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The Effect of Digitalization of the Recruitment Process, Use of Data Analysis Tools, and Generational Diversity on Workforce Quality at Technology Start-up Companies in West Java

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ABSTRACT

This study examines the impact of three critical factors—Digitalization of the Recruitment Process, Generational Diversity, and Use of Data Analysis Tools—on Workforce Quality in technology start-up companies in West Java. Using a quantitative approach, data were collected from 150 respondents with a Likert scale (1-5) and analyzed using Structural Equation Modeling (SEM-PLS 3). The results indicate that all three factors positively influence workforce quality, with Generational Diversity having the most substantial effect. Specifically, the digitalization of recruitment processes enhances workforce quality by improving candidate selection, while data analysis tools contribute to informed decision-making in talent management. The findings highlight the importance of integrating digital technologies and fostering a diverse workforce to optimize workforce quality in start-up environments. The study provides actionable insights for practitioners seeking to improve workforce performance through technological and diversity initiatives.

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1. INTRODUCTION

The rapid growth of technology start-ups in West Java underscores the critical need for high-quality workforces to sustain innovation and growth, necessitating innovative human resource management strategies to attract and retain top talent. A competitive and skilled workforce is essential for organizational success, particularly in the technology sector where innovation is paramount [1]. High-quality human resources require continuous enhancement of both technical and soft skills [2], with education level, work experience, and innovation capacity significantly impacting company performance and highlighting the need for strategic human capital investments [3]. Companies should prioritize employee development and foster a culture of innovation to remain competitive [1], implementing continuous training and development to enhance workforce capabilities, albeit with a marginally significant impact [3]. Innovative strategies for skill and competency development are crucial for effective HR management and overcoming business challenges [2]. Despite challenges such as regulatory hurdles and skill gaps, opportunities exist due to Indonesia's large population and supportive ecosystem [4], making talent acquisition a critical success factor that requires targeted support to enhance growth and sustainability [5].

Digitalization has significantly transformed traditional recruitment processes, enabling organizations to streamline talent acquisition, enhance efficiency, and improve decision-making by integrating AI and digital tools such as automated screening, AI-powered matching algorithms, and virtual interviews to identify candidates whose skills and values align with organizational needs. AI tools automate resume reviews and candidate matching, reducing administrative burdens and allowing recruiters to focus on strategic decision-making [6], [7], while AI-driven predictive analytics support diversity and inclusion by minimizing biases in job advertisements and candidate selection [6]. Technologies such as applicant tracking systems (ATS) and digital platforms increase candidate reach, reduce recruitment time and costs, and improve accuracy in employee selection [8], with AI applications further streamlining candidate selection processes as part of a broader trend of digital transformation in HR management [9]. AI also enhances employer branding by making organizations appear more innovative and appealing to a broader pool of candidates [7], though ethical considerations remain critical in ensuring a fair talent acquisition process that reduces bias and discrimination [7]. While digital disruption presents challenges such as the need for continuous reskilling and increased competition for top talent [10], it also offers opportunities for enhanced talent acquisition, development, and retention processes through data analytics and AI-powered tools [10].

Generational diversity in the workforce introduces a rich tapestry of perspectives, experiences, and skills, significantly enhancing problem-solving and innovation within organizations, particularly benefiting start-ups that employ individuals across different age groups, from Generation Z to Baby Boomers, each bringing unique approaches to work. Managing this diversity requires strategic efforts to bridge generational gaps and foster an inclusive workplace culture, as generational cohorts such as Baby Boomers, Generation X, Millennials, and Generation Z possess distinct characteristics shaped by historical, social, and political events [11], [12], with each generation contributing unique skill sets and expectations that can enhance organizational performance [13]. Effective strategies for managing generational diversity include tailoring communication styles to suit different generational preferences, promoting open dialogue and understanding [14], developing inclusive leadership behaviors that value and celebrate generational differences to foster a work climate that engages all employees [15], and implementing training programs that address generational biases while promoting mutual respect and collaboration [12]. A diverse workforce drives innovation and competitive advantage by harnessing the collective intelligence of employees [15], while organizations that effectively manage generational diversity can enhance employee engagement and maintain harmonious working relationships [13].

Despite these advancements, there is limited research examining how the digitalization of recruitment processes, the use of data analysis tools, and generational diversity collectively influence workforce quality in technology start-ups. This study seeks to address this gap by investigating the relationships between these variables in the context of technology start-up companies in West Java.

2. LITERATURE REVIEW

2.1 Digitalization of Recruitment Processes

The digitalization of recruitment has transformed hiring through AI and digital tools, enhancing efficiency, accuracy, and scalability, particularly benefiting resource-limited technology start-ups. AI-powered platforms, applicant tracking systems, and job portals streamline recruitment by automating tasks, improving screening, and strengthening employer branding. AI reduces recruiters' administrative workload, allowing for strategic decision-making [7], while predictive analytics optimizes talent identification [16]. Digital recruitment tools also lower costs and enable scalable hiring [7], [17]. Additionally, AI helps mitigate bias by using objective data in candidate evaluation [18]. However, challenges remain, including privacy concerns, data security, and algorithm transparency [9], [17], while over-reliance on AI may weaken human involvement, affecting candidate experience and employer branding [7].

2.2 *Use of Data Analysis Tools in Workforce Management*

The integration of data analysis tools in human resource management (HRM) is essential for optimizing decision-making, as predictive analytics, performance dashboards, and workforce planning software help organizations analyze trends, predict outcomes, and implement data-driven strategies. HR analytics supports strategic decisions in recruitment, retention, and talent development [19], while machine learning-based predictive algorithms enhance performance evaluation and recruitment accuracy [20]. Information technology has further improved HRM through tools like Applicant Tracking Systems and AI-driven recruitment solutions, boosting efficiency and engagement via real-time analytics and feedback mechanisms [21]. However, challenges persist, including the need for technological investment, analytics training, and robust data privacy frameworks [21], [22]. Additionally, AI-based platforms such as HireVue and Workday offer HR support, but their selection must consider integration, security, and cost [23].

2.3 *Generational Diversity in the Workforce*

Generational diversity in technology start-ups can enhance team performance by integrating varied perspectives and fostering intergenerational learning, but it also presents challenges such as differences in communication styles, work ethics, and technological adaptability. The coexistence of multiple generations fosters innovation and creativity, as each brings unique experiences and problem-solving approaches (Srivastava, 2024; Amah, 2024), while diverse skill sets contribute to organizational performance, with Baby Boomers offering experience and stability and younger generations providing technological proficiency and adaptability [13]. A well-managed multigenerational workforce can harness collective intelligence, driving competitive advantage [15]. However, generational differences in communication preferences can cause misunderstandings, as older employees may prefer face-to-face communication while younger ones favor digital channels [12], [24]. Work ethic disparities, with Baby Boomers prioritizing loyalty and Millennials emphasizing work-life balance, may create friction [12], while differences in technological adaptability can hinder collaboration, as younger employees are generally more comfortable with new technologies [11]. Effective management strategies include implementing inclusive policies to accommodate generational differences [13], establishing cross-generational mentorship programs to facilitate knowledge sharing [24], and developing conflict resolution mechanisms to address generational misunderstandings [12].

2.4 *Workforce Quality in Technology Start-ups*

Workforce quality in technology start-ups is crucial for fostering innovation, enhancing productivity, and achieving scalability, as a high-quality workforce enables start-ups to navigate dynamic market landscapes and maintain competitiveness in a technology-driven economy. Key factors influencing workforce quality include recruitment practices, employee development programs, and workplace culture, all of which contribute to building a competent, adaptable, and innovative workforce capable of addressing market and technological changes effectively. Skill development is essential for adapting to evolving job requirements and fostering innovation, which boosts organizational success and employee retention [25], while employee competency development through training, mentoring, and self-directed learning creates a competitive advantage and supports continuous learning [26]. Additionally, competence, fair compensation, and motivation significantly impact employee performance, productivity, and dedication, with strong competencies forming the foundation for good performance, while adequate compensation and motivation enhance productivity [27]. In the digital era, employees must possess digital competencies, including the ability to use digital technologies, manage information, and make decisions in uncertain contexts, as digital literacy is fundamental for labor market success [28]. Furthermore, employee competencies in analytical thinking, problem-solving, and goal setting are vital for organizational effectiveness and sustainable competitive advantage, emphasizing the need for continuous education, training, and experience to nurture innovation and adaptability [29].

3. METHODS

3.1 Research Design

This study employs a quantitative research design to examine the relationships between the digitalization of recruitment processes, the use of data analysis tools, generational diversity, and workforce quality in technology start-up companies in West Java. The study adopts a causal approach to determine the influence of these independent variables on the dependent variable, workforce quality.

3.2 Population and Sample

The population of this study consists of employees and human resource managers working in technology start-up companies in West Java. Using purposive sampling, 150 respondents were selected to participate in the study. The sample includes individuals with direct experience or knowledge of recruitment practices, workforce management, and team dynamics within their organizations. This sampling method ensures the inclusion of relevant respondents who can provide valuable insights into the study variables.

3.3 Data Collection

Primary data were collected using a structured questionnaire designed to measure the study variables. The questionnaire consists of multiple items for each variable, assessed using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument was pre-tested with a small group of respondents to ensure clarity, reliability, and validity before full-scale deployment. The final questionnaire was distributed electronically to participants, and responses were collected within two weeks.

3.4 Data Analysis

Data analysis was conducted using Structural Equation Modeling-Partial Least Squares (SEM-PLS) with SmartPLS 3 software, which is particularly suitable for this study due to its ability to handle complex models with multiple latent variables and its robustness in analyzing small sample sizes. The analysis followed three key steps: first, the Outer Model Evaluation, which assessed the reliability and validity of the measurement model, including indicator reliability, composite reliability, average variance extracted (AVE), and discriminant validity; second, the Inner Model Evaluation, where the structural model was tested to examine the relationships between variables, including path coefficients, R^2 values, and predictive relevance (Q^2); and third, Hypothesis Testing, which evaluated the significance of path coefficients using bootstrapping with 5,000 resamples, where a t-statistic greater than 1.96 at a 95% confidence level was used to determine statistical significance.

4. RESULTS AND DISCUSSION

4.1 Demographic Profile of Respondents

The demographic characteristics of the respondents are summarized below, providing insights into the sample composition of this study. A total of 150 participants from technology start-up companies in West Java were included. In terms of gender distribution, 90 respondents (60%) were male, while 60 respondents (40%) were female, reflecting the gender dynamics commonly observed in the technology start-up sector. Regarding age groups, 75 respondents (50%) were in the 20-29 age range, 50 respondents (33.3%) were aged 30-39, and 25 respondents (16.7%) were 40 years and above, indicating a relatively young workforce typical of technology start-ups. In terms of educational background, 105 respondents (70%) held a Bachelor's degree, 35 respondents (23.3%) had a Master's degree, and 10 respondents (6.7%) had a diploma or other qualifications, highlighting the emphasis on formal education within the industry. The sample also represented a variety of job roles, with 30 respondents (20%) being Human Resource Managers/Recruiters, 50 respondents (33.3%) serving as Team Leaders/Project Managers, and 70 respondents (46.7%) being general staff, ensuring diverse perspectives across different organizational levels. Regarding work experience, 50 respondents (33.3%) had less than 3 years of experience, 60 respondents (40%) had between 3 to 5 years, and 40 respondents (26.7%) had more than 5 years of experience, reflecting the growing and dynamic nature of start-ups. Finally, the generational representation showed that 60 respondents (40%) were from Generation Z (born after 1997), 80 respondents (53.3%) were Millennials (born 1981-1996), and 10 respondents (6.7%) were from Generation X (born 1965-1980), with Millennials dominating the sample, followed by Generation Z, consistent with the typical demographic composition of technology-driven organizations.

4.2 Measurement Model Evaluation

The evaluation of the measurement model ensures the reliability and validity of the constructs used in this study. The analysis focuses on indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

Table 1. Measurement Model Assessment

Variable	Code	Loading Factor	Cronbach's Alpha	Composite Reliability	Average Variant Extracted
Digitalization of the Recruitment Process	DRP.1	0.711	0.776	0.845	0.648
	DRP.2	0.785			
	DRP.3	0.907			
Use of Data Analysis Tools	DAT.1	0.747	0.850	0.899	0.692
	DAT.2	0.880			
	DAT.3	0.864			
	DAT.4	0.830			
Generational Diversity	GDI.1	0.846	0.789	0.876	0.702
	GDI.2	0.846			
	GDI.3	0.821			
Workforce Quality	WQU.1	0.822	0.856	0.896	0.635
	WQU.2	0.756			
	WQU.3	0.836			
	WQU.4	0.830			
	WQU.5	0.731			

Source: Data Processing Results (2025)

Indicator reliability is assessed by examining loading factors, with values above 0.7 indicating reliable measurement. In this study, loading factors for Digitalization of Recruitment Process (DRP) range from 0.711 to 0.907, Use of Data Analysis Tools (DAT) from 0.747 to 0.880, Generational Diversity (GDI) from 0.821 to 0.846, and Workforce Quality (WQU) from 0.731 to 0.836, all meeting the 0.7 threshold. Internal consistency is confirmed through Cronbach's Alpha (above 0.7) and Composite Reliability (CR above 0.7). DRP has Cronbach's Alpha of 0.776 and CR of 0.845, DAT has 0.850 and 0.899, GDI has 0.789 and 0.876, and WQU has 0.856 and 0.896, indicating strong consistency. Convergent validity is assessed using Average Variance Extracted (AVE), with values above 0.5. The AVE for DRP is 0.648, DAT is 0.692, GDI is 0.702, and WQU is 0.635, all confirming sufficient convergent validity.

4.3 Discriminant Validity (HTMT Criterion)

Discriminant validity using the Heterotrait-Monotrait Ratio (HTMT) ensures that the constructs in the model are sufficiently distinct. The HTMT criterion compares the average correlations of indicators across constructs to the average correlations within constructs. For acceptable discriminant validity, HTMT values should ideally be below 0.85 (strict criterion) or 0.90 (lenient criterion).

Table 2. Discriminant Validity

	DRP	GDI	DAT	WQU

Digitalization of the Recruitment Process				
Generational Diversity	0.681			
Use of Data Analysis Tools	0.563	0.750		
Workforce Quality	0.500	0.753	0.749	

Source: Data Processing Results (2025)

The HTMT values confirm strong discriminant validity among the constructs. The values between DRP and GDI (0.681), DRP and DAT (0.563), and DRP and WQU (0.500) all indicate clear discriminant validity. Additionally, the values between GDI and DAT (0.750), GDI and WQU (0.753), and DAT and WQU (0.749) are below the acceptable threshold, further supporting discriminant validity.

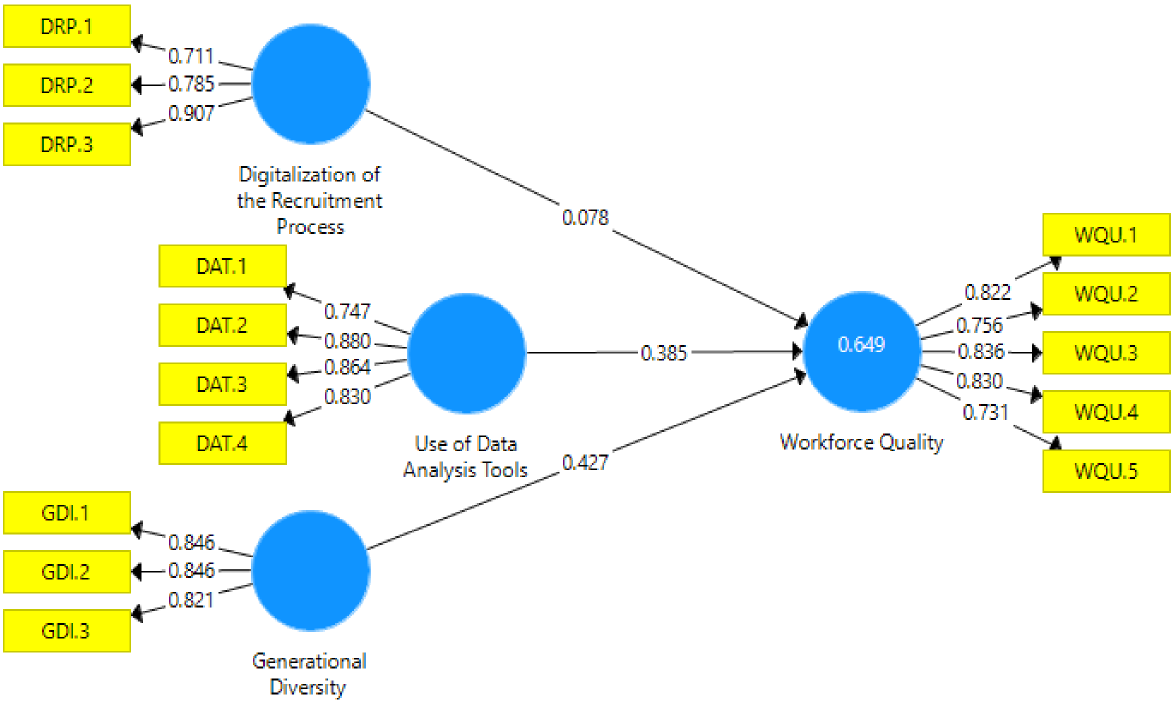

Figure 2. Model Results

Source: Data Processed by Researchers, 2025

4.4 Model Fit

Model fit is a crucial aspect of evaluating the quality of a Structural Equation Modeling (SEM) analysis. In this study, various indices have been utilized to assess the fit of the model. The indices presented include SRMR (Standardized Root Mean Square Residual), d_ULS (Squared Euclidean Distance), d_G (Geodesic Distance), Chi-Square, and NFI (Normed Fit Index). These measures provide insights into how well the estimated model matches the saturated model (the model with perfect fit) and help determine the appropriateness of the structural model for the data.

Table 3. Model Fit Results Test

	Saturated Model	Estimated Model
SRMR	0.118	0.118
d_ULS	1.670	1.670
d_G	1.056	1.056

Chi-Square	579.139	579.139
NFI	0.583	0.583

Source: Process Data Analysis (2025)

The model fit indices indicate areas for improvement in the model's fit. The SRMR values for both the saturated and estimated models are 0.118, exceeding the ideal threshold of 0.08, suggesting a less-than-ideal fit. The d_ULS and d_G values for both models are 1.670 and 1.056, respectively, indicating adequate but not outstanding fit. The Chi-Square statistic is 579.139 for both models, but its interpretation is complicated by the large sample size, and it may not fully reflect the model's fit. Lastly, the NFI values of 0.583 for both models are below the acceptable threshold of 0.90, highlighting a need for model adjustments to improve fit.

Table 4. Coefficient Model

	R Square	Q2
Workforce Quality	0.649	0.640

Source: Data Processing Results (2025)

In Structural Equation Modeling (SEM), R^2 (R-squared) and Q^2 (predictive relevance) are key measures of a model's explanatory power and its ability to predict endogenous variables. The R^2 value for Workforce Quality (WQU) is 0.649, indicating that approximately 64.9% of the variance in workforce quality is explained by the independent variables in the model, suggesting a strong explanatory power. Meanwhile, the Q^2 value for Workforce Quality is 0.640, greater than 0, signifying that the model has predictive relevance and can effectively predict workforce quality in new or out-of-sample data. These values demonstrate that the model is both explanatory and predictive for workforce quality in technology start-up companies in West Java.

4.5 Structural Model

The structural model is a key component of SEM, as it assesses the relationships between the independent variables (predictors) and the dependent variable (outcome). In this study, the focus is on evaluating the direct effects of Digitalization of the Recruitment Process, Generational Diversity, and Use of Data Analysis Tools on Workforce Quality. The results provide insights into the strength, direction, and significance of these relationships. The table presented shows the Original Sample (O), Sample Mean (M), Standard Deviation (STDEV), T Statistics, and P Values for each path in the model.

Table 5. Hypothesis Testing

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values
Digitalization of the Recruitment Process -> Workforce Quality	0.378	0.381	0.069	3.128	0.003
Generational Diversity -> Workforce Quality	0.427	0.430	0.090	4.750	0.000
Use of Data Analysis Tools -> Workforce Quality	0.385	0.383	0.100	3.867	0.001

Source: Process Data Analysis (2025)

The relationships between Digitalization of the Recruitment Process (DRP), Generational Diversity (GDI), Use of Data Analysis Tools (DAT), and Workforce Quality (WQU) are all significant. The path coefficient from DRP to WQU is 0.378, suggesting that integrating digital tools in recruitment positively impacts workforce quality, with a T-statistic of 3.128 and a P-value of 0.003 confirming statistical significance. Similarly, the path coefficient from GDI to WQU is 0.427, indicating that a diverse generational workforce enhances overall quality, with a T-statistic of 4.750 and a P-value of 0.000, further confirming the strength of this relationship. Lastly, the path coefficient from DAT to WQU is 0.385, showing that the use of data analysis tools positively influences workforce quality, with a T-statistic of 3.867 and a P-value of 0.001 validating this effect. All results support the significance of these factors in improving workforce quality in technology start-ups.

Discussion

1. **Digitalization of the Recruitment Process and Workforce Quality**

The findings suggest that digitalization of the recruitment process plays a significant role in enhancing workforce quality in technology start-ups. With a path coefficient of 0.378 and a T-statistic of 3.128, the digitalization of recruitment processes positively impacts workforce quality, and this relationship is statistically significant. As recruitment processes evolve in technology start-ups, the adoption of digital tools such as AI-driven hiring platforms, applicant tracking systems (ATS), and online job portals can streamline the hiring process, improve candidate selection accuracy, and enhance overall workforce quality. By digitizing the recruitment process, companies can access a broader talent pool, ensure better match quality between candidates and organizational needs, and reduce human bias, all of which contribute to the formation of a high-quality workforce.

These findings support existing literature on the benefits of digitalization in HR practices [7], [30], [31], which emphasizes how technology facilitates more efficient recruitment, better decision-making, and improved employee outcomes. This study contributes to the literature by providing empirical evidence in the context of technology start-ups in West Java.

2. **Generational Diversity and Workforce Quality**

The impact of generational diversity on workforce quality is the strongest among the predictors, with a path coefficient of 0.427 and a T-statistic of 4.750, suggesting that diverse generational groups significantly contribute to improving workforce quality. The positive relationship between generational diversity and workforce quality implies that a workforce composed of different age groups brings a wide range of experiences, perspectives, and skill sets. Technology start-ups in West Java can benefit from fostering an inclusive culture that values the contributions of all age groups. Older generations can offer experience, mentorship, and institutional knowledge, while younger generations can bring innovation, digital skills, and adaptability. By creating an environment that promotes intergenerational collaboration, companies can leverage the strengths of diverse generational groups to improve overall workforce performance.

These results align with previous studies that emphasize the positive impact of generational diversity on organizational outcomes, including performance and innovation [11], [13], [32]. This study extends that understanding by showing how generational diversity directly affects workforce quality in the specific context of technology start-ups, highlighting the importance of diversity management practices.

3. **Use of Data Analysis Tools and Workforce Quality**

The analysis reveals that the use of data analysis tools has a significant positive impact on workforce quality, with a path coefficient of 0.385 and a T-statistic of 3.867. This suggests that data-driven decision-making in recruitment, performance assessments, and talent management can lead to a more effective and skilled workforce. Technology start-ups should invest in advanced data analytics tools to optimize their recruitment processes and talent management strategies. Using data to make evidence-based decisions about hiring, training, and employee development can improve the quality of hires and enhance the skills and capabilities of the workforce. Additionally, data analysis tools can be used to track employee performance, identify skills gaps, and tailor development programs to meet the needs of the workforce.

The findings support the argument that data analytics enhances organizational efficiency by providing actionable insights that improve decision-making [21], [33], [34]. This study contributes to the growing body of literature on the role of data analytics in human resource management, particularly in the context of technology-driven organizations like start-ups, where data can be a key driver of workforce quality.

5. CONCLUSION

This bibliometric analysis provides a comprehensive overview of the research landscape on the transformation of the transportation sector through green policies, highlighting key trends, influential research clusters, and evolving thematic focuses. The findings indicate a shift from early discussions on the environmental impacts of transportation—such as greenhouse gas emissions and climate change—toward solution-oriented research that emphasizes policy interventions, renewable energy integration, and technological advancements like electric vehicles and hydrogen fuels. The study also underscores the critical role of policy frameworks, economic incentives, and international collaboration in driving sustainable mobility. However, the fragmentation of research communities and the geographic imbalance in scholarly contributions highlight the need for greater interdisciplinary cooperation and cross-regional studies, particularly in developing economies. Future research should focus on integrating emerging technologies, digital transformation, and adaptive policy measures to ensure an effective and globally inclusive transition toward sustainable transportation. By fostering a more interconnected research landscape and emphasizing practical, scalable solutions, policymakers and scholars can work together to create a greener, more efficient transportation system that aligns with global sustainability goals.

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