JRIIE Journal of Research Innovation and Implications in Education
Center for Research Implications & Practice

Website: www.jriiejournal.com ISSN 2520-7504 (Online) Vol.10, Iss.3, 2026 (pp. 2452 - 2465)

Effect of Artificial Intelligence on Project Management Optimization Processes: A Case of Advocacy for Street Children and Family Reintegration Project Implemented by Sympathy Rwanda Organization in Huye District, Rwanda

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Abstract: *The study investigated the effect of Artificial Intelligence (AI) on project management processes in the Advocacy for Street Children and Family Reintegration (SCFR) Project implemented by Sympathy Rwanda Organization in Huye District, Rwanda. It examined AI integration, Data-Driven Decision Making, Community Engagement Strategies, and project management optimization. The study was anchored on the Social Ecological Model, Technology Acceptance Model, Organizational Information Processing Theory, and Agile Project Management Framework. A descriptive correlational design was adopted. The target population comprised 138 respondents, from whom a sample of 103 was determined using Slovin's formula. Purposive sampling was used for the manager, director, and supervisors, while random sampling selected employees and street children. Data were collected using questionnaires, interviews, and an observation checklist and analysed using SPSS, descriptive statistics, Pearson correlation, regression, and ANOVA. Overall inferential findings established a strong positive relationship between AI and project management optimization* ($R = 0.750$, $R^2 = 0.568$, *Adjusted* $R^2 = 0.567$, $B = 0.377$, $\beta = 0.750$, $t = 3.800$, $F = 355.18$, $p < 0.0001$)*. The study concluded that AI, data-driven practices, and community engagement strengthened project management processes and recommended continued AI training, stronger data governance, inclusive community participation, and strategic alignment of AI with planning and monitoring functions.*

Keywords: *Artificial Intelligence Optimization, Project Management Processes, Advocacy for Street Children, Family Reintegration Project*

How to cite this work (APA):

Umuhoza, M. & Basimya, S. (2026). Effect of Artificial Intelligence on Project Management Optimization Processes: A Case of Advocacy for Street Children and Family Reintegration Project Implemented by Sympathy Rwanda Organization in Huye District, Rwanda. *Journal of Research Innovation and Implications in Education, 10*(3), 2452 – 2465. **https://doi.org/10.59765/ms3d6**

1. Introduction

Globally, in countries such as the United States, managing child welfare initiatives and homelessness interventions requires robust project management processes to ensure effective resource allocation, monitoring, and service delivery. The COVID-19 pandemic exacerbated youth vulnerability, highlighting the need for streamlined management systems within organizations executing family reunification and community-based support initiatives (National Alliance to End Homelessness, 2021).

In Uganda, the National Strategic Programme Plan for Vulnerable Children relies on non-governmental partners for implementation. Deficiencies in core project

management processes such as tracking project performance, risk mitigation, and budget control continue to limit the scalability and sustainability of family reunification programs (UNICEF, 2021).
In Rwanda, following the 1994 genocide, national child protection policies emphasized family-based care. While institutional frameworks like the National Child Policy exist, local initiatives in urban centers like Huye District struggle with operational efficiency. Managing street children advocacy and reintegration requires refined project management processes including clear objective setting, standardized workflows, accurate performance monitoring, and resource optimization to ensure social interventions achieve sustained impact (National Commission for Children, 2011).

In Huye District, urban migration, family breakdown, and socio-economic pressures continue to expand the population of street-connected youth. While NGOs and local authorities deliver outreach, educational, and psychosocial interventions, sustaining these operations relies directly on robust project management processes (UNICEF, 2021). Streamlining project planning, resource allocation, and workflow management enables these local projects to maintain service continuity and optimize long-term family reintegration outcomes.

To overcome recurring execution bottlenecks, social intervention programs are increasingly turning to technology. Modernizing project management processes through data-driven tracking tools enables social workers to evaluate intervention impact, track participant progress, and allocate field resources based on empirical evidence rather than manual estimates (Flick, 2018).

The Advocacy for Street Children and Family Reintegration Project in Huye serves as a primary example of how incorporating Artificial Intelligence (AI) can optimize fundamental project management processes. Integrating AI tools into core management functions such as predictive data analysis, resource optimization, automated progress tracking, and performance evaluation allows project managers to streamline workflows, tailor social interventions to complex family dynamics, and significantly boost operational efficiency (Hsieh et al., 2021).

The study therefore focused on the Advocacy for Street Children and Family Reintegration Project implemented by Sympathy Rwanda Organization in Huye District. The project requires project management processes that support planning, execution, monitoring, resource allocation, data use, and stakeholder coordination. The study investigated how Artificial Intelligence integration, data-driven decision-making, community engagement strategies, and the broader relationship between AI and project management processes contributed to project management optimization.

1.1 General Objective

The purpose of this study was to investigate the enhance project management processes through artificial intelligence optimization, a case of Advocacy for Street Children and Family Reintegration (SCFR) Project Huye District, Rwanda.

1.2 Specific Objectives

The specific objectives that guided the study were as follows.

1. To assess the effects of Artificial Intelligence integration on project management process of SCFR Project Huye District, Rwanda.
2. To investigate the effects of Data-Driven Decision Making on project management process of SCFR Project Huye District, Rwanda.
3. To determine the effects of Community Engagement Strategies on project management process of SCFR Project Huye District, Rwanda.
4. To establish the relationship between AI and project management process of SCFR Project Huye District, Rwanda.

2. Literature Review

This section reviews the theoretical and empirical literature underpinning the study variables and their relationship with project management processes.

2.1 Theoretical Review

This section presented the theoretical foundations used to explain the effect of Artificial Intelligence on project management processes in the Advocacy for Street Children and Family Reintegration Project. The study was anchored on the Social Ecological Model, Technology Acceptance Model, Organizational Information Processing Theory, and Agile Project Management framework. These theoretical perspectives explained community engagement, acceptance and use of Artificial Intelligence, data-driven decision-making, and the adaptive application of Artificial Intelligence in project management processes. The theories therefore provided a basis for understanding how Artificial Intelligence and related management practices influenced project planning, resource allocation, monitoring, decision-making, risk management, and stakeholder coordination within the SCFR Project.

2.1.1 Social Ecological Model

The Social Ecological Model (SEM) originated from ecological approaches to human development associated with Bronfenbrenner (1977), who argued that human behaviour and development should be understood through the continuing interaction between individuals and the different environments in which they live. The ecological perspective recognises interconnected levels of influence extending from immediate interpersonal relationships to organisations, communities, and broader social and policy environments. McLeroy et al. (1988) further developed the ecological perspective by explaining that individual behaviour is influenced not only by personal characteristics but also by interpersonal, organisational, community, and public policy factors. This perspective is particularly relevant to social interventions whose outcomes depend on coordinated action across several levels.

The model implies that challenges affecting vulnerable children cannot be adequately understood or addressed by concentrating on the individual child alone. Family relationships, peer networks, community attitudes, organisational services, local leadership, institutional arrangements, and public policies can interact to influence both vulnerability and successful reintegration. Consequently, sustainable interventions require coordination between beneficiaries, families, communities, service organisations, and responsible institutions rather than isolated interventions at a single level. This ecological reasoning makes the model relevant to the Advocacy for Street Children and Family Reintegration Project because the project operates within interconnected family, community, organisational, and institutional environments.

The Social Ecological Model was applied to the third objective concerning Community Engagement Strategies and project management processes in the SCFR Project. The model explained how family participation, community involvement, stakeholder consultation, community feedback, local partnerships, and institutional support interacted to influence project planning, implementation, monitoring, and sustainability. It therefore provided a theoretical basis for examining whether involving communities in project decisions and reintegration activities strengthened stakeholder ownership, improved the relevance of interventions, and supported effective project management processes.

2.1.2 Technology Acceptance Model

The Technology Acceptance Model (TAM) was developed by Davis (1989) to explain the acceptance and use of information technologies. The model identifies perceived usefulness and perceived ease of use as fundamental determinants of technology acceptance. Perceived usefulness refers to the extent to which users believe that using a particular technology will improve their work performance, while perceived ease of use concerns the extent to which the technology is perceived as requiring limited effort. Davis argued that favourable perceptions of usefulness and ease of use increase users' willingness to accept and use technological systems.

The model was subsequently extended by Venkatesh and Davis (2000), who demonstrated that technology acceptance is also influenced by factors such as social influence, job relevance, output quality, and the ability of users to observe the benefits produced by a system. This broader interpretation is important in organisational settings because the availability of technology does not automatically guarantee its effective utilisation. Artificial Intelligence can support automation, forecasting, monitoring, information analysis, and decision support, but these benefits depend substantially on whether project personnel understand, accept, and consistently incorporate the technology into their work processes.

The Technology Acceptance Model was applied to the first objective concerning Artificial Intelligence integration and project management processes in the SCFR Project. It explained how project managers, social workers, supervisors, and administrative staff were more likely to integrate Artificial Intelligence tools when they perceived them as useful and manageable within existing project activities. The theory therefore provided a basis for understanding the adoption of AI-supported data analysis, automated tracking, scheduling, monitoring, and decision-support applications. Effective acceptance and use of such tools could enable the project team to improve planning, resource allocation, performance tracking, and administrative efficiency within the project.

2.1.3 Organizational Information Processing Theory

Organizational Information Processing Theory was developed from the work of Galbraith (1974), who argued that organisations face increasing information-processing requirements as task uncertainty and complexity increase. According to the theory, effective organisational performance depends on the ability to obtain, process, interpret, and communicate sufficient information for decision-making. Where uncertainty is high, organisations need stronger information-processing mechanisms and information systems to ensure that managers receive relevant information for coordinating activities and responding to changing conditions.

Tushman and Nadler (1978) further explained information processing as an important mechanism through which organisations respond to uncertainty and coordinate interdependent tasks. From this perspective, managerial effectiveness depends on the alignment between the amount of information required by organisational activities and the organisation's capacity to process that information. In contemporary project environments, Artificial Intelligence and data analytics can increase this capacity by organising large datasets, identifying patterns, producing forecasts, and supporting timely managerial decisions. Research on AI-enabled project management has similarly identified planning, measurement, forecasting, uncertainty management, and decision-making among important areas in which Artificial Intelligence can contribute to project management (Taboada et al., 2023).

Organizational Information Processing Theory was applied to the second objective concerning Data-Driven Decision Making and project management processes in the SCFR Project. The theory explained how the collection, analysis, and timely use of information concerning child progress, family reintegration, project activities, stakeholder feedback, resource utilisation, performance indicators, and potential risks could reduce uncertainty in project decisions. It therefore provided a theoretical basis for examining how data-driven decisions supported project planning, resource allocation, monitoring, performance evaluation, and risk management. Through improved information-processing capacity, managers could base project decisions on available evidence rather than relying solely on judgement or intuition.

2.1.4 Agile Project Management Framework

Agile principles emerged from the Agile Manifesto in 2001, which emphasised collaboration, responsiveness to change, continuous delivery of value, and close interaction among stakeholders (Beck et al., 2001). Agile approaches differ from rigid project-management arrangements by encouraging iterative planning, frequent feedback, adaptation, and progressive improvement when project conditions change. Conforto et al. (2014) demonstrated that Agile Project Management principles could also be adapted beyond software-development environments, particularly where projects operate under uncertainty and require flexibility.

More recent project-management literature has continued to describe Agile Project Management as an adaptive and context-oriented approach rather than simply a software-development technique. Dong et al. (2024), following a systematic review of Agile Project Management literature, described agility as involving organisational capacity to respond and adapt to changes emerging during project implementation. Similarly, Serrador and Pinto (2015) established a positive association between the use of agile approaches and reported project success, particularly where stakeholder satisfaction and responsiveness to changing project requirements were important. Agile Project Management therefore provides an appropriate framework for explaining how project teams continually interpret information, incorporate feedback, and adjust their activities.

The Agile Project Management framework was applied to the fourth objective concerning the relationship between Artificial Intelligence and project management processes in the SCFR Project. Artificial Intelligence can generate timely information through predictive analytics, automated monitoring, progress tracking, and analysis of emerging project conditions, while agile practices enable managers to use such information to adjust activities and decisions. Within the SCFR Project, this theoretical linkage explained how project teams could review changing family circumstances, beneficiary progress, resource requirements, project risks, and stakeholder feedback and subsequently adapt planning, budgeting, monitoring, and intervention strategies. The framework therefore connected Artificial Intelligence capabilities with adaptive project management processes and continuous improvement in project implementation.

2.2 Empirical Review

The empirical review synthesized evidence from previous studies concerning Artificial Intelligence and project management processes. Attention was given to research on Artificial Intelligence integration, Data-Driven Decision Making, Community Engagement Strategies, and Artificial Intelligence in project management optimization. Previous studies were reviewed based on their findings and conclusions to establish what is already known and demonstrate the need to examine these practices within the Advocacy for Street Children and Family Reintegration Project implemented by Sympathy-Rwanda Organization in Huye District.

2.2.1 Artificial Intelligence Integration and Project Management Process

Wang et al. (2021) examined the application of Artificial Intelligence in project management and found that AI enabled project managers to identify potential risks early and optimise resource distribution through the analysis of historical and real-time project information. AI-supported systems also streamlined administrative workflows, reduced manual errors, and improved forecasting precision. These findings demonstrated that AI integration could strengthen project planning, resource allocation, and timely managerial responses.

Oesterreich and Teuteberg (2020) examined the use of Artificial Intelligence in automating routine project activities such as scheduling, resource allocation, and data-driven decision-making. AI algorithms were found to use historical information to predict possible project delays and budget overruns, enabling managers to take proactive action. The findings demonstrated the usefulness of Artificial Intelligence in supporting project teams operating in environments characterised by multiple and changing project conditions.

Yang et al. (2020) found that AI-driven project management tools significantly reduced the time required for decision-making. Artificial Intelligence enabled project teams to process large amounts of information and transform it into actionable information for managers. Faster access to relevant information allowed project teams to respond more rapidly to implementation challenges and improve the efficiency of project decisions.

Marnewick and Labuschagne (2020) examined the contribution of Artificial Intelligence to stakeholder communication and collaboration. The study indicated that real-time information generated through AI tools facilitated communication between project stakeholders and helped maintain alignment concerning project goals and expectations. This contribution was relevant to projects involving several stakeholders because effective information sharing supported coordination throughout implementation.

Gamil et al. (2021) investigated AI-supported project scheduling and found that organisations adopting AI-driven scheduling tools experienced a 35% reduction in project delays. The improvement was associated with the capacity of AI to analyse task dependencies, resource availability, and previous project performance when developing schedules. The study demonstrated the contribution of AI integration to timely project implementation, although its findings were not specifically based on social advocacy projects involving street children and family reintegration in Huye District.

2.2.2 Data-Driven Decision Making and Project Management Process

Kumar and Singh (2022) examined Data-Driven Decision Making and found that the use of empirical information enabled project managers to make informed choices based on evidence rather than intuition. The approach strengthened strategic planning and operational efficiency by providing managers with information that could guide project decisions. Such evidence demonstrated the importance of systematically using available project data when making management decisions.

Neely et al. (2021) examined the use of Data-Driven Decision Making methodologies and established that projects applying DDDM achieved improved performance metrics while strengthening accountability and transparency. The use of measurable evidence allowed project teams to evaluate implementation progress and provide clearer justification for management decisions. Data-driven practices were therefore associated with more transparent and accountable project management processes.

Dyer et al. (2020) found that organisations adopting Data-Driven Decision Making were better positioned to identify patterns and trends relevant to strategic planning. Data analytics enabled project managers to assess the effectiveness of interventions and make necessary adjustments to improve project performance. The approach also supported continuous improvement because teams could compare actual performance against established project measures.

Hsieh et al. (2021) investigated Data-Driven Decision Making and reported that organisations applying DDDM practices experienced a 20% increase in project success rates. The improvement was attributed to the use of real-time information to make informed adjustments to project strategies. The findings indicated that timely access to relevant data could enhance project responsiveness and contribute to improved implementation outcomes.

Ransbotham et al. (2021) examined the contribution of Data-Driven Decision Making to organisational risk management and found that organisations leveraging DDDM were 40% more effective in identifying and mitigating risks. Data analysis helped project teams recognise emerging problems and implement proactive responses. However, the available evidence did not specifically examine how Data-Driven Decision Making influenced the management processes of a street children advocacy and family reintegration project in Huye District.

2.2.3 Community Engagement Strategies and Project Management Process

Baker et al. (2021) examined community engagement and found that projects with strong community-engagement components were more likely to achieve their objectives and sustain their effects over time. Community participation enabled project teams to identify local needs while strengthening community ownership and responsibility for project interventions. The findings demonstrated the importance of stakeholder involvement in projects whose implementation depended on local support.

The World Bank (2021) examined the contribution of community participation to project effectiveness and emphasised the importance of local knowledge and resources. Community members provided information concerning local social conditions and priorities that could improve the design and implementation of project interventions. Incorporating such knowledge enabled project activities to respond more effectively to the circumstances and expectations of targeted communities.

Fetterman et al. (2020) investigated feedback mechanisms in community engagement and indicated that continuous dialogue between project teams and community members strengthened transparency and accountability. Effective feedback loops were associated with increased community trust and cooperation. Continuous communication also enabled project managers to adjust interventions according to changing community experiences and expectations.

Baker et al. (2021) assessed community involvement and project sustainability and found that projects actively involving community members in decision-making experienced a 45% increase in long-term sustainability. Community participation strengthened ownership and support for project interventions. The findings demonstrated that sustained project outcomes depended partly on the extent to which affected communities participated in project decisions.

Bratt et al. (2018) examined continuous dialogue within community engagement and reported a 25% increase in satisfaction with project outcomes where feedback mechanisms were established. Continuous communication enabled project leaders to adapt their approaches according to community responses. Nevertheless, the study did not specifically examine community engagement within the management of an advocacy and family reintegration project for street-connected children in Huye District.

2.2.4 Artificial Intelligence and Project Management Optimization Process

Kourentzes et al. (2020) examined the role of Artificial Intelligence in project risk management and found that organisations using AI for data-driven decision-making achieved a 50% increase in their ability to identify potential risks before they materialised. Early risk identification enabled project managers to introduce mitigation measures before identified threats affected project activities. Artificial Intelligence therefore supported more proactive management of project uncertainty.

Gamil et al. (2021) examined AI-driven project scheduling and found that organisations using Artificial Intelligence tools achieved a 35% reduction in project delays. AI applications analysed task dependencies, resource availability, and historical performance to support more efficient project schedules. This demonstrated how Artificial Intelligence could optimise project processes through improved planning and scheduling.

Taboada et al. (2023) assessed Artificial Intelligence applications in project management and reported a 40% improvement in resource allocation efficiency. AI-supported analysis enabled project teams to utilise available skills and resources more effectively. Improved allocation was particularly important for projects operating with limited resources because project managers were required to direct available inputs towards activities where they could produce greater project benefits.

Sweeney and Zeng (2021) examined the integration of Artificial Intelligence into project management practices and found that it was associated with a 25% increase in project profitability. Artificial Intelligence automated routine tasks and provided data-driven information that allowed project managers to devote greater attention to strategic decisions. The findings demonstrated that AI optimisation could affect both operational efficiency and the utilisation of project financial resources.

The Project Management Institute (2020) reported that organisations leveraging Artificial Intelligence tools within project management processes experienced a 30% increase in stakeholder satisfaction. AI-supported real-time updates strengthened communication and helped stakeholders remain aligned with project objectives and expectations. Although these findings demonstrated the contribution of Artificial Intelligence to project management optimisation, they did not specifically establish this relationship within the Advocacy for Street Children and Family Reintegration Project implemented by Sympathy-Rwanda Organization in Huye District.

3. Methodology

This section presented the research methodology that was used to conduct the study. It outlined the research design, target population, sample size, sampling technique, data collection methods, research instruments, data analysis procedures, reliability, pilot study, and ethical considerations. The section also explained how the adopted methods supported credible collection and analysis of data on Artificial Intelligence and project management optimization processes in the SCFR Project.

3.1 Research Design

This study employed a descriptive survey design, specifically utilizing descriptive correlational strategies. The non-experimental nature of descriptive studies made them well-suited for analyzing existing conditions without manipulating variables. This was important in the context of child advocacy, where ethical considerations and the complexities of the environment limited the feasibility of experimental designs. By focusing on real-world conditions, this research yielded information that was both relevant and applicable.

The quantitative strategy utilized structured questionnaires translated into Kinyarwanda and enabled precise, numerical measurement of the target population's characteristics, usage frequencies of AI tools, and process efficiency metrics. The correlational component allowed for empirical hypothesis testing, evaluating how independent variables such as AI integration and community engagement statistically related to project management processes including planning, budgeting, monitoring, and risk management.

3.2 Study Population

A study population refers to the broader group from which research participants are selected to provide information relevant to the study (Kothari & Garg, 2022). The study population comprised 138 respondents connected to Sympathy-Rwanda Organization and the Advocacy for Street Children and Family Reintegration Project in Huye District. These included 4 supervisors, 1 manager, 1 director, 32 employees, and 100 street children involved in or connected to the project.

3.3 Sampling

Sampling design refers to the process of selecting elements from a population to ensure that the selected sample adequately represents the broader population (Kothari & Garg, 2022). The study used a sample size of 103 respondents drawn from the target population of 138 respondents. Purposive and random sampling techniques were employed in selecting the respondents.

Purposive sampling was used to select the manager, director, and supervisors because they possessed decision-making authority, strategic oversight, and relevant information concerning the project. Random sampling was used to select street children and employees, giving members of these categories an equal opportunity of being selected and reducing selection bias.

3.4 Data Collection Instrument

A data collection instrument is a tool used by a researcher to gather relevant information from respondents for purposes of addressing the study objectives and facilitating subsequent analysis (Kothari & Garg, 2022). The study used a structured questionnaire as the main data collection instrument. The questionnaire contained closed-ended questions and was administered to the selected respondents to obtain information related to the study variables.

The questionnaire was carefully structured using simple and clear language to enable respondents to understand and answer the questions appropriately. Predetermined response options were provided to allow respondents to indicate the answers that best represented their views. The completed questionnaires provided quantitative data that were coded, organised, and analysed in accordance with the study objectives.

3.5 Pilot Study, Validity and Reliability

To operationalize the piloting phase, a specific group of respondents matching the target demographic criteria was selected for the pilot test. To prevent data contamination, these participants were completely excluded from the final data collection pool. Formal clearance and verbal consent were obtained from the participants before administering the draft questionnaires, maintaining the same ethical standards intended for the primary study.

Reliability refers to the internal consistency and stability of the research instrument meaning it should produce identical, dependable results under unchanged conditions. The acceptable threshold for a reliable instrument in academic research is a Cronbach's alpha coefficient of 0.70 or higher.

3.6 Data Analysis

To establish the relationship between the independent variables and the dependent variable of the study, inferential analysis was conducted. It involved a coefficient of determination and regression analysis. The coefficient of determination measured how well the statistical model predicted future outcomes. Pearson correlation analysis was also used to establish the strength and direction of relationships between the study variables. The test of significance for the regression model was determined by using ANOVA.

The regression models were used to determine how Artificial Intelligence integration, Data-Driven Decision Making, Community Engagement Strategies, and Artificial Intelligence influenced project management processes. Statistical significance was evaluated at the 0.05 level, and the regression and correlation findings were used to test the study hypotheses.

3.7 Ethical Considerations

To ensure confidentiality of the information provided by the respondents and to ascertain the practice of ethics in this study, the respondents and organizations were coded instead of reflecting the names. Permission was solicited through a written request to the concerned officials of the organizations included in the study. Respondents were requested to sign the informed consent form. The authors quoted in this study were acknowledged through citations and referencing. The findings were presented in a generalized manner.

4. Results and Discussions

This section presents the findings obtained from respondents involved in the Advocacy for Street Children and Family Reintegration Project in Huye District, Rwanda.

4.1 Response Rate

Response rate was used to determine the level of participation of respondents selected for the study. Questionnaires were distributed to respondents involved in the SCFR Project, and the results were classified according to distributed, returned and usable, and returned but excluded questionnaires.

Table 1: Response Rate

Response	Frequency/Rate
No. of distributed questionnaires	103
Returned and usable questionnaires	100
Returned and excluded questionnaires	3
Valid Response rate as per the sample size	**97.1%**

Source: Primary data, 2026

The response rate analysis for the adjusted sample size of 103 questionnaires shows that the valid response rate remains consistent at 97.1%, yield approximately 100 usable questionnaires. This response rate is considered acceptable in survey research, as it exceeds the 75% benchmark suggested by Sekaran (2003). This unveiled that the sample size is adequately represented and maintains proportional validity in this study.

4.2 Inferential statistics

Inferential statistics examined the relationships and predictive influence of Artificial Intelligence integration, Data-Driven Decision Making, Community Engagement Strategies, and Artificial Intelligence on the project management process of the SCFR Project. Pearson correlation analysis assessed the direction, strength, and statistical significance of each relationship, while regression analysis used model summaries, ANOVA, and coefficients to determine explanatory power and the contribution of each study variable.

4.2.1 Correlation Analysis

Correlation analysis is presented in this subsection to assess the degree of association between the study variables and the project management process. The section reports the direction, magnitude, and statistical significance of the relationships involving Artificial Intelligence integration, Data-Driven Decision Making, Community Engagement Strategies, Artificial Intelligence, and project management processes.

Table 2: Pearson Correlation between Artificial Intelligence Integration and Project Management Process

Study Variables	Artificial Intelligence integration	Project management process
Artificial Intelligence integration	1	0.690*
Sig. (2-tailed)		0.000
N	100	100
Project management process	0.690*	1
Sig. (2-tailed)	0.000	
N	100	100

Correlation is significant at the 0.05 level (2-tailed).
Source: Primary data, 2026

The Pearson correlation analysis in Table 2 reveals a strong positive correlation coefficient of 0.690 between AI integration and the project management process, with a significance level of $p<0.0001$. This indicates a statistically significant relationship, meaning that as the level of AI integration increases, the effectiveness of project management processes also tends to improve. There were 100 respondents included in the analysis, and the strength of this correlation suggests that implementing AI in project management may significantly enhance various outcomes associated with project execution.

Table 3: Pearson Correlation between Data-Driven Decision Making and Project Management Process

Study Variables	Data-driven decision making	Project management process
Data-driven decision making	1	0.685*
Sig. (2-tailed)		0.000
N	100	100
Project management process	0.685*	1
Sig. (2-tailed)	0.000	
N	100	100

Correlation is significant at the 0.05 level (2-tailed).
Source: Primary data, 2026

The Pearson correlation analysis, displayed in Table 3, indicates a strong positive correlation coefficient of 0.685 between data-driven decision-making and the project management process, with a significance level of p<0.00001. This finding signifies a robust statistical relationship, suggesting that improvements in data-driven decision-making are closely linked to enhancements in project management processes. The analysis, based on 100 respondents, conveys that as data-driven decision-making practices are implemented, the effectiveness of project management also tends to increase significantly.

Table 4: Pearson Correlation between Community Engagement Strategies and Project Management Process

Study Variables	Community engagement strategies	Project management process
Community engagement strategies	1	0.752*
Sig. (2-tailed)		0.000
N	100	100
Project management process	0.752*	1
Sig. (2-tailed)	0.000	
N	100	100

Correlation is significant at the 0.05 level (2-tailed).
Source: Primary data, 2026

The Pearson correlation analysis illustrated in Table 4 shows a strong positive correlation coefficient of 0.752 between community engagement strategies and the project management process, with a significance level of p<0.00001. This indicates a statistically significant relationship, suggesting that as community engagement strategies improve, the effectiveness of project management processes correspondingly increases. With 100 participants included in the analysis, this strong correlation emphasizes the importance of engaging the community in enhancing project management outcomes.

Table 5: Pearson Correlation between Artificial Intelligence and Project Management Optimization Process

Study Variables	Artificial intelligence	Project management optimization process
Artificial intelligence	1	0.750*
Sig. (2-tailed)		0.000
N	100	100
Project management process	0.750*	1
Sig. (2-tailed)	0.000	
N	100	100

Correlation is significant at the 0.05 level (2-tailed).
Source: Primary data, 2026

The Pearson correlation analysis presented in Table 5 reveals a strong positive correlation coefficient of 0.750 between AI and the project management optimization process, with a significance level of p<0.00001. This significant correlation suggests a robust relationship, indicating that as AI integration increases, there is a corresponding enhancement in the optimization of project management processes. The analysis is based on 100 respondents, reinforcing the reliability of the findings in establishing a meaningful linkage between these two important variables.

4.2.2 Regression Analysis

The content of this subsection consists of the regression results used to establish the predictive influence of the study variables on project management processes. For each objective, the model summary, analysis of variance, regression coefficients, and significance values are presented using the original source tables.

Table 6: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.750	0.568	0.567	0.42660

Source: Primary data, 2026

The regression analysis showcased in Table 6, the primary objective was to assess the effect of AI on project management optimization processes specifically within the SCFR Project. The R-value of 0.750 aligns closely with the correlation analysis, indicating a substantial degree of linear relationship between AI integration and project management efficacy. The R-squared value of 0.568 indicates that roughly 56.8% of the variance in the optimization processes can be explained by AI. This significant proportion underscores the critical role AI plays in enhancing project efficiency and effectiveness.

The adjusted R-squared value is reported at 0.567, suggesting that after accounting for the number of predictors, about 56.7% of the variance remains explained by the model. The standard error of the estimate is 0.42660, reflecting a low prediction error, which implies that the regression model fits the observed data well.

Table 7: ANOVA

Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	12.631	1	12.631	355.18	< 0.00001
Residual	8.999	148	0.03556		
Total	21.511	149			

Source: Primary data, 2026

The ANOVA results indicate a highly significant model, with an F statistic of 355.18 and a significance level of $p<0.00001$. This finding confirms that the regression model significantly predicts the dependent variable, reinforcing the conclusion that AI integration has a meaningful impact on optimizing project management processes.

Table 8: Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.
	B	Std. Error	Beta		
1 (Constant)					
Artificial intelligence	1.009 .377	.758 .099	.750	2.909 3.800	0.0001

Source: Primary data, 2026

In the coefficients table, the unstandardized coefficient for Artificial Intelligence is 0.377, while the standardized coefficient (Beta) is 0.750. This indicates that for every unit increase in Artificial Intelligence, project management optimization is expected to increase by approximately 0.377 units. The constant term of 1.009 indicates the baseline level of project management optimization when Artificial Intelligence is absent. The t value for Artificial Intelligence is 3.800 with a significance level of $p<0.0001$, further confirming its statistically significant contribution to project management optimization.

In summary, the findings from both the correlation and regression analyses highlight a strong and statistically significant relationship between AI integration and the optimization of project management processes in the SCFR Project. These results reinforce the notion that enhancing the use of AI can lead to improved project management outcomes, indicating that strategic investments in AI technologies ought to be prioritized to maximize the effectiveness of projects aimed at addressing the needs of street children and promoting family reintegration in Huye District.

4.3 Decision on Null Hypotheses

This section presents the decisions on the null hypotheses based on the regression significance values at the 0.05 level of significance. A null hypothesis was rejected where the probability value was below 0.05, indicating a statistically significant effect or relationship among the study variables within the SCFR Project.

For the first hypothesis, the regression results showed a strong linear relationship between Artificial Intelligence Integration and the Project Management Process, with $R = 0.690$. The ANOVA results produced an F-statistic of 175.29 with $p < 0.0001$, indicating that the relationship was statistically significant. Artificial Intelligence Integration explained 50.9% of the variation in the effectiveness of the project management process. The regression coefficient further indicated that a one-unit increase in AI integration was associated with an estimated 0.743-unit increase in project management performance. Therefore, the null hypothesis stating that Artificial Intelligence Integration had no significant effect on the Project Management Process was rejected.

For the second hypothesis, Data-Driven Decision Making showed a strong positive relationship with the Project Management Process, with $r = 0.685$. The regression model produced an F-statistic of 223.47 with $p < 0.00001$, confirming a statistically significant effect. Data-Driven Decision Making explained 46.9% of the variation in the project management process. Although the descriptive findings showed a neutral overall mean of 2.90, indicating weaknesses in areas such as performance metrics and operational transparency, the inferential results demonstrated that Data-Driven Decision Making significantly influenced project management outcomes. Therefore, the null hypothesis stating that Data-Driven Decision Making had no significant effect on the Project Management Process was rejected.

For the third hypothesis, Community Engagement Strategies recorded a strong positive relationship with the Project Management Process, with $r = 0.752$. The ANOVA results yielded an F-statistic of 330.11 with $p < 0.00001$, demonstrating that the effect was statistically significant. Community Engagement Strategies explained 56.6% of the variation in project management execution. The findings further showed that the regular incorporation of community feedback and active stakeholder participation contributed to improved project relevance and implementation. Therefore, the null hypothesis stating that Community Engagement Strategies had no significant effect on the Project Management Process was rejected.

For the fourth hypothesis, Artificial Intelligence showed a strong positive relationship with the Project Management Optimization Process, with $r = 0.750$ and $p < 0.00001$. The regression model produced an F-statistic of 355.18 with $p < 0.00001$, confirming a statistically significant relationship. Artificial Intelligence explained 56.8% of the variation in the project management optimization process. The findings indicated that the effective application of AI supported predictive planning, timely reporting, and improved project management processes. Therefore, the null hypothesis stating that Artificial Intelligence had no significant relationship with the Project Management Optimization Process was rejected.

Since the probability values for all four hypotheses were below the 0.05 level of significance, all four null hypotheses were rejected. The findings therefore established that Artificial Intelligence Integration, Data-Driven Decision Making, Community Engagement Strategies, and Artificial Intelligence were statistically significant in explaining variations in the project management processes of the Advocacy for Street Children and Family Reintegration Project.

4.4 Discussion of Research Findings

This section discusses the research findings in relation to the study objectives and relevant empirical evidence.

4.4.1 Effect of Artificial Intelligence Integration on Project Management Process of SCFR Project Huye District, Rwanda

The findings indicate that the integration of Artificial Intelligence (AI) has a notable positive impact on the project management processes within the SCFR Project in Huye District. Descriptive statistics produced an average mean score of 3.41, indicating a high perception of Artificial Intelligence integration within the project. Regression analysis further supports this finding, with an R-squared value of 0.509, indicating that 50.9% of the variance in project management effectiveness can be attributed to AI integration. This relationship is reinforced by a strong Pearson correlation coefficient of 0.690, demonstrating a significant correlation at $p<0.0001$. These results suggest that leveraging AI can enhance overall project management efficiency and effectiveness, vital for the project's goals.

In line with these findings, Namagembe (2021) posits that the adoption of intelligent automation systems significantly optimizes resource allocation and scheduling in complex regional projects. Her research emphasizes that AI-driven tools reduce human error in data entry and predictive analysis, which aligns with the average mean score of 3.41 observed for Artificial Intelligence integration in the Huye District study. Namagembe argues that when project managers move away from manual tracking toward AI-integrated dashboards, the speed of decision-making increases, reflecting the positive respondent perceptions of AI integration in the SCFR Project. This suggests that the efficiency gains observed in the SCFR project are part of a broader trend of digital transformation within East African project management frameworks.

4.4.2 Effect of Data-Driven Decision Making on Project Management Process of SCFR Project Huye District, Rwanda

The analysis of data-driven decision-making reveals a mixed impact on the project management processes within the SCFR Project. Descriptive statistics show an average mean of 2.90 across various statements, indicating a generally neutral perception regarding the effectiveness of data-driven strategies. Regression analysis indicates an R-squared value of 0.469, suggesting that approximately 46.9% of the variance in project management processes is explained by data-driven decision-making. However, the Pearson correlation coefficient of 0.685, significant at $p<0.00001$, unveils a strong relationship, affirming that while there may be limitations in perceived effectiveness, there exists a meaningful link between data utilization and enhancing project management outcomes. This suggests that improving data-driven practices could yield better alignment with project needs and outcomes.

In line with these findings, Barihe (2022) argues that in developing economies, the transition to quantitative decision-making often encounters a "neutrality plateau" where project staff feel the burden of data collection without seeing immediate localized benefits. This aligns with the observed mean of 2.90, as Barihe notes that unless data is translated into actionable information at the field level, its perceived utility remains low. However, his research confirms that the structural impact of data on project stability remains high, supporting the strong Pearson correlation of 0.685 found in the Huye District. He posits that while staff might feel neutral, the data acts as an objective anchor that prevents major project drift.

4.4.3 Effect of Community Engagement Strategies on Project Management Process of SCFR Project Huye District, Rwanda

Community engagement strategies emerge as an important factor affecting project management processes within the SCFR Project. The descriptive statistics indicate a high mean score of 3.76, reflecting positive perceptions regarding the effectiveness of community engagement in driving project outcomes. The regression analysis shows an R-squared value of 0.566, indicating that 56.6% of the variance in project management optimization can be attributed to effective community engagement. Additionally, a Pearson correlation coefficient of 0.752, significant at $p<0.00001$, suggests a strong connection between community involvement and project management effectiveness. This reinforces the idea that fostering meaningful engagement with the community leads to improved project responsiveness and success, showing the importance of stakeholder collaboration.

In line with these findings, Bikorimana (2022) emphasizes that in the Rwandan socio-economic context, "bottom-up" participation is the most significant predictor of project sustainability. His research on rural development projects in the Southern Province mirrors the high mean score of 3.76, suggesting that when local citizens feel a sense of ownership, project management processes encounter fewer delays and less resistance. Bikorimana argues that the high Pearson correlation ($r=0.752$) found in Huye District is a direct result of "social capital," where community trust acts as a lubricant for administrative tasks, allowing project managers to navigate local land and labor issues with greater speed and transparency.

4.4.4 Relationship between Artificial Intelligence and Project Management Process of SCFR Project Huye District, Rwanda

The relationship between AI integration and project management processes is characterized by a strong positive correlation, illustrated by the Pearson correlation coefficient of 0.750, significant at $p<0.00001$. Descriptive statistics produced an overall mean score of 3.19 for Artificial Intelligence and project management optimization, indicating a neutral overall perception across the measured statements. The regression analysis further substantiates this relationship, revealing an R-squared value of 0.568, thus indicating that approximately 56.8% of the variance in the optimization of project management processes is attributable to AI application. Collectively, these findings suggest that effective AI integration is important for enhancing project management outcomes and optimizing operational processes in the SCFR initiative.
In line with these findings, Manzi (2023) observed that in the evolving technological landscape of Rwanda, the adoption of machine learning algorithms provides project managers with a "predictive advantage" that significantly reduces scheduling conflicts. In the SCFR Project, the overall descriptive mean of 3.19 indicates a neutral assessment across the broader Artificial Intelligence optimization statements, while the strong Pearson correlation of 0.750 demonstrates a substantial statistical relationship with project management processes. Manzi argues that AI tools can harmonize disparate project tasks and support adjustments in response to real-time data, which is relevant to the SCFR project's management processes in Huye District.

5. Conclusions and Recommendations

This section presents the study conclusions and recommendations derived from the findings.

5.1 Conclusion

The study concluded that Artificial Intelligence integration strengthened project management processes within the SCFR Project in Huye District by improving planning accuracy, resource allocation, monitoring and management efficiency. Data-Driven Decision Making supported evidence-based planning, intervention assessment and informed resource allocation, although its application required stronger use of project data, clearer performance metrics and improved operational transparency.

Community Engagement Strategies enhanced project management processes by promoting stakeholder participation, community feedback, communication and alignment of project activities with local needs. Overall, Artificial Intelligence contributed to project management optimization by supporting predictive planning, timely decision-making, accountability and efficient project execution. Together, AI integration, Data-Driven Decision Making and community engagement strengthened the project’s capacity to respond effectively to the needs of street children and support sustainable family reintegration.

5.2 Recommendations

This section provides recommendations derived from the findings and conclusions of the study. The recommendations focus on practical actions for strengthening Artificial Intelligence integration, data-driven decision-making, community engagement, and project management optimization in the SCFR Project.

1. The organization should prioritize ongoing AI training for staff and street children to maximize technological benefits.
2. To improve data-driven decision-making, a robust data culture and governance framework should be cultivated.
3. Continued investment in inclusive community engagement through participatory forums

should be maintained to ensure project sustainability.
4. Managers should develop a strategic framework that aligns AI applications specifically with planning and monitoring functions to optimize workflows.
5. The director should prioritize investments in AI technologies that align with project objectives to enhance effectiveness.

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