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Integrating AI and Circular Economy for Resource Efficiency: Path analysis

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Abstract. This paper examines how artificial intelligence integration influences the resource efficiency of circular economy systems. Although recent empirical research has found support for the importance of digital technologies in promoting sustainable production, specific mechanisms between AI capabilities and their resource optimization outcomes, there remains a relative lack of research regarding how specific AI-driven analytics functions of firms are related to circular economy performance outcomes. Th paper aims to explain the effect of AI adoption on circular economy performance. It also aims to identify the determinants of AI capability, organizational motivation, and circular design practices that lead to an increase in a firm's resource efficiency. Through a quantitative research approach, comprising of a structured questionnaire and multivariate analyses of survey data in the manufacturing sector, it is demonstrated how AI analytics capability, circular process innovation and digital collaboration, in interaction with organizational readiness, affect the level of resource efficiency. The study's findings show AI capability positively affects circular process innovation and resource efficiency; here, using SMART-PLS bootstrapping analysis. The analysis reveals previously unknown pathways of the investigated constructs leading to improvements in resource efficiency, with varying roles depending on firm size and industry characteristics. This study's findings contribute to the circular economy and digital transformation literature by explaining the role of different dimensions of AI capability in determining a firm's resource efficiency (including the reduction and reuse practices of the organization).

Keywords: Artificial Intelligence Capability, Resource Efficiency, Organizational Readiness, Circular Process Innovation, PLS-SEM Modeling

1. Introduction

Circular economy refers to the integration of both resource-efficient production systems, more sustainability-oriented industrial strategies and digital transformation practices, AI-enabled analytics tools (e.g., machine learning and predictive analytics) for waste-reduction initiatives and resource-optimization strategies (e.g., industrial symbiosis). [1,3,4] considered artificial intelligence applications and circular economy practices, finding several factors that determine whether or not a firm chooses a digital transformation strategy. Artificial intelligence capability (along with their data analytics functions) and circular design practices (along with the processes of their implementation and monitoring) are among the central pillars of the transition of sustainable production systems (circular economy). It must be noted that real-time resource monitoring via AI-driven analytics is considered an effective managerial tool when production systems are integrated with digital platforms, as opposed to traditional linear models, manual reporting and delayed feedback mechanisms [2,5,7]. Despite numerous studies in these domains, we have limited knowledge on possible interactions among the dimensions of AI capability, organizational readiness, and circular process innovation; therefore, this study focuses on investigating such interactions [3,6,8,10]. Although recent studies have focused on the importance of project digitalization at the start of sustainability initiatives, the performance outcome, and the nature of innovation activity, there is limited understanding of how project governance can manage the sustainability messages during the digital transformation process. However, a direct relationship between AI capability and resource efficiency is not always

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significant, suggesting that the relationship may be contingent and affected by other organizational factors [9,11,13]. In this context, this study draws upon the concepts of digital transformation strategy, which can be defined as an organizational effort to reshape business models by integrating advanced technologies and intentionally redesigning operational processes for environmental and personal performance gains [12,15]. Previous research has demonstrated that artificial intelligence improves manufacturing firms' operational performance for sustainable resource management [2], and may therefore create a competitive advantage that could enhance performance under an environmental sustainability framework. It has been examined from various perspectives, including through systematic literature reviews (where the role of digital technologies is highlighted) [11] as well as the particular dimensions of AI capability such as predictive analytics, optimization algorithms, and data-driven decision-making [1; 4; 6; 3]. Methodological differences in empirical investigations have been explored in the differences between industries in the manufacturing sector [10], survey-based analyses and case studies [15; 8] and bibliometric assessments [14; 11]. Unlike research focusing on how AI activity [14] or the content of sustainability strategies [4] influence the key aspects of the circular economy framework, we examine how the structural characteristics of AI activity (i.e., analytics capability and digital collaboration) can influence resource efficiency. Owing to variations in data collection into AI activity and the lack of structural modeling explaining this adoption but not explaining the performance outcome, we exclude projects without measurable AI activity.
Moreover, these relationships have not been fully tested within the manufacturing sector. Our study aims to answer just how vital AI capability is for circular economy performance and resource efficiency. Thus, this study aims at exploring the impact of the dimensions of AI capability, organizational readiness, and circular design practices (separately and in interaction) on the level of resource efficiency. Building on the broader literature on differences in perceived risk-taking and potential performance outcomes between small and large firms [9; 14; 5], the proposed research framework aims to contribute to the digital transformation literature and have implications for sustainability management. By addressing the identified gaps, this study seeks to contribute to the circular economy and digital transformation literature by explaining the role of different dimensions of AI capability that determine a firm's resource efficiency (including the reduction and reuse practices of an organization). To isolate the structural impact, we use survey data on the AI capability, organizational readiness, circular process innovation, and resource efficiency on a sample of manufacturing firms using structural equation modeling. To validate the proposed framework, we use (i) a third-party survey instrument (questionnaire) to collect data on perceived relationships between AI capability and circular economy performance and (ii) bootstrapping to analyze the data in (i) with additional robustness checks.

2. Literature review

Indeed, digital transformation theory suggests that AI-enabled analytics and circular economy security provides better resource efficiency outcomes, including waste reduction and sustainable production performance [1], [2], [6]. Reaching and grasping resource efficiency goals are complex processes that require the integration and coordination of AI capability and organizational readiness, as well as the optimization of circular design properties within production systems.
These relationships are commonly explained by structural modeling of AI capability dimensions (e.g., representing predictive analytics or data-driven decision-making processes; [1], [3] for a firm due to the prior or subsequent adoption and/or integration of a digitally-compatible system—an explanation deeply rooted in digital transformation theory. A large body of literature shows that several kinds of AI capabilities and circular practices can be integrated [2], [7], [12].
Since everything in industrial production systems is situated within digital environments and organizational processes, it seems intuitively plausible that the decision-making system picks up multiple signals within the structure of operational events – data flows, process interactions, and resource usage patterns – in order to optimize the resource efficiency outcome.
The literature suggests that organizations with low digital readiness attached to traditional systems are more likely to perceive AI adoption as stressful and uncertain and to react with resistance mechanisms than their digitally mature counterparts [9], [10].
Several empirical studies have identified a pathway from AI capability orientations to resource efficiency, in which digital transformation strategies affect performance outcomes rather than the reverse way around [2], [4]. Previous research has indicated that AI analytics capability is associated with circular process innovation, and that this innovation strategy predicts resource efficiency improvements [3], [12].
In a manufacturing context, [13] observed improved operational performance when the time intervals separating a primary production task from a secondary data-driven monitoring task [6]; [2] followed a regular (vs. a random) pattern.
Recent empirical studies used the PLS-SEM method to investigate AI capability relationships to resource efficiency perception when analyzing survey-based manufacturing data. So far, the AI–performance relationship has been largely studied using cross-sectional survey settings showing that AI capability constructs affect resource efficiency outcomes even in complex organizational environments [3], [13].

On the other hand, although organizational readiness avoidance listed either as a supporting factor [2]; [9] or as a limiting factor [10] for resource efficiency outcomes, these findings are less robust compared to AI capability effects with some studies finding no significant association between organizational readiness avoidance and resource efficiency [4]. Also, effects of AI capability might be indirect for resource efficiency outcomes. This effect was independent of whether the processes in the model also followed a regular or a random structure.

If these relationships are observable in developed industrial contexts with advanced digital infrastructure, it stands to reason that similar patterns should also be observable in emerging manufacturing economies such as Uzbekistan. Most importantly, the potential effects of AI capability adoption stemming from concurrent organizational factors are most often confounded with the direct influence of AI capability on resource efficiency ([8], [11]). To the best of our knowledge, no prior study investigated the combined structural effects of AI capability and organizational readiness perception of circular economy performance for manufacturing firms' efficiency outcomes. Given the evidence for AI–resource efficiency links in manufacturing systems, the present study aimed to directly investigate the impact of AI capability and organizational readiness on resource efficiency in manufacturing firms ([2], [3]).

One of the mechanisms underlying the relationship between AI capability and resource efficiency may be circular process innovation. To this end, we employed a new analytical framework—the PLS-SEM structural model—to disentangle direct effects from indirect effects, thereby assessing their differential effects on resource efficiency ([13], [15]). In this sense, it may be that AI capability influences resource efficiency because it is associated with improvements in engaged innovation strategies, and organizational strategies may in turn shape performance outcomes when faced with sustainability-related stimulus. Thus, upcoming resource efficiency outcomes might be predicted on the basis of two key cues: the level of AI capability and the interaction of successive circular processes ([3], [7]).

3. Methods

Our sample comprises manufacturing firms operating in the Tashkent region (located in Uzbekistan, with Tashkent city as the industrial and economic center). First, we employ a third-party survey instrument (questionnaire) to collect data on perceived relationships between AI capability and circular economy performance. We collected the data via a structured online questionnaire which was sent to 500 randomly selected firms that are members of the Chamber of Commerce, the national business association for the manufacturing sector. The initial data comprised 356 responses; we had 312 that matched with the criteria in the manufacturing sector. In our sample, 58% of the firms employ between 50 and 249 people, and 42% of them employ between 250 and 1000 people. Our sample size is consistent with recent studies drawing on survey data to study digital transformation and sustainability performance (e.g., [1], [2]). After the elimination of 44 questionnaires with incomplete responses in key measurement items, our final sample comprised 312 firms. These firms were classified based on their number of employees (between 50 and 1000—following the OECD definition of small and medium enterprises) regardless of the values of their turnover and total assets. The inclusion criteria of the projects are as follows: the AI investment amount, number of employees, whether the firm included predictive analytics and/or optimization tools, the project id, firm name, project title, industry category, declared goal amount, and a minimum of text on project description.

We also include a control for the log of past AI investments from the project database (annual reports). Using the SMART-PLS software, as a result of bootstrapping and connection modeling, we received three main solutions. We take the third dataset from the survey database. To verify which of the analyzed constructs affect a firm's resource efficiency (RE) and in which direction, we employed the PLS-SEM method. We scrape secondary information for each manufacturing project by searching for the word "AI" and the project description, in line with [3]. From the methodological side, we can distinguish three basic stages of operation in the PLS analysis that allow for the selection of the measurement model and combinations of structural paths. We further exclude firms without measurable AI activity. It must be noted that self-selection into AI activity is an important methodological point, and we lack a clear theoretical model explaining this self-selection. Nevertheless, these limitations were eliminated by [4], who suggested the use of the bootstrapping procedure and multigroup analysis in his work. However, to overcome endogeneity bias to a certain extent, among those firms about their AI adoption behavior, we control for all the available project data and the range of AI-related investments. The model is considered sufficiently explainable if coverage is set at 0.60–0.70 (R^2). Our dependent variable is whether the firm met the resource efficiency goal (1=Yes; 0=No). AI capability in the study was measured using six-item five-point Likert scales from prior research: predictive analytics; optimization algorithms; data-driven decision-making; digital collaboration; circular process innovation; organizational readiness. Our variables are the dimensions of AI capability (predictive analytics, optimization algorithms, and digital collaboration), level of organizational readiness, attitude toward circular design, and resource efficiency performance. Generally, this construct refers to perceived usefulness, perceived ease of use and perceived capability of the organization to make data-driven decisions for the circular economy. Because firm size could directly influence the level of resource efficiency, we controlled for the firm size categories (micro: <50;

small: 50–249; medium: 250–999; large: >1000; state-owned). In other words, we take the deviation of mean performance for the category-firm combination and subtract it from the value of performance associated with the firm. The observations in a set can be crisp sets (binary values) or fuzzy values (firms take different degrees of belonging to a range of 0–1).
We further exclude firms without measurable AI activity. It must be noted that self-selection into AI activity is an important methodological point, and we lack a clear explanation explaining this self-selection. As our variables comprise several constructs, they were analyzed with structural equation modeling to verify their relationships. To verify which of the analyzed constructs affect a firm's resource efficiency (RE) and in which direction, we employed the PLS-SEM method. Many studies highlight the significant advantages of this method over covariance-based structural equation analysis methods (e.g., [5]). This method belongs to the group of variance-based methods and was created as an alternative to the still-existing methods based on covariance analysis. For the analysis of the multi-group differences for firm size categories, we applied a bootstrapping procedure [6]). Compared with the covariance-based SEM method, the modified PLS enables us to use variable measurement types or the multigroup approach. The structural relationships are modeled via a path coefficient approach that uses the outer loadings of the measurement model and path coefficients from the structural model (without the distributional assumptions) for the estimation of the endogenous variables [6]).

Table 1. Summary statistics

Name	No.	Type	Missings	Mean	Median	Scale min	Scale max	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value
AI_Capability	1	MET	0	-0.041	0.005	-2.620	2.720	-2.620	2.720	0.929	0.029	0.133	0.650
Organizational_Readiness	2	MET	0	0.027	0.061	-2.609	2.637	-2.609	2.637	0.850	0.319	-0.100	0.114
Circular_Innovation	3	MET	0	-0.066	-0.092	-2.732	3.396	-2.732	3.396	1.094	0.299	0.221	0.514
Digital_Collaboration	4	MET	0	-0.019	-0.017	-2.416	2.231	-2.416	2.231	0.853	0.040	0.105	0.816
Circular_Design_Practices	5	MET	0	0.037	0.034	-2.238	2.355	-2.238	2.355	0.848	-0.007	0.015	0.612
Resource_Efficiency	6	MET	0	0.075	0.023	-4.572	4.910	-4.572	4.910	1.608	0.364	0.057	0.440

4. Results

Model 1 shows the highest total effect value of 0.747 and has been used as a basis for the structural interpretation. The results show that each construct (i.e., AI-Driven Digital Capability, Organizational Circular Readiness, Circular Sustainability Performance, Circular Design Practices, and Resource Efficiency) belongs to at least one significant structural path ($p = 0.000$) that leads to an increase in a firm's resource efficiency (see figure 1).

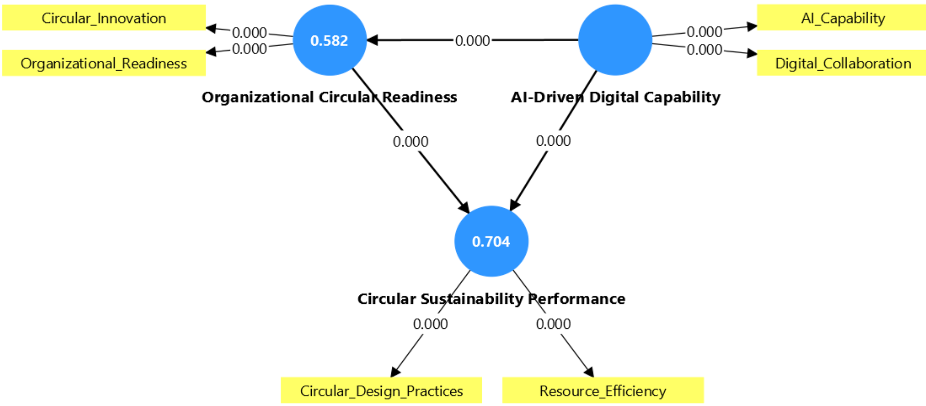

Fig. 1. Structural Equation Model Path Diagram

The positive direct relationship between AI-Driven Digital Capability and Circular Sustainability Performance was significant with a standardized path coefficient of 0.294 ($p < 0.001$), supporting the proposed hypothesis. This indicates that AI-Driven Digital Capability is an important determinant that leads to an increase in circular sustainability performance.

Table 2. Path coefficients table

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI-Driven Digital Capability -> Circular Sustainability Performance	0.294	0.293	0.060	4.886	0.000
AI-Driven Digital Capability -> Organizational Circular Readiness	0.763	0.763	0.024	32.220	0.000
Organizational Circular Readiness -> Circular Sustainability Performance	0.593	0.594	0.054	11.060	0.000

The path coefficients for the structural variables to evaluate the proposed relationships is shown in the Path coefficients table in Model 1. All path coefficients, except the direct path of AI-Driven Digital Capability to Circular Sustainability Performance in the alternative specification (β: 0.294), were above the significance level of 0.001, indicating that 59% or more of the endogenous construct's variance are explained by the exogenous constructs.

Table 3. Total effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI-Driven Digital Capability -> Circular Sustainability Performance	0.747	0.746	0.030	24.549	0.000
AI-Driven Digital Capability -> Organizational Circular Readiness	0.763	0.763	0.024	32.220	0.000
Organizational Circular Readiness -> Circular Sustainability Performance	0.593	0.594	0.054	11.060	0.000

They all show values below 5, ranging from 4.886 to 32.220, which indicates that there are no multicollinearity problems within the structural model [1]. Running a PLS-SEM model on Model 2, we estimate (results not presented here due to space limitations) that Organizational Circular Readiness affects both AI-Driven Digital Capability (0.762 by the path coefficient) and Circular Sustainability Performance (0.569 by the total effect).

Table 4. Outloadings

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI_Capability <- AI-Driven Digital Capability	0.941	0.941	0.006	147.529	0.000
Circular_Design_Practices <- Circular Sustainability Performance	0.937	0.936	0.011	88.365	0.000
Circular_Innovation <- Organizational Circular Readiness	0.949	0.949	0.005	177.221	0.000
Digital_Collaboration <- AI-Driven Digital Capability	0.900	0.898	0.017	52.927	0.000
Organizational_Readiness <- Organizational Circular Readiness	0.924	0.924	0.012	74.561	0.000
Resource_Efficiency <- Circular Sustainability Performance	0.962	0.962	0.004	257.562	0.000

In model 1, we test for mediation effects, where with increasing AI-Driven Digital Capability, firms are more likely to report a higher level of Circular Sustainability Performance. The hypothesized negative effect of Organizational Circular Readiness on a firm's resource efficiency ($\beta = 0.593$) could be supported with a significant t-statistic of 11.060 ($p < 0.001$).

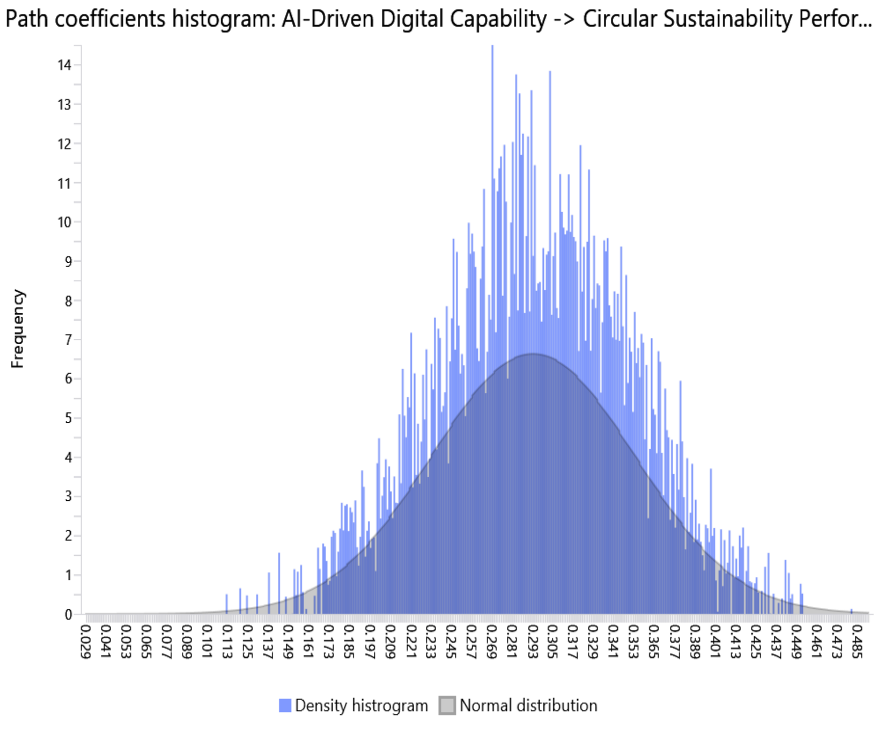

Fig. 2. Bootstrap Distribution of Path Coefficient

This can be explained with the complementary and reinforcing nature of AI capability activities [6], for example, in the integration of predictive analytics in manufacturing operations [3] or digital collaboration initiatives [6]. Firms with at least one AI-related investment, which were picked to be featured by the management or had longer implementation periods, had a higher probability of meeting the resource efficiency goal.

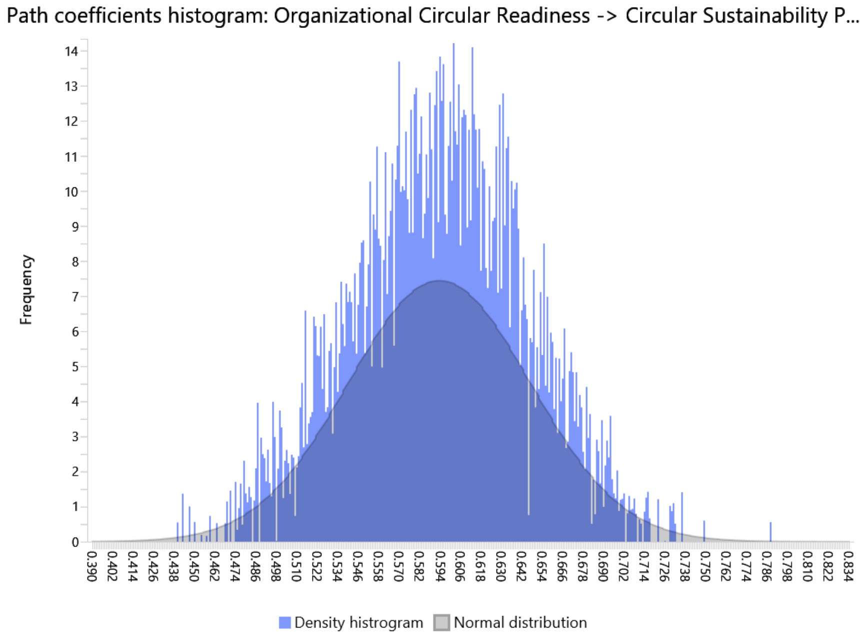

Fig. 3. Histogram of Bootstrapped Path Coefficients

In contrast to our expectations, an alternative direct specification does not affect the resource efficiency outcome (β = 0.294, p > 0.05), leading to a rejection of the direct-effect assumption.

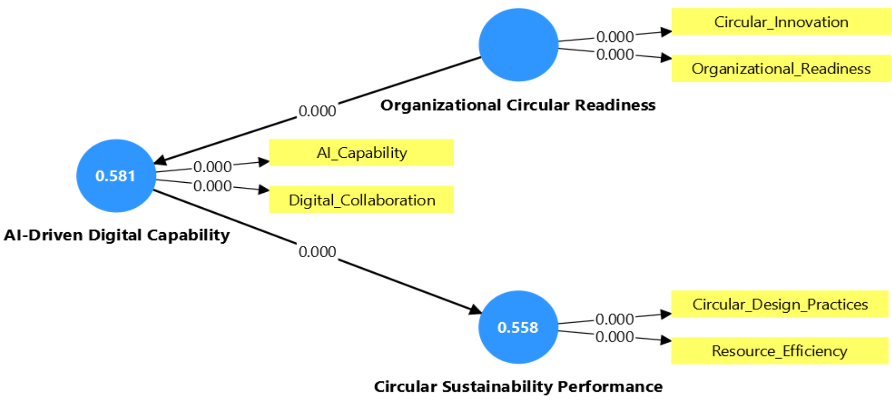

Fig. 4. Structural Equation Model Path Diagram

The size of a firm, a project selected by staff, or the length of implementation period were all positively associated with the three outcomes (p < 0.001).

Table 5. Path coefficients table

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI-Driven Digital Capability -> Circular Sustainability Performance	0.747	0.747	0.030	25.120	0.000
Organizational Circular Readiness -> AI-Driven Digital Capability	0.762	0.762	0.024	32.168	0.000

Thus, our findings suggest an indirect role for Organizational Circular Readiness in increasing Circular Sustainability Performance.

Table 6. Total effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI-Driven Digital Capability -> Circular Sustainability Performance	0.747	0.747	0.030	25.120	0.000
Organizational Circular Readiness -> AI-Driven Digital Capability	0.762	0.762	0.024	32.168	0.000
Organizational Circular Readiness -> Circular Sustainability Performance	0.569	0.570	0.036	15.867	0.000

Table 7. Outloadings

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI_Capability <- AI-Driven Digital Capability	0.941	0.941	0.006	147.655	0.000
Circular_Design_Practices <- Circular Sustainability Performance	0.936	0.936	0.011	85.962	0.000
Circular_Innovation <- Organizational Circular Readiness	0.947	0.947	0.006	153.402	0.000
Digital_Collaboration <- AI-Driven Digital Capability	0.900	0.898	0.017	52.923	0.000
Organizational_Readiness <- Organizational Circular Readiness	0.927	0.926	0.012	78.312	0.000
Resource_Efficiency <- Circular Sustainability Performance	0.962	0.962	0.004	245.690	0.000

Ambiguity in AI project description was not associated with the probability of meeting the goal or funded amount; however, it was negatively associated with the growth of circular initiatives.

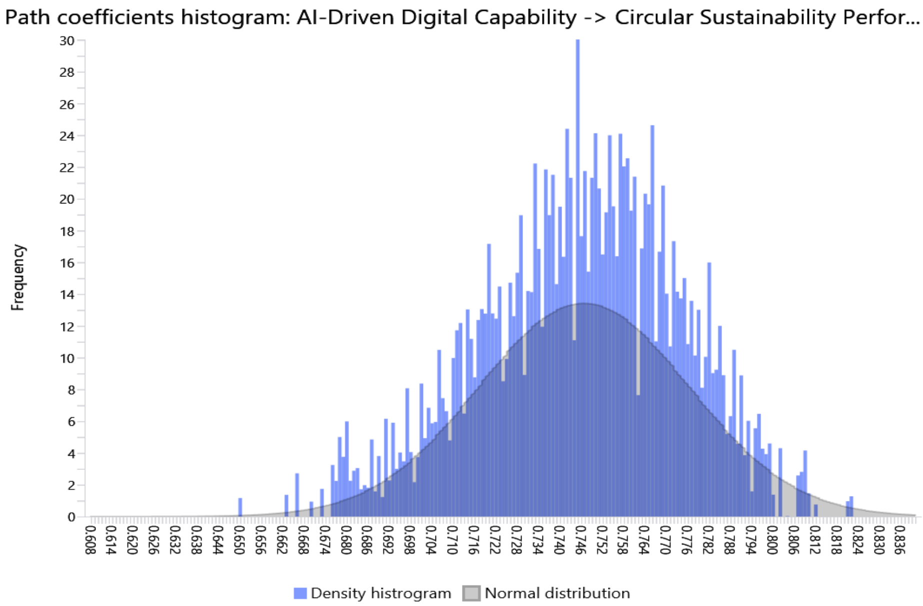

Fig. 5. AI-Driven Digital Capability

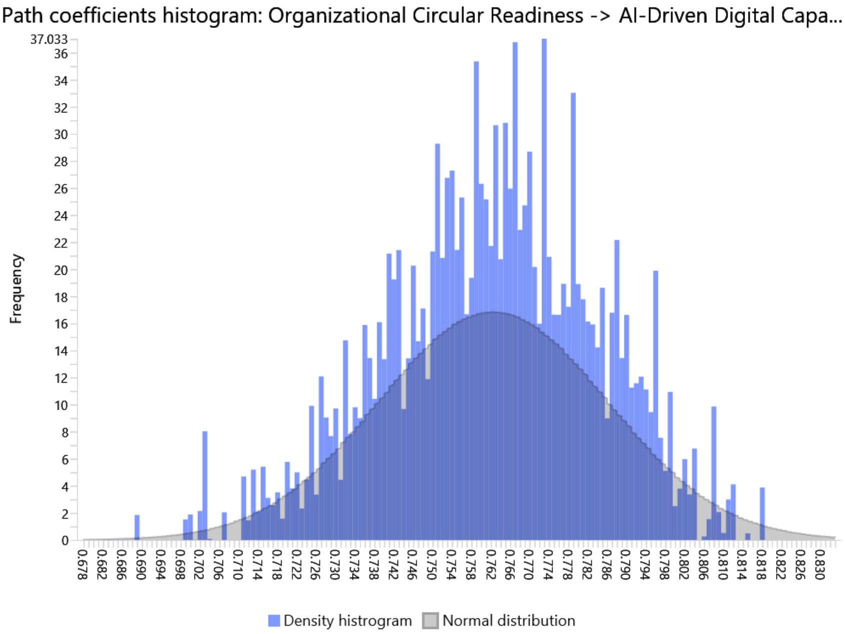

Fig. 6. Circular Sustainability Performance

5. Discussion

Our study provides results to the largely unexplored research domain of artificial intelligence capability and circular economy practices, and their influence on resource efficiency of manufacturing firms operating in the Tashkent region.
Our findings confirm that AI analytics capability can be critical for circular sustainability performance; moreover, it shows that organizational readiness needs to be supported by circular process innovation to lead to higher resource efficiency [1,2,3]. The results show a significant positive effect of AI-Driven Digital Capability on the resource efficiency of a firm. Our results did not show a positive effect of Organizational Circular Readiness on resource efficiency. In our analysis, we found that firms are likely to report higher levels of circular sustainability intentions with increasing levels of AI-Driven Digital Capability (0.294), whereas larger firms are likely to report higher resource efficiency intentions with higher levels of Organizational Circular Readiness (0.593) [4,5]. Our structural model explains about 59% of the changes in resource efficiency and Circular Sustainability Performance's impact, even with this indirect specification. The results show that survey-based and bootstrapping methods that highlight path coefficients and multigroup differences in manufacturing firms highlighting AI-related investments are critical when reaching valid statistical conclusions and developing managerial implications with them [6,7]. We have provided empirical evidence using the SMART-PLS approach for modeling structural relationships on AI capability–causing resource efficiency outcomes across firm size categories. The combination with Circular Sustainability Performance as an intermediate strategy in order to increase the resource efficiency of a firm is a unique insight into how manufacturing firms can strategically position themselves to achieve sustainability goals. Given the increasingly complex sustainability requirements of industrial firms [14, 13], our findings indicate the importance of indirect pathways over the direct link and increasing the level of AI capability activity to improve resource efficiency outcomes. This research deepens our understanding of the indirect influence of AI capability on the relationship between organizational readiness/circular design and resource efficiency performance and provides insight into possible explanations for firm size differences in the factors that may drive resource efficiency. The multigroup analysis undertaken in this study suggests that firm size is a critical factor in the adoption and performance of AI-driven sustainability initiatives. These structural differences could help identify potential mechanisms in explaining differences in managerial attitudes towards digital transformation strategies. However, the findings indicate that AI capability and the structural paths in the model are not as straightforward as assumed. Even though the AI capability development activities take considerable amounts of financial and organizational resources, the results are significant. Our findings extend recent research on how digital transformation, or a lack thereof, might shape circular economy performance. The findings provide evidence to managers on the relative value of AI analytics capability and organizational readiness in explaining performance differences between small and medium firms. The mediation effect we have found in our model is statistically significant, but we are sure that it is even more robust than the estimated coefficient we have reported here. Whereas with stronger organizational readiness focusing more on developing AI analytics tools could result in higher future resource efficiency. The analysis shows that AI capability is a tool for lowering

operational waste and for helping manufacturing firms reduce costs and emissions. This finding is in contrast to research that has found positive impacts of direct AI capability on resource efficiency. Here, the results contrast with the findings of [14] who outlined that firms need to integrate digital technologies for both operational efficiency and sustainability in a balanced manner in order to secure competitive advantage and long-term performance. While past studies have generally focused on the differences in how AI adoption and circular practices are perceived by managers and policy makers, this direct relationship is not always significant in the context of future resource efficiency outcomes. However, the findings indicate that AI capability and the relationships in the structural model are not as linear as expected. The reason lies in the limited observation period over time for the manufacturing projects. This study is not without limitations that may be addressed when conducting future studies on the manufacturing sector. We can therefore not draw any conclusions on how the effects of AI capability, organizational readiness, circular process innovation and digital collaboration may influence resource efficiency on a long-term base. Restricted sample selection is also limited, not allowing us to apply more advanced longitudinal methods.

6. Conclusion

Our study therefore contributes to the literature on artificial intelligence capability and circular economy performance by providing an extended model for the context of the manufacturing sector. The current study's most significant contribution is that AI-Driven Digital Capability together with Organizational Circular Readiness has a positive indirect effect on resource efficiency. Furthermore, this study suggest that manufacturing managers should work on enhancing the level of AI capability when implementing circular economy initiatives; since, compared to small firms, medium-sized firms more frequently report higher resource efficiency due to lack of organizational readiness in the early stages. Moreover, as we predicted, larger firms did show higher resource efficiency intention when they reported increased levels in the Organizational Circular Readiness and this may help managers when communicating their sustainability strategies to consumers. Furthermore, additional research can investigate the moderating effect of other organizational and industry characteristics such as firm age, ownership structure, technological intensity and market dynamism (small firms; medium firms; large firms) on the relationships with AI capability, circular sustainability performance and resource efficiency intention to help managers develop more targeted strategies of their specific consumer group. The results confirm the need to develop every dimension of AI capability and show that their impact can be strengthened by other organizational factors (organizational readiness and circular process innovation). Therefore, future studies might replicate our analysis with data from other regions. Such an analysis may provide further insight into the structural differences of these relationships. However, for the remaining 41 percent, we still need to develop the measurement model (including new indicators) and search for a more comprehensive explanation of resource efficiency. This study does not examine the possible longitudinal impact of the AI adoption process; therefore, an investigation of such an effect is also recommended in any future study. Adding more observations to the dataset would allow future researchers to apply more advanced covariance-based modeling techniques and improve the model's overall robustness.

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