelated gaps in the existing literature. First, it extends BI research beyond organizational-level outcomes to examine workforce agility at the employee level. Second, it assesses the relative importance of individual BI dimensions rather than treating BI as a single, unified construct. Third, it examines the relationship between these variables within two evolving banking systems with dual banking structures. Fourth, it uses moderation analysis in order to examine the robustness of the observed relationships.

The conceptual framework is shown in Fig. 1. It was proposed that data mining speed, simulation usage, and analytics use would positively correlate with workforce agility (H1a-H1c), while bank type would be tested for potential moderation (H2). This model is correlational but not causal.

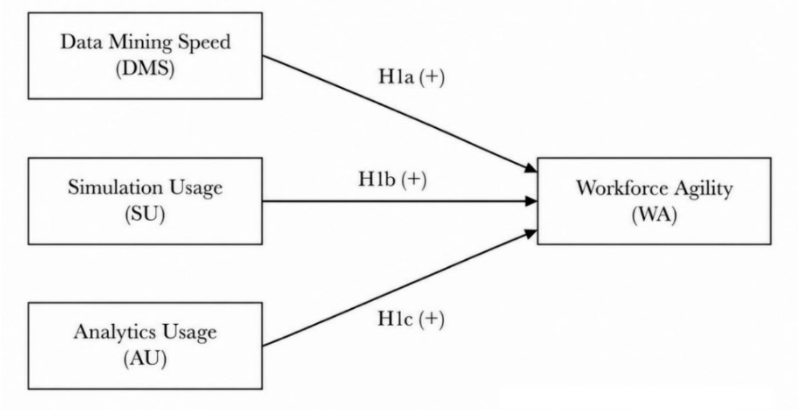

Fig. 1. Conceptual framework

3. Methodology

3.1. Research Design and Context

The research used an associational research design with a cross-sectional approach to study the relationships among three variables related to BI, which include data mining speed, simulation usage, and analytics usage, on workforce agility in the banking industry in Jordan and Malaysia. A Cross-sectional research design was chosen as the most appropriate approach for this research, since there was no intention to establish cause-and-effect relationships among the variables studied.

The countries chosen for the study are Jordan and Malaysia because they are relevant to the research question and provide a comparative context for examining emerging banking systems with varied technological capabilities. Both Jordan and Malaysia have dual banking systems, but they are at very different stages of digitalization, analytics development, and technological maturity. This presents an opportunity to analyze whether the relationship between BI capabilities and workforce agility holds across different institutional and technological environments.

3.2. Population, Sampling, and Data Collection

The target group comprised individuals who worked in both the conventional and Islamic banking industries in Jordan and Malaysia, and each participant had at least 1 year of work experience and regularly used business intelligence systems, dashboards, and/or analytics. A stratified non-random sampling design was used to include respondents from different countries, bank types, and job roles. It should be noted that consideration of practical accessibility issues related to banks led to such a sampling choice.

A preliminary power analysis using G* Power with a moderate effect size ($f^2 = .15$) per Cohen (1988) yielded a minimum required sample size of 77 participants. The total number of respondents, 412, exceeded this threshold, indicating sufficient statistical power for structural equation modeling and group comparisons.

The data collection process involved an electronic survey administered between April and June 2024 using a pretested, standardized self-report questionnaire. The questionnaires were sent to the subjects via online media. After the screening process, 412 valid responses were obtained from 702 questionnaires distributed, resulting in a response rate of 58.7%. The participation in the study was purely voluntary and anonymous.

Non-response bias was evaluated by comparing the characteristics of early responders (the first 25%) and late responders (the last 25%) using the procedure outlined by Armstrong and Overton (1977). Independent-samples t-tests indicated no significant difference between early and late responders (all $p > .10$).

3.3. Measurement, Validity, and Common Method Bias

Measurement Instrument: The survey questions were taken from previous validated scales. Four questions on data mining speed were taken from Cheng et al. (2020) and Monfared and Akbari (2019). Four questions on the use of simulation were taken from Sharda et al. (2020) and Alolayyan et al. (2022). Five questions on the use of analytics were taken from Tripathi et al. (2020) and English and Hoffmann (2018). Six questions on workforce agility were taken from Seyadi and Elali (2021) and Nyamrunda and Freeman (2021). The items were adapted to the banking context while preserving their original conceptual meaning. All the questions were answered on a five-point Likert scale from strongly disagree to strongly agree.

Translation and Pilot Testing: To achieve conceptual equivalence, the instrument was back-translated from English to Arabic. In the pilot study conducted among 35 bank employees, several items were unclear and required clarification to provide better context for the study. The time taken to complete the questionnaire was assessed by the pilot participants.

Validity and Reliability: The model's content validity was assessed by three scholars specializing in information systems and organizational behavior. Construct validity was assessed using CFA. Convergent validity was established through factor loadings greater than 0.70 and AVE greater than 0.50. Discriminant validity was established based on both the Fornell-Larcker criterion and HTMT values lower than 0.85. Reliability was assessed using Cronbach's alpha, and CR values greater than 0.80.

Common Method Bias: Because the research design relied on self-reports, various procedural and statistical techniques were employed to minimize Common Method Bias (CMB). The former involved anonymity, separation of the predictor from the outcome variables, and inclusion of one reverse-scored question. As for statistics, Harman's single-factor analysis revealed that the first factor explained only 28.7% of the variance, less than the suggested 50%. Additionally, a marker-variable approach was implemented following Lindell and Whitney (2001). Also, there was no correlation between the marker variable, which is theoretically unrelated to the dependent variable, "my work computer runs efficiently" ($r = 0.03$, $p = 0.48$).

3.4. Data Analysis, Model Assessment, and Robustness Procedures

Data Analysis Strategy: SPSS version 29 and SmartPLS 4 were used for data analysis. PLS-SEM was chosen because the research involved prediction, theory development, multiple latent variables, moderation, and the evaluation of explained variance and predictive relevance. Descriptive statistics, measurement model evaluation, and PLS-SEM analysis were done. Standard error and confidence interval were obtained through 5,000 bootstrap samples. The moderating effect of the bank type (commercial bank = 0; Islamic bank = 1) was evaluated using the product indicator method. Multicollinearity was evaluated using VIF values, which ranged from 1.48 to 2.31, all falling below the 5 threshold.

Model Fit and Predictive Relevance: Model fit was assessed using the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI). The predictive validity was assessed using Stone-Geisser's Q^2, computed via a blindfolding procedure. These indices were selected to evaluate both overall model adequacy and predictive capability within the PLS-SEM framework.

Multi-Group Analysis and Measurement Invariance: Jordan and Malaysia have been compared using Multi-Group Analysis (MGA) to assess the Measurement Invariance of Composite Models (MICOM) method, as suggested by Henseler et al. (2016). The results show that configural and compositional invariances hold, implying partial measurement invariance, thus enabling path coefficient comparison. Permutation tests were then used to estimate p-values for cross-country differences.

E-Value Sensitivity Analysis: An e-value sensitivity analysis was conducted following VanderWeele and Ding (2017) to assess the potential impact of unobserved confounders on the strongest observed relationship in the model. An E-value refers to the value of the association that the unobserved confounder should have with the predictor variable as well as the outcome to completely eliminate the relationship in question. The E-value computed in this study is 2.43.

Robustness Checks**:** Two more robustness tests were conducted. The first included quadratic terms for each BI dimension to investigate possible diminishing-returns effects (Doz, 2020). The addition of quadratic terms did not yield any statistically significant results, thereby confirming the validity of the chosen linear model. In the second test, the structural model was re-estimated using covariance-based structural equation modeling (CB-SEM) with maximum likelihood estimation, implemented via the Lavaan package in R. Path coefficients calculated by means of CB-SEM showed high consistency with those calculated in PLS-SEM (analytics usage = 0.46 vs. 0.44; simulation usage = 0.31 vs. 0.30; data mining speed = 0.24 vs. 0.23).

3.5. Ethical Considerations and Methodological Limitations

Ethical Considerations: Ethical clearance for the research was obtained from the IRB of The International University, Jordan, on 12 May 2026. All participants took part voluntarily, and their consent was obtained electronically prior to data collection. The purpose of the study, the voluntary nature of participation, and the right to withdraw without penalty were explained to all participants. All participant information was anonymized and stored on secure servers accessible only to the research team. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki (World Medical Association, 2013) and applicable institutional guidelines governing social science research involving human participants.

Methodological Limitations: A number of methodological issues are important to consider. Firstly, the cross-sectional research design precludes causal inference. Thus, all associations described are purely associative, and no causality can be inferred from the results. Secondly, the research employed subjective measures of BI application, such as respondents' perceptions of the extent of BI use, rather than objective indicators at the system level. Thirdly, a non-probability sampling approach was adopted, which may limit the generalizability of the findings. Finally, although measures ensured the reliability and validity of the findings, more longitudinal research and multi-source studies would have further validated them and helped establish causal pathways in the BI-agility relationship.

4. Results

4.1. Non-Response Bias Test

The initial and final 25% of the respondents (n = 103) were analyzed for similarities and differences using an independent-samples t-test, as described by Armstrong and Overton (1977). No significant differences were found on the four main variables of the study, as shown in Table 1 below. These results suggest that non-response bias is unlikely to affect the findings.

Table 1. Non-response bias test: early vs. late respondents

Variable	Early respondents (n=103) mean (SD)	Late respondents (n=103) mean (SD)	t-value	p-value
Data Mining Speed	3.84 (0.67)	3.80 (0.71)	0.42	0.68
Simulation Usage	4.03 (0.62)	3.99 (0.66)	0.45	0.65
Analytics Usage	4.20 (0.59)	4.16 (0.63)	0.48	0.63
Workforce Agility	4.09 (0.56)	4.05 (0.60)	0.50	0.62

Note: Equal variances assumed (Levene's test $p > 0.05$ for all variables), Standard Deviation (SD).

4.2. Respondents Demographic Profile

The total number of questionnaires collected was 412, with 412 valid responses from employees in commercial and Islamic banks in Jordan and Malaysia. The demographic profile of the respondents is illustrated in Table 2 below. The sample was quite balanced with respect to both countries, although more commercial bank participants were included than those from Islamic banks. The sample also included different age groups and levels of work experience, adding heterogeneity.

Table 2. Demographic characteristics of respondents (n = 412)

Variable	Category	Frequency	Percentage (%)
Gender	Male	231	56.1
	Female	181	43.9
Age	Less than 30 years	98	23.8
	30–39 years	176	42.7
	40–49 years	102	24.8
	50 years and above	36	8.7
Banking Type	Commercial banks	287	69.7
	Islamic banks	125	30.3
Country	Jordan	214	51.9
	Malaysia	198	48.1
Work Experience	Less than 5 years	84	20.4
	5–10 years	173	42.0
	More than 10 years	155	37.6

4.3. Descriptive Statistics of Study Variables

Table 3 displays the means and Standard Deviations (SDs) for the three BI dimensions and workforce agility. Analytics usage had the highest mean, followed by workforce agility, simulation usage, and data mining speed.

Table 3. Descriptive statistics

Variable	Mean	Standard deviation
Data Mining Speed	3.82	0.69
Simulation Usage	4.01	0.64
Analytics Usage	4.18	0.61
Workforce Agility	4.07	0.58

4.4. Measurement Model Assessment

Reliability and validity were assessed prior to hypothesis testing. Table 4 reports Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Cronbach's alpha and CR values were greater than 0.80, and all AVE values were above 0.65, indicating adequate reliability and convergent validity for all measures.

Table 4. Reliability and convergent validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Data Mining Speed	0.84	0.88	0.65
Simulation Usage	0.87	0.90	0.69
Analytics Usage	0.89	0.92	0.72
Workforce Agility	0.91	0.93	0.74

Discriminant validity was evaluated using the Fornell-Larcker criterion (Table 5). For each construct, the square root of the AVE (diagonal elements) was greater than its correlations with other constructs. Heterotrait-Monotrait (HTMT) ratios for all construct pairs were below 0.85 (highest = 0.78), providing additional evidence of discriminant validity and confirming adequate distinction among the latent constructs.

Table 5. Fornell-Larcker discriminant validity (square roots of ave on diagonal)

Construct	DMS	SU	AU	WA
Data Mining Speed (DMS)	0.81			
Simulation Usage (SU)	0.56	0.83		
Analytics Usage (AU)	0.61	0.67	0.85	
Workforce Agility (WA)	0.64	0.71	0.78	0.86

Note: All correlations are significant at $p < 0.01$.

4.5. Bivariate Correlations

Table 6 presents the Pearson correlation matrix. All BI dimensions were positively and significantly correlated with workforce agility. Analytics usage showed the strongest correlation with workforce agility, followed by simulation usage and data mining speed.

Table 6. Pearson correlation matrix

Variable	1	2	3	4
1. Data Mining Speed	1.00			
2. Simulation Usage	0.56**	1.00		
3. Analytics Usage	0.61**	0.67**	1.00	
4. Workforce Agility	0.64**	0.71**	0.78**	1.00

**$p < 0.01$ (two-tailed).

4.6. Structural Model Fit and Predictive Relevance

The Standardized Root Mean Square Residual (SRMR) was .061, which is less than .08. A Normed Fit Index (NFI) of .91 also indicates a good fit. R^2 (coefficient of determination) for Workforce Agility was .69. The Q^2 statistic from blindfolding was .42. These indicators demonstrate satisfactory model fit and predictive relevance. Taken together, these indicators suggest satisfactory model adequacy, explanatory power, and predictive capability.

4.7. Hypothesis Testing Results (H1a–H1c)

Table 7 summarizes the path coefficients, standard errors, t-values, bias-corrected 95% confidence intervals, and p-values for H1a–H1c

Table 7. Structural model and hypothesis testing results (H1a–H1c)

Hypothesis	Path	β	SE	t-value	95% BCa CI	p-value	Decision
H1a	DMS → Workforce Agility	0.24	0.055	4.37	[0.135, 0.345]	<0.001	Supported
H1b	SU → Workforce Agility	0.31	0.053	5.82	[0.207, 0.413]	<0.001	Supported
H1c	AU → Workforce Agility	0.46	0.057	8.11	[0.349, 0.571]	<0.001	Supported

Note: DMS = Data Mining Speed, SU = Simulation Usage, AU = Analytics Usage. BCa CI refers to the bias-corrected and accelerated confidence interval calculated using 5,000 bootstrap resamples.

There were significant positive associations between all three aspects of BI and workforce agility. The strongest standardized path coefficient was observed for analytics utilization (β = 0.46), indicating that the ability to analyze information contributes more to workforce agility than quick access to data. Simulation utilization had a moderate impact on workforce agility (β = 0.31), whereas data mining speed had the smallest impact among the three predictors (β = 0.24). These findings show that all three dimensions of BI are significantly related to workplace agility, though the strength of each relationship varies for each dimension.

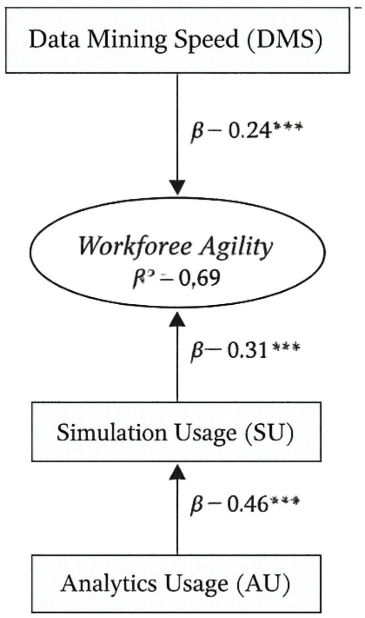

Fig. 2. Structural model results

Note. β = standardized path coefficient; R^2 = coefficient of determination for workforce agility; *** $p < 0.001$.
Effect sizes (f^2) for each predictor are presented in Table 8.

4.8. Moderation Analysis: Bank Type (H2)

To test H2, which posits that bank type moderates the relationships between BI and agility, the product indicator technique in PLS-SEM was applied. Commercial banks were coded 0, whereas Islamic banks were coded 1. The interaction results are presented in Table 9.

Table 8. Effect sizes (f^2)

Predictor	f^2	Effect Size Interpretation
Data Mining Speed	0.12	Small to medium
Simulation Usage	0.21	Medium
Analytics Usage	0.34	Large

Table 9. Moderation Effects of Bank Type (Commercial vs. Islamic)

Interaction Path	β (interaction)	SE	t-value	p-value	95% CI	Decision
DMS × Bank Type → Workforce Agility	-0.03	0.042	0.71	0.48	[-0.112, 0.052]	Not significant
SU × Bank Type → Workforce Agility	0.02	0.038	0.53	0.60	[-0.054, 0.094]	Not significant
AU × Bank Type → Workforce Agility	-0.05	0.045	1.11	0.27	[-0.138, 0.038]	Not significant

None of the interaction terms was statistically significant. H2 is rejected. These results show that no statistically significant relationship exists whereby bank type changes the impact of BI dimensions on employee agility in the sampled banks.

4.9. Multi-Group Analysis: Jordan vs. Malaysia

Tests of Measurement Invariance of Composite Models (MICOM) were conducted prior to the multi-group analysis. The results of the MICOM assessment supported both configural invariance and compositional invariance, thereby establishing partial measurement invariance and enabling meaningful comparisons of structural relationships across countries.

Table 10 shows the path coefficients and their permutation-based p-values for the differences in each country.

Table 10. Multi-group analysis (Jordan vs. Malaysia)

Path	Jordan (n=214) β	Malaysia (n=198) β	Permutation p-value (difference)
DMS → Workforce Agility	0.29	0.20	0.18
SU → Workforce Agility	0.33	0.29	0.42
AU → Workforce Agility	0.42	0.51	0.09

Note: Permutation p-values based on 5,000 permutations. None are significant at $p < 0.05$.

The p-values for all permutation-based comparisons failed to reach statistical significance at the 0.05 level. Therefore, no statistically significant differences were identified between Jordanian and Malaysian respondents regarding the structural relationships examined in the model.

4.10. Sensitivity and Robustness Analyses

An E-value sensitivity analysis following VanderWeele and Ding (2017) yielded an E-value of 2.43 for the relationship between analytics usage and workforce agility. This represents the minimum strength of association that an unmeasured confounding variable would need to have with both variables in order to completely account for the observed relationship.

Quadratic terms were included for each BI dimension to examine potential non-linear or diminishing-returns effects. The findings are presented in Table 11.

Table 12 compares the PLS-SEM path coefficients with those obtained from covariance-based SEM (CB-SEM) using maximum likelihood estimation in lavaan (R).

All coefficients remained statistically significant ($p < 0.001$) across both estimators, supporting the robustness of the findings. The similarity in the estimates obtained through the two methods further substantiates the robustness and stability of the reported relationships across different estimation approaches.

Table 11. Quadratic term robustness check

Path	β	SE	t-value	p-value	95% CI
DMS^2 → Workforce Agility	-0.02	0.021	0.95	0.34	[-0.061, 0.021]
SU^2 → Workforce Agility	0.03	0.024	1.25	0.21	[-0.017, 0.077]
AU^2 → Workforce Agility	-0.04	0.024	1.67	0.09	[-0.087, 0.007]

None of the quadratic coefficients were statistically significant at $\alpha = 0.05$, indicating that linear associations are adequate.

Table 12. Comparison of PLS-SEM and CB-SEM coefficients

Path	PLS-SEM β	CB-SEM β	Difference
DMS → Workforce Agility	0.24	0.23	0.01
SU → Workforce Agility	0.31	0.30	0.01
AU → Workforce Agility	0.46	0.44	0.02

5. Discussion

5.1. Interpretation of Main Findings

This research explored three aspects of BI: data mining speed, simulation use, and analytics use as predictors of workforce agility in the Banking sector of Jordan and Malaysia. In addition, there were no moderating effects of bank type, nor were there statistically significant differences between the countries studied (Jordan and Malaysia). These findings are consistent with DDDM theory, which identifies the use of analytical evidence as an important mechanism through which organizations can improve their ability to interpret, predict and respond to changing conditions under uncertainty (Sharda et al., 2020). More specifically, the findings suggest that BI capabilities related to information interpretation and decision support are more strongly associated with workforce agility than capabilities primarily concerned with information access and retrieval. The findings extend prior organizational-level BI research to employee-level agility outcomes.

Simulation use was found to be strongly positively associated with workforce agility. Simulation use may improve employees preparedness and adaptive response capabilities. This finding is consistent with the Dynamic Capabilities Perspective, where it is argued that organizations can improve their responsiveness through the capabilities of “sensing” and “adaptive preparedness” (Schoemaker et al., 2018) as well as with past studies that have demonstrated an association between the utilization of forecasting and simulation tools with operational flexibility and adaptability (Doz, 2020; Seyadi and Elali, 2021). Additionally, this study suggests that using simulation tools may help employees evaluate alternative scenarios before operational challenges arise, thereby improving organizational preparedness and enhancing workforce adaptability under uncertainty.

The correlation between data mining speed and workforce agility was the lowest of all correlations in this study. It also demonstrated a statistically significant relationship. Therefore, the findings provide partial support for DeLone and McLean’s (2003) “Information Systems Success Model”, in which both the quality of information systems and the level of access to them are seen as important factors in an organization’s success. However, while the quality of the information provided by data mining is very important for workforce agility, it is even more important how quickly that information can be analyzed and interpreted. These findings suggest that analytical interpretation contributes more strongly to workforce agility than rapid data retrieval alone.

However, this does not undermine the significance of system quality or timely access to information. Rather, it indicates that information accessibility and analytical capabilities may function as complementary competencies, with analytical capabilities exhibiting a relatively stronger association with workforce agility.

The multigroup analysis did not show statistically significant differences between Jordan and Malaysia. These results suggest similar patterns or relationships exist between BI capabilities and workforce agility in emerging banking environments, regardless of variance in technology development and the state of digital infrastructure. Similarly, no moderation effects were observed by bank type. That is, both commercial and Islamic banks appear to benefit similarly with regard to workforce agility as a result of BI capability.

The absence of statistically significant differences among the countries in this study suggests that the relationship between BI capability and workforce agility is consistent across the two banking systems studied. However, these results should be viewed with caution due to the limited number of countries (only two). Further studies examining a larger variety of institutions will allow for stronger conclusions about the applicability of these relationships across national boundaries.

Additionally, there were no significant moderating effects of bank type, indicating that the advantages of BI capabilities may be applicable regardless of banking model. Commercial and Islamic banks have different governance structures and regulatory environments. However, no empirical evidence was found to support differences in the relationships between BI capabilities and workforce agility across both banking systems.

5.2. Theoretical Implications

The research contributes to the BI and workforce agility literature in three ways. First, the findings provide stronger support for DDDM theory than for IS Success Theory by emphasizing the importance of interpretive analytics over processing speed alone. Second, the results suggest that BI needs to be regarded as a multidimensional concept, as the use of analytics, the use of simulations, and the speed of data mining showed varying relationships with the agility of the labor force, with the use of analytics showing the strongest relationship.

The findings above contribute to current discussions on how Business Intelligence capabilities can be conceptualized and demonstrate that different dimensions of BI can affect employee-level outcomes in distinct ways. Conceptualizing Business Intelligence as an integrated construct allows researchers to measure the impact of individual BI capabilities separately rather than assuming that each component of BI has the same impact.

Third, since the data indicate very little, if any, moderation by country or bank type, this supports the hypothesis that the link between Business Intelligence capabilities and employee-level Agility may hold true regardless of the institutional environment or banking type in Emerging Markets.

The results from this study provide initial evidence that some BI-related mechanisms operate similarly (in terms of how they are linked with workforce agility) across different organizational levels and types within new banking system environments. To confirm these results, additional research will be required. The data suggest a degree of contextuality in the relationship between BI capability and the agile workforce. Finally, the E-value testing for unobserved confounders enhances the overall transparency of the methods used to assess potential unobserved confounders.

E-value sensitivity analysis represents an additional methodological approach that addresses the growing emphasis on rigor in observational management research. Although such analyses cannot fully resolve concerns about omitted variables, they provide valuable information about the robustness of observed relationships and support a more transparent interpretation of empirical findings.

5.3. Practical Implications

Banking institutions seeking to enhance their organizational flexibility should consider investing in analytics and simulation, as well as in employees digital and analytical skills. The results indicate that BI capabilities that offer interpretation and prediction have a stronger influence on organizational flexibility than speed alone. Furthermore, both conventional and Islamic banks can pursue the same BI strategy to enhance organizational flexibility, although certain technical modifications are required due to compliance issues (Nyamrunda and Freeman, 2021).

From a managerial perspective, it can be argued that while there is a need to invest in BI infrastructure, there is an equal need to invest in employees skills to analyze data, consider alternative strategies and incorporate evidence-based thinking into decision-making.

At the same time, the importance of simulation training programs, scenario planning approaches and decision support systems can be emphasized. The adoption of such tools can lead to improved employee preparedness, more effective responses to environmental changes, and greater workforce agility within banks.

Moreover, managers should keep in mind that technological advancements alone cannot bring about workforce agility. Activities aimed at developing analytical thinking, learning and evidence-based decision-making can play an equally crucial role.

5.4. Limitations and Future Research Directions

Several limitations must be considered. First, the cross-sectional nature of the study prevents causal interpretation. Both directions of effect are possible, and other variables, such as organizational culture, leadership, and technological advancement, may also affect the use of BI and workforce agility. Even though there was some level of robustness found through the use of E-value analysis, no causal inference can be made.

Second, all variables were based on self-reports, which may introduce perception bias and common method variance. Although the former appeared relatively low, it would be useful to find alternative data sources for further studies, such as BI system utilization logs, supervisor evaluations, or operational responses to BI.

Third, the study's sampling strategy was non-probability, drawing on bank employees from two developing countries. There is a need to validate the hypotheses in other nations and sectors, such as insurance, fintech, and retail banking.

Fourth, the possible mediating constructs linking BI skills to workplace agility have not been explored. It is necessary to test factors such as decision quality, role clarity, psychological empowerment, and organizational learning as possible mediators.

In future research, researchers could also consider other potential mechanisms by which BI contributes to workforce agility, including knowledge-sharing practices, digital competencies, employee commitment and organizational learning capabilities, to build on this study's findings.

Finally, the use of multi-group analyses can also result in lower-than-expected statistical power due to limited sample sizes, thereby reducing the likelihood of detecting statistically significant moderator effects in context.

Further research may employ longitudinal research designs, multi-source data, and objective measures of BI utilization to strengthen causal inferences and minimize potential measurement bias. In addition, multilevel research designs may provide a clearer understanding of how organizational-level BI capabilities interact with individual-level factors to influence workforce agility over time.

6. Conclusion

This study assessed the relationship between three BI, namely data mining speed, simulation usage, and analytics usage, and workforce agility in Jordanian and Malaysian banks. Using a cross-sectional study of 412 bank employees and PLS-SEM analysis, this study found that the three BI dimensions were significantly and positively associated with workforce agility. The strongest relationship was found in analytics usage, followed by simulation usage, and the weakest in data mining speed. Multi-group analysis showed no significant differences between Jordanian and Malaysian banks, nor between bank types (commercial and Islamic). The E value of 2.43 for the main effect shows a moderate degree of robustness against omitted variable bias, but causality cannot be established. This study contributes to the body of knowledge in BI and workforce agility literature by operationalizing BI dimensions and comparing two emerging banking systems.

These results add to theory by demonstrating that different dimensions of BI exhibit varying degrees of association with workforce agility, thereby supporting the conceptualization of BI as a multidimensional capability rather than a single organizational resource. Furthermore, the stronger association with analytics usage underscores the importance of interpretive and decision-support capabilities in enhancing employee adaptability in dynamic banking environments. The study adds to methodological knowledge by integrating cross-country comparative research, moderation research and an E-value sensitivity assessment for analyzing the relationship's robustness and contextuality. However, there are several constraints for this type of study. First, the cross-sectional design limits causal interpretation. Second, self-reports may create perceptual bias. Third, non-probabilistic sampling restricts generalization. Future studies will be able to improve the validity of their results and better understand the mechanisms underlying the association between BI agility when longitudinal designs are employed, objective systems-based measurement tools are utilized, and larger samples of institutions are examined.

From a practical perspective, these findings suggest that banking institutions could improve their use of BI as an investment by adding employee development strategies (e.g., improving analytical abilities and using simulations) to support employees in making data-driven decisions. In this way, banks can maximize the potential value they receive from their BI systems and be more agile within rapidly changing digital banking marketplaces.

Future studies should also continue to investigate how workforce agility is facilitated by BI capabilities through potential mediating factors such as decision quality, organizational learning, psychological empowerment and knowledge-sharing processes. These studies should be conducted across additional countries, industries and institutional contexts to enhance the generalization of relationships found in this study.

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Institutional Review Board Statement

The study received ethical approval from the Institutional Research Ethics Committee (IRB) of The International University, Jordan, on 12 May 2026. Participation was voluntary, electronic informed consent was obtained from all participants prior to data collection, and all responses were anonymized and treated confidentially. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki (World Medical Association, 2013) and applicable institutional guidelines governing social science research.

Declaration of Artificial Intelligence (AI) Tools

Grammarly was used solely for minor language editing and to improve readability. The author reviewed and verified all content and takes full responsibility for the accuracy and integrity of the manuscript.

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Maryam Khalid Obeidat is a Lecturer in the Department of Computer Information Systems, King Abdullah College of Information Technology, at the University of Jordan. She holds a master's degree in business intelligence and Data Analysis from the University of Jordan. Her academic and research interests include business intelligence, data analytics, information systems, digital transformation, decision support systems, artificial intelligence applications in organizations, and workforce agility. She is currently engaged in teaching and research in information systems and business analytics**.**