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A Multi-Dimensional Model of Supply Chain Digitization, AI, and HRM Effectiveness for Sustainable Outcomes

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ABSTRACT

This research constructs and empirically tests a multi-dimensional model of the impacts of Supply Chain Digitization (SCD), Big Data Analytics-Artificial Intelligence (BDA-AI) and Supply Chain Agility (SCA) on Overall Sustainable Supply Chain Performance (OSSCP), and explores the moderating role of HRM (AI) Acceptance and Perceived HR Effectiveness. It utilized a quantitative, cross-sectional research design that involved the collection of primary data through structured questionnaires of 300 supply chain professionals in Pakistani logistics companies based on purposive sampling (Amin et al., 2023). Direct, mediating, and moderating relationship tests were conducted with the use of structural equation modeling (SEM). Results substantiate that SCD is positively related to BDA-AI and SCA which in turn mediate between SCD and OSSCP which supports the Resource-Based View and Dynamic Capabilities Theory. Almelhem et al. (2025) Although HRM (AI) Acceptance did not play any significant role in moderating the hypothesized relationships, Perceived HR Effectiveness significantly mediated the connection between SCD and SCA, which underscores the importance of aligned HR practices in enhancing the digital transformation effects. The research has theoretical implications, as it combines technological and human aspects of supply chain sustainability and offers practical suggestions to managers on how to strategically invest in digitization, analytics, agility, and efficient HR practices in order to improve sustainable supply chain performance. Discussion of limitations and future research directions are provided.

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1. Introduction

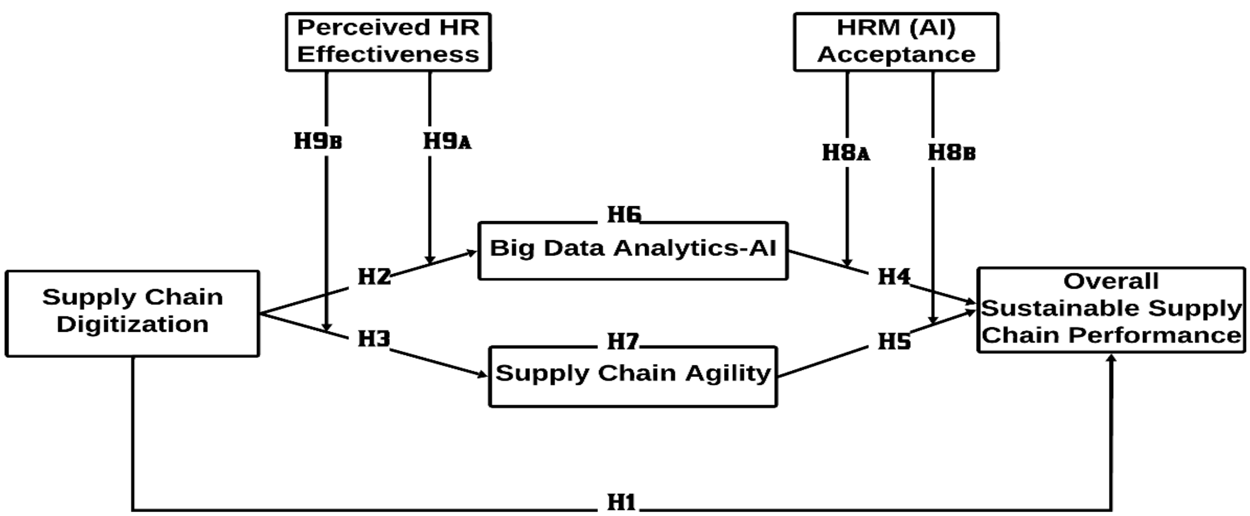
Sustainability is no longer a sidelining issue it has become a performance driver in the supply chain that are no longer judged in terms of effectiveness and service provision but also on their ability to produce integrated economic, environmental, and social results across various partners. This change is motivated by the realization that material sustainability impacts, such as emissions, waste, labor practices, resource consumption, all take place over longer value chains and not in the immediate operations of the firm (Al Tera, Alzubi, & Iyiola, 2024). Three integrated contributions are made in this paper. First, it goes past direct-effects reasoning by simulating sustainable performance as the outcome of capability-building by means of digitization. Second, it streamlines dual mediation through the Big Data Analytics-AI (BDA-AI) and Supply Chain Agility (SCA), which is limited by single-mechanism explanations. Third, it presents HR boundary conditions (HRM AI Acceptance and Perceived HR Effectiveness) to understand why certain digitizing supply chains are more successful than others. Khan, Khan and Aslam (2024) There are a number of gaps in the literature.

The majority of the empirical research is on direct impacts or individual mediators, which provide limited answers to the questions of how digitization can contribute to sustainability. Moreover, theories to explain why digitization concentrates differently results, especially when it comes to contingencies between people and systems, are still in development. As explained by Khan, Parahyanti and Hussain (2024) that the concept of AI acceptance has not been popularly operationalized into an organizational boundary condition in the sustainability models. Also, the majority of the available studies are based on self-reported, cross-sectional designs, which restrict causal inference (Bag et al., 2021). Research Questions test the relationships between Supply Chain Digitization (SCD) and the specified relationships; the mediating effect of BDA-AI and SCA; and the moderating roles of HRM AI Acceptance and Perceived HR Effectiveness. The Research Objectives provide answers to each of these questions in a structured and systematic way, and will seek to establish the strength and direction of these relationships, including mediating and moderating processes, and how digitization, analytics, agility and HR factors combine to achieve sustainable supply chain results (Atieh Ali et al., 2024).

2. Literature Review

The literature review lays the theoretical and empirical groundwork of how Supply Chain Digitization (SCD), Big Data Analytics-Artificial Intelligence (BDA-AI), Supply Chain Agility (SCA), HRM (AI) Acceptance, and Perceived HR Effectiveness (HRE) have a cumulative effect on Overall Sustainable Supply Chain Performance (OSSCP). Narimissa, Kangarani-Farahani and Molla-Alizadeh-Zavardehi (2020) Generally, the concept of Overall Sustainable Supply Chain Performance (OSSCP) is a multi-dimensional construct that represents the triple bottom line, which is economic, environmental, and social results. In comparison to the traditional performance measures, which are based on cost and efficiency, OSSCP considers ecological stewardship and social responsibility as driving forces of performance (Bag, Gupta, & Wood, 2022). The literature highlights that OSSCP is a network level operation that goes beyond firm-level, and the scope. Multi-tier response to suppliers, sharing information and joint governance among supply chain partners are likely to lead to sustainable outcomes. Therefore, the realization of OSSCP needs not only the internal organizational work but also the common standards, monitoring systems, and relational coordination. OSSCP has three dimensions: economic (cost-efficiency, productivity, service levels, competitiveness); environmental (emission reduction, energy and resource efficiency, waste minimization); and social (labor conditions, sourcing ethically, human rights, stakeholder welfare) (Ozen, Zorlu, & Karabulut, 2025). These dimensions can either be complementary to each other or there can be trade-offs, which makes OSSCP an aggregate measure of collective sustainability results. Methodologically, measurement has been a thorn in the flesh; scholars usually depend on perceptual measures by managers because it is hard to get objective measures of sustainability within multi-tier networks. Others consider OSSCP a more advanced reflective construct and others use a formative composite method. Queiroz and Wamba (2022) The critical mechanisms of governance, including supplier codes of conduct, audits, certifications, and collaborative programs, are important in operationalizing sustainability outside the focal firm. OSSCP is therefore positioned as the final dependent variable in digitization-capability-HR models where by the digital technologies and organizational processes are converted to quantifiable sustainability improvements. The term Supply Chain Digitization (SCD) means the use of modern digital technologies (AI, blockchain, IoT, cloud computing, and big data analytics) to automate operations, allow real-time data gathering, improve transparency, and make decisions (Dubey et al., 2021). Digitization is placed as a strategic asset that develops competitive advantage through generating efficiency, traceability and responsiveness. Big Data Analytics-AI (BDA-AI) is a type of machine learning, predictive analytics, and AI applied to structured and unstructured supply chain data. The technologies offer predictive insights, maximize resource utilization, strengthen integration, agility, resilience, and sustainability (Zhang, Sun, & Huo, 2023).

Figure 1: Research Framework



BDA-AI is progressively perceived to be revolutionary to supply chain operations. The ability to react swiftly to market fluctuations, customer requirements and other unforeseeable disturbances is referred to as Supply Chain Agility (SCA). Agility includes the adaptive operations, quick decision-making, and flexibility in sourcing, production, and distribution. (Karameros, Chassiakos, & Tryfonas, 2025) It plays a critical role in remaining competitive and attaining the objectives of sustainability in volatile environments. HRM (AI) Acceptance is the readiness of the employees and managers to use AI-based HR systems in recruitment, performance evaluation, and learning and development. It encompasses the attitudes, perceptions, and willingness to embrace AI in HR practices (Dubey et al., 2022). Perceived HR Effectiveness (HRE) is the perceptions of employees on the effectiveness of the HR department in serving organizational objectives, such as the delivery and support of digital and AI-powered HR systems (Tiwari et al., 2024). The two constructs emphasize the human aspect of digital transformation. The literature also mentions that digital technologies (IoT, blockchain, analytics) provide increased transparency, traceability, and accountability, which have a direct positive impact on OSSCP. Other areas, like environmental cooperation between supply chain members, including joint emission reduction plans, resource sharing, sustainability-oriented innovation, also enhance OSSCP, especially in the case of Scope 3 emissions. As mentioned by Ivanov (2022), the presence of institutional factors, pressure on organizations (such as EU Corporate Sustainability Due Diligence Directive) and a responsibility-oriented organizational culture have a favorable impact on OSSCP. Lastly, AI and optimization algorithms make it possible to anticipate analytics, plan for scenarios, and do intelligent optimization, which is an unmistakable direction towards technology-driven decision-making as a point of force in enhancing sustainable supply chain performance.

3. Data and Methodology

This work utilized a quantitative research design that included descriptive and explanatory as well as cross-sectional factors to analyze the relationships between Supply Chain Digitization (SCD), Supply Chain Integration (SCI), Supply Chain Agility (SCA), Supply Chain Resilience (SCR), Big Data Analytics-Artificial Intelligence (BDA-AI), Overall Sustainable Supply Chain Performance (OSSCP), The target population included employees of Pakistan and international logistics and supply chain firms that are active in digital transformation and sustainability efforts, as they were chosen based on their involvement in such efforts. A purposive sampling was used to focus on supply chain managers, operations managers, digital transformation officials, HR managers, and sustainability managers. The determination of the sample size was based on Structural Equation Modeling (SEM) principles whereby a minimum of ten responses to each observed variable were needed to give a target of 300 respondents to give sufficient statistical power and model stability. Structured questionnaires on demographics, supply chain digitization, capabilities (SCA, BDA-AI), OSSCP, HRM(AI) acceptance, and perceived HR effectiveness were used to gather primary data. A questionnaire survey was conducted through email, WhatsApp, and Google Forms. Multi-item Likert-type scales (1 strongly disagree) through 5 strongly agree) were used to measure all constructs. The questionnaire was refined on a pilot study of 50 respondents to identify the clarity, consistency and reliability of the questionnaire, which reached a Cronbach's Alpha of 0.90. The purposive (non-probability) sampling was also explained because it was the right choice to sample professionals that have direct experience in supply chain management, digital transformation, and AI-driven HRM. The industry directories, LinkedIn, professional associations, and internal websites were used as recruitment resources. This sampling method was considered appropriate considering the complexity of the research model and the requirement to have informed respondents who would be able to give relevant and accurate data.

4. Data Analysis and Results

The demographic analysis gave a summary of the population of the respondents in this study. The following table is a summary of the demographic characteristics of the respondents in terms of gender, marital status, age, education level and work experience. The gender distribution was fairly equal with most of the respondents being male (59.70) as opposed to female (40.30). Marital status, the greatest number of respondents were married people (70.70%), and fewer were unmarried (29.30%). The age distribution reveals that, the respondents are more concentrated towards older age groups with the highest proportion of 56 and above age group (36.70%), and the second group is the 18-30 age group (24.00%). On education, the majority of the respondents were graduate students who acquired an advanced degree with 45.70% attaining M.Phil./PhD and 24.70% attaining Master degree. There was a low percentage of those who had finished in intermediate or matriculation (14.30%). The number of years working experience was the greatest with 21-30 years of experience among the highest respondents (28.00%), 31 and above years (33.70%), which was an indicator of an experienced worker. These demographic variables are analyzed to give an understanding of the points of view and the insights that the respondents put forward in this study.

Table 1: Demographic Variables

Demographic Variables	Details	Responses	Percentage
Gender	Male	179	59.70
	Female	121	40.30
Marital Status	Unmarried	088	29.30
	Married	212	70.70
Age	18-30	072	24.00

	31-43	061	20.30
	44-55	057	19.00
	56 and above	110	36.70
Education Level	Matriculation	012	04.00
	Intermediate	031	10.30
	Bachelor	046	15.30
	Master	074	24.70
	M.Phil./PhD	137	45.70
Experience	1-10 Years	044	14.70
	11-20 Years	071	23.70
	21-30 Years	084	28.00
	31 and above Years	101	33.70

Descriptive statistics are vital in giving a clear and concise summary of the vital characteristics of the data obtained in the course of conducting the research. Descriptive statistics will enable a researcher to have an idea of the underlying pattern in the data before undertaking more analysis by studying the central tendencies, dispersion, and shape of the distribution. In this area, the descriptive statistics of each variable in the study are presented. The mean, standard deviation, skew, and excess kurtosis are the statistics used, which are very informative on the nature of the responses. The descriptive statistics of each item are tabulated in Table 2, which contains the mean, the standard deviation, excess kurtosis, and the skewness. The average of the items lies between 3.570 and 4.060 implying that there is an overall high trend of response across the items. The level of standard deviation ranges between 0.961 and 1.340 which indicates that the responses are not only widely varied. Majority of the items are showing negative skewness that is, the data is slightly biased towards the left so that values are more towards the upper portion of the scale. This implies that the respondents tend to grade the items highly. The values of excess kurtoses are largely positive indicating that there is a more peaked distribution as compared to the normal distribution especially to the item of OSSCP6 (1.042), OSSCP8 (1.176), and OSSCP16 (1.090). The findings suggest that, although majority of the responses are concentrated around the mean there are at times extreme responses that are used to make up the total distribution. The descriptive statistics offer a background conception of the overall nature of the data and its preparation in the form of additional statistical test.

Table 2: Descriptive Statistics

Items	Mean	Standard deviation	Excess kurtosis	Skewness
BDA1	3.783	1.187	0.223	-1.039
BDA2	3.937	1.116	0.777	-1.161
BDA3	3.833	1.131	0.384	-1.002
BDA4	3.787	1.222	0.128	-1.027
BDA5	3.833	1.151	0.333	-1.027
BDA6	3.867	1.156	0.338	-1.053
BDA7	3.880	1.134	0.292	-1.017
HRE1	3.830	1.149	-0.031	-0.868
HRE2	3.823	1.145	0.199	-0.973
HRE3	3.877	1.117	0.082	-0.908
HRE4	3.837	1.106	-0.003	-0.861
HRE5	3.907	1.091	0.309	-0.989
HRE6	3.873	1.118	0.060	-0.898
HRE7	3.870	1.058	0.187	-0.875
HRE8	3.890	1.107	0.620	-1.086
HRE9	3.693	1.183	-0.073	-0.832
HRMAI1	3.820	1.132	0.227	-0.931
HRMAI2	3.777	1.096	-0.086	-0.786
HRMAI3	3.763	1.244	-0.094	-0.953
HRMAI4	3.717	1.170	0.027	-0.875
OSSCP1	3.807	1.167	-0.030	-0.895

OSSCP10	3.983	1.085	0.990	-1.227
OSSCP11	3.843	1.171	0.364	-1.068
OSSCP12	3.853	1.168	0.418	-1.086
OSSCP13	3.930	1.163	0.623	-1.168
OSSCP14	3.777	1.241	0.017	-0.999
OSSCP15	3.703	1.340	-0.480	-0.874
OSSCP16	3.847	1.261	0.036	-1.052
OSSCP2	3.830	1.120	0.401	-1.005
OSSCP3	3.857	1.118	0.277	-0.952
OSSCP4	3.910	1.075	0.813	-1.131
OSSCP5	3.983	1.133	0.632	-1.170
OSSCP6	4.023	0.961	1.042	-1.090
OSSCP7	3.900	1.170	0.142	-1.008
OSSCP8	4.060	1.050	1.176	-1.266
OSSCP9	3.987	1.131	0.566	-1.126
SCA1	3.570	1.185	0.161	-1.025
SCA10	3.650	1.181	0.061	-0.893
SCA11	3.780	1.160	0.032	-0.903
SCA12	3.780	1.221	0.027	-0.963
SCA13	3.763	1.276	-0.264	-0.904
SCA2	3.730	1.229	-0.168	-0.870
SCA3	3.610	1.267	-0.488	-0.758
SCA4	3.720	1.195	-0.197	-0.812
SCA5	3.833	1.154	0.182	-0.952
SCA6	3.793	1.171	-0.034	-0.882
SCA7	3.840	1.181	0.187	-1.005
SCA8	3.820	1.155	-0.114	-0.870
SCA9	3.900	1.079	0.242	-0.937
SCD1	3.853	1.148	0.153	-0.958
SCD2	3.800	1.143	-0.009	-0.840
SCD3	3.710	1.249	-0.199	-0.872
SCD4	3.760	1.184	-0.024	-0.881
SCD5	3.787	1.164	0.005	-0.891
SCD6	3.840	1.146	0.044	-0.910
SCD7	3.883	1.215	0.294	-1.108

Convergent validity is the degree to which the items are supposed to measure the same construct and when high, it means that the items are measuring exactly the same underlying concept. In PLS-SEM, convergent validity is measured by Average Variance Extracted (AVE), wherein a value that is above 0.5 is considered to be acceptable. High value of AVE indicates that the construct accounts more than 50 percent of the items that measures it, which points out that the items converge to a similar concept. Convergent validity is essential as it will be used to assure that the measurement items are well capturing the essence of the latent variable that they are intended to assess. In this part, we determine the AVE values of each of the constructs in the model such that the constructs should show a strong convergent validity and add up to the overall quality of the measurement model. The findings of this evaluation are crucial to the ascertainment of reliability and accuracy of the items used to measure the study.

Table 3: Factor loadings, Cronbach's Alpha values, CR and AVE values

Variables	Items	Factors Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Big Data Analytics-AI (BDA)	BDA1	0.716	0.880	0.907	0.583
	BDA2	0.746			
	BDA3	0.752			
	BDA4	0.807			
	BDA5	0.799			
	BDA6	0.812			

	BDA7	0.704			
Perceived HR Effectiveness (HRE)	HRE1	0.796	0.921	0.934	0.612
	HRE2	0.793			
	HRE3	0.788			
	HRE4	0.785			
	HRE5	0.761			
	HRE6	0.779			
	HRE7	0.822			
	HRE8	0.779			
	HRE9	0.738			
HRM (AI) Acceptance (HRMAI)	HRMAI1	0.859	0.882	0.919	0.740
	HRMAI2	0.867			
	HRMAI3	0.879			
	HRMAI4	0.834			
Overall Sustainable Supply Chain Performance (OSSCP)	OSSCP1	0.741	0.940	0.946	0.526
	OSSCP10	0.631			
	OSSCP11	0.716			
	OSSCP12	0.733			
	OSSCP13	0.746			
	OSSCP14	0.766			
	OSSCP15	0.744			
	OSSCP16	0.761			
	OSSCP2	0.742			
	OSSCP3	0.750			
	OSSCP4	0.686			
	OSSCP5	0.741			
	OSSCP6	0.713			
	OSSCP7	0.712			
	OSSCP8	0.718			
	OSSCP9	0.687			
Supply Chain Agility (SCA)	SCA1	0.684	0.927	0.937	0.534
	SCA10	0.737			
	SCA11	0.715			
	SCA12	0.750			
	SCA13	0.710			
	SCA2	0.729			
	SCA3	0.727			
	SCA4	0.748			
	SCA5	0.707			
	SCA6	0.761			
	SCA7	0.751			
	SCA8	0.730			
	SCA9	0.748			
Supply Chain Digitization (SCD)	SCD1	0.800	0.900	0.921	0.625
	SCD2	0.812			
	SCD3	0.806			
	SCD4	0.806			
	SCD5	0.810			
	SCD6	0.753			
	SCD7	0.742			

Factor loadings, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) were used to determine the reliability and validity of the measurement model. The factor loading of all constructs was above the acceptable level of 0.7, and Big Data Analytics-AI (BDA) items had a range of 0.704 to 0.812 which means that there are strong item-to-construct correlations. The Alpha values of Cronbach were higher than 0.7 in all constructs with Perceived HR Effectiveness (HRE) having the highest value of 0.921. The values of Composite Reliability were 0.900 (Supply Chain Digitization) and 0.946 (Overall Sustainable Supply Chain Performance) which showed outstanding internal consistency.

Convergent validity was determined by AVE values, with all of them being above the recommended 0.5 values. The AVE of HRM (AI) Acceptance was the highest (0.740), whereas, the Overall Sustainable Supply Chain Performance (OSSCP) had the lowest but still acceptable (0.526). These findings indicate that both of the constructs have a significant percentage of variance in the indicators. Taken together, the measurement model demonstrates decent reliability and convergent validity, which forms a strong base to further structural analysis and interpretation.

Figure 2: Results of Measurement Model

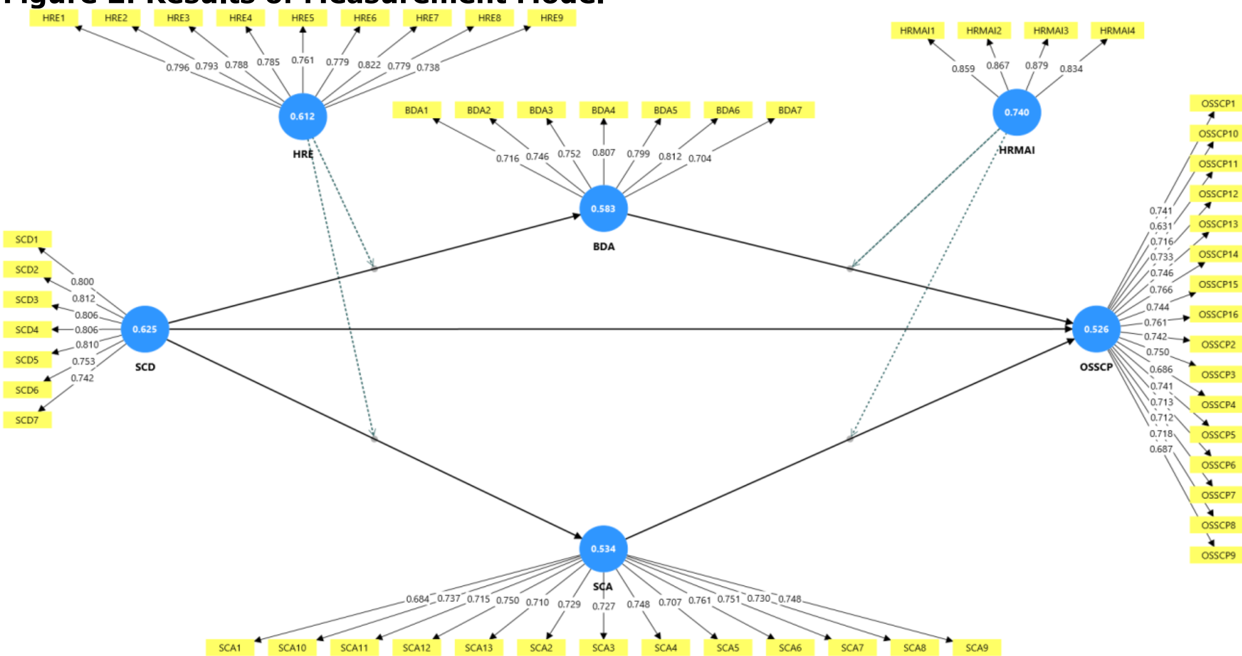


Figure 2 presents the average variance extracted (AVE) of each of the constructs of the measurement model. AVE is a significant scale to provide information on the convergent validity of a construct, which denotes the amount of variance in the variables that is observed and explained by the latent construct. That the value is above 0.5 is usually acceptable because it means that the construct accounts for better than a half of the variation in its items. In this figure, the value of AVE of such constructs as HRM (AI) Acceptance (HRMAI) and Perceived HR Effectiveness (HRE) are somewhat higher (0.740 and 0.612 respectively), which indicates high convergent validity. Nevertheless, such constructs as Big Data Analytics-AI (BDA) and Supply Chain Agility (SCA) have lower AVE (0.583 and 0.534), which means that the explained variance is a bit lower than it should be. On the one hand, they are still within the acceptable range, but additional discussion can probably be required to enhance the validity of the constructs in question. Discriminant validity guarantees that the constructs in a measurement model do not overlap. The study used both Fornell-Larcker criterion and Heterotrait-Monotrait Ratio (HTMT) to establish discriminant validity. In case of Fornell-Larcker, the square root of each construct AVE was higher than its correlations with other constructs.

Table 4: Fornell-Larcker criterion

Variables	BDA	HRE	HRMAI	OSSCP	SCA	SCD
BDA	0.763					
HRE	0.746	0.783				
HRMAI	0.736	0.710	0.860			
OSSCP	0.515	0.777	0.789	0.795		
SCA	0.718	0.622	0.787	0.741	0.731	
SCD	0.600	0.612	0.787	0.731	0.715	0.790

All the values in the above table meet the criteria of Fornell-Larcker discriminant validity as all the digonal values are higher than the off-diagonal values.

Table 5: Heterotrait-monotrait ratio (HTMT)

Variables	BDA	HRE	HRMAI	OSSCP	SCA	SCD
BDA						
HRE	0.826					
HRMAI	0.835	0.895				
OSSCP	0.892	0.826	0.857			
SCA	0.856	0.886	0.868	0.784		
SCD	0.808	0.892	0.884	0.786	0.721	

The values of all HTMT were under the case of 0.85 or 0.90 and the maximum was 0.900 (SCD and BDA) and 0.835 (HRE and HRMAI). Therefore, the measurement model is shown to have a good discriminant validity.

Table 6: Hypotheses Testing of Direct Relations

Relations	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H1: SCD -> OSSCP	0.453	0.448	0.112	4.054	0.000	Supported
H2: SCD -> BDA	0.860	0.860	0.048	18.072	0.000	Supported
H3: SCD -> SCA	0.504	0.507	0.059	8.577	0.000	Supported
H4: BDA -> OSSCP	0.750	0.745	0.088	8.571	0.000	Supported
H5: SCA -> OSSCP	0.188	0.198	0.074	2.547	0.011	Supported

In following table hypothesis decision those are proved from this study are listed as supported or not supported in the last column. Table 6 summaries the results of direct relations and table 7 shows the mediation and lastly, table 8 lists the moderation results. Mediating effects of PLS-SEM aid in the explanation of the working processes involved in the effect of an independent variable to a dependent variable via a mediating variable. This part aims at testing the mediation hypotheses to determine whether the relationship between the constructs is indirect where the effects of the independent variables on dependent variables are mediated through one or more mediators. Considering the importance of these mediation paths, we are informed about the paths that drive the links in the proposed model.

Table 7: Hypotheses Testing of Mediation Relations

Relations	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H6: SCD -> BDA -> OSSCP	0.645	0.641	0.088	7.365	0.000	Supported
H7: SCD -> SCA -> OSSCP	0.095	0.100	0.038	2.509	0.012	Supported

Moderating effects in PLS-SEM are examined to investigate the strength or direction of the relationship between two variables that are variable to be analyzed changes with the presence of a third variable which is called the moderator. We in this section, we test the moderating effects to determine the effect that some of the constructs including HRM (AI) Acceptance (HRMAI) and Perceived HR Effectiveness (HRE) have on the direct relationships among other constructs within the model. Through such moderating paths, we are in a position to know whether certain things facilitate or deter the associations between the independent variable and the dependent variable.

Table 8: Hypotheses Testing of Moderating Relations

Relations	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H8a: HRMAI x BDA -> OSSCP	0.012	0.013	0.052	0.226	0.821	Not Supported
H8b: HRMAI x SCA -> OSSCP	-0.016	-0.013	0.055	0.287	0.774	Not Supported
H9a: HRE x SCD -> BDA	-0.005	-0.004	0.039	0.120	0.904	Not Supported
H9b: HRE x SCD -> SCA	0.052	0.052	0.026	2.020	0.043	Supported

5. Finding and Discussion

This part summarizes the empirical findings and related them with theoretical frameworks and existing literature. The research revealed that Supply Chain Digitization (SCD) has a positive impact on Big Data Analytics-AI (BDA), Supply Chain Agility (SCA), and Overall Sustainable Supply Chain Performance (OSSCP). Direct impacts make SCD a competitive resource that fosters a more data-driven decision-making and responsiveness, which is in line with the Resource-Based View (RBV) and Dynamic Capabilities Theory. Mediation analysis showed that both BDA and SCA play a significant role in mediating between SCD and OSSCP. This shows that digitization is translated into performance improvements mainly in the form of better analytical functions and organizational agility, and the significance of data-driven and agile supply chains. Moderating effects were inconclusive. HRM (AI) Acceptance (HRMAI) did not significantly mediate the relations between BDA and OSSCP as well as between SCA and OSSCP. In comparison, Perceived HR Effectiveness (HRE) had a significant moderating role in the relationship between SCD and SCA, and there is evidence that effective HR practices like training, leadership, and engagement enhance the effect of digitization on agility. These results comply with Contingency Theory, which focuses on match of technological investments and organization capabilities.

Theories are incorporated in the discussion. RBV defines digitization as a valuable and inimitable asset; Dynamic Capabilities Theory introduces agility as an important ability to adapt, and Technology Acceptance Model (TAM) is the model that provides a perspective on AI adoption although non-significant outcomes of HRMAI may indicate that other organizational characteristics (e.g., digital infrastructure, leadership commitment) are more relevant. Theoretical implications can be seen in the progress of the knowledge on the interaction between digital transformation and human resources in influencing the results of the supply chain. The practical implications encourage managers to make strategic investment on SCD and BDA, develop SCA, and align HR practices with the digital initiatives in order to maximize agility and sustainability. Limitations are the cross-sectional design, industry focus (which limits generalizability), possible common method error due to self-reported surveys, and lack of extraneous variables (e.g., economic or geopolitical situation). Longitudinal research designs should be used in future studies to address the causal dynamics in the long-run, address other moderating variables like market conditions or regulatory shifts, and understand the role of organizational culture and HR practices in various industries and geographical studies. Overall, Chapter 5 reaffirms the importance of digitization, analytics, and agility as key to sustainable supply chain performance, with a subtle role of HR effectiveness. The results provide a sound basis to theory construction as well as practical strategy, and also make clear directions on where more empirical investigation can be conducted.

6. Conclusion

The research explored the impact of Supply Chain Digitization (SCD), Big Data Analytics-Artificial Intelligence (BDA-AI), and Supply Chain Agility (SCA) on the performance of the supply chain in terms of Overall Sustainable Supply Chain Performance (OSSCP), as well as the mediating and moderating roles of HRM (AI) Acceptance (HRMAI) and Perceived HR Effectiveness (HRE). Empirical results also established that SCD greatly increases BDA-AI and SCA that increase OSSCP. These findings correspond to the Resource-Based View, which places digitization as a strategic asset to competitive advantage, and the Dynamic Capabilities Theory, which emphasizes organization flexibility and data-driven responses to environmental changes. The mediation analyses found that BDA-AI and SCA are essential processes by which digitization impacts sustainable performance. On the issue of moderation, there was no significant moderation of the connection between BDA-AI and SCA by HRMAI. Nevertheless, the relationship between SCD and SCA was moderate, with Perceived HR Effectiveness, meaning that coordinated HR practices increase the positive impact of digitization on agility. This highlights the importance of aligning the strategies of digital transformation and human resource. To practitioners, the results suggest that strategic investment in SCD and BDA-AI can be made to improve the decision-making and responsiveness. The development of SCA is crucial in order to overcome market disruptions. Moreover, HR departments ought to promote a sense of success with the help of leadership, training, and engagement of employees, and not just by accepting AI. The non-significant findings of HRMAI imply that other variables, including digital infrastructure and organizational preparedness might be more important to the successful adoption of AI. Overall, the study adds to the comprehension of the role of digital transformation in achieving sustainable supply chain performance, as well as the determination of HR effectiveness as a boundary condition. Further research ought to delve into the long-term impacts of digitalization and the dynamic and multifaceted interactions between human resources and new technologies.

6.1. Limitations and Future Research

Despite the fact that this study is a good contribution to the body of literature on the connection between digital transformation, big data analytics, supply chain agility, and overall performance, it has some limitations which must be taken into consideration. The research targets a narrow set of industries, and this could be a constraint of the results to other fields with varying dynamics. In addition, cross-sectional data limits the possibility of investigating a cause-and-effect relationship over time and the use of self-reported survey data can lead to common method bias due to the perception of respondents. Also, the external factors that could affect the performance of the supply chain, including economic conditions, geopolitical, market competition, and regulatory changes are not taken into account completely in the study. Thus, longitudinal designs should be used in future studies to investigate how these relationships change with time and the long-term impacts of digital investments on the sustainability and performance of the supply chain. The moderating effects of external environmental factors, as well as the unexplored implications of HRM (AI) Acceptance and Perceived HR Effectiveness should also be explored in future studies. Moreover, studying how HR practices and organizational culture facilitate the implementation of digital tools and AI in various industries and geographical settings would contribute to the increased generalizability of the results and offer more applicable suggestions to scholars and practitioners.

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