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Factors Influencing Generative AI Adoption for Knowledge Management in South Africa's Automotive Sector

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Abstract. South Africa's automotive sector is under increasing pressure to sustain competitiveness amid Fourth Industrial Revolution (4IR) transitions, persistent operational inefficiencies, and workforce ageing. Generative AI (GenAI) presents a potential pathway to strengthen knowledge management (KM) by supporting faster knowledge capture, synthesis, retrieval, and decision support. This study identifies the determinants of GenAI adoption for improving KM practices in South Africa's automotive context. A quantitative, hypothesis-driven design was employed, integrating constructs from the PPOA, TEOG, and IEO frameworks to provide a consolidated adoption perspective. Survey data were collected from 142 industry participants and analysed using SPSS (correlation and multiple regression). The model demonstrated strong explanatory power (Adjusted $R^2 = 0.624$, $p < 0.001$). Results indicate that GenAI adoption is significantly and positively influenced by FATAA ethical principles, KM practices, GenAI tool capability, perceived enjoyment, perceived usefulness, compatibility, competition intensity, organisational size, mimetic pressure, and normative pressure ($p < 0.05$). In contrast, perceived ease of use and coercive pressure were not statistically significant in this context ($p > 0.05$). The study contributes a context-specific, integrated adoption model for GenAI-enabled KM in an under-researched setting and offers actionable implications for managers and policymakers focused on responsible, effective GenAI deployment.

Keywords: Generative AI; Knowledge Management; Automotive Manufacturing; Technology Adoption; Ethical Governance (FATAA)

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1. INTRODUCTION

The Fourth Industrial Revolution (4IR)—driven by technologies such as Artificial Intelligence (AI), big data analytics, and the Internet of Things (IoT)—is reshaping how organisations compete, collaborate, and create value in international markets [1]. Within this landscape, the rapid emergence of Generative AI (GenAI) tools signals a new wave of AI-driven innovation that not only improves technical performance but also lowers barriers to use by making advanced capabilities more accessible to non-specialists [2]. GenAI is increasingly positioned as a productivity enabler because it can automate routine and knowledge-intensive tasks such as data capture, document review, summarisation, and analysis—activities that often consume significant organisational time and resources [3]. By reducing repetitive work, GenAI has the potential to improve efficiency, lower operational costs, and strengthen communication and knowledge sharing across organisational units [4]. Evidence from industrial settings further suggests that GenAI-enabled systems can enhance decision speed and accuracy; for example, in automotive manufacturing, AI-supported robotics can improve sequencing and part-selection precision, reducing errors and, in some cases, limiting reliance on manual intervention [5]. Beyond production, GenAI applications in areas like IT helpdesks and knowledge management (KM) are expanding, particularly where organisations need to handle unstructured information at scale, automate knowledge processes, and provide tailored guidance to employees in real time [4], [6]. Given that KM practices are widely recognised as strategic assets for organisations regardless of size [7], the integration of GenAI into KM represents a potentially transformative shift in how knowledge is created, stored, shared, and reused.

This potential is especially relevant in the automotive sector, a global industry that produces more than 70 million vehicles annually and plays a major role in economic development and societal well-being across both developed and developing economies [8]. In South Africa, manufacturing is one of the country's largest industries and includes key subsectors such as metals, plastics, and automotive manufacturing [9]. However, the South African automotive sector faces persistent and emerging pressures that threaten performance and competitiveness in a rapidly digitising environment. These challenges include an ageing engineering workforce, slow defect detection cycles, losses linked to robotic breakdowns, and the difficulty of keeping pace with fast-evolving 4IR technologies [10]. Collectively, these pressures create a practical problem: organisations must increase operational resilience and innovation capacity while simultaneously ensuring that critical knowledge—technical know-how, process expertise, maintenance insights, and lessons learned—is captured and transferred effectively. When KM systems and practices are weak or fragmented, firms are more vulnerable to skills erosion, repeated mistakes, slower response to equipment failures, and reduced adaptability during technology transitions. In this context, GenAI offers a promising mechanism to strengthen KM by accelerating knowledge capture, improving retrieval, supporting troubleshooting and decision-making, and enabling faster dissemination of best practices across functions.

Despite increasing global interest in GenAI and growing evidence of its usefulness for KM in various settings, the academic literature remains uneven in terms of context and sector coverage. Existing studies highlight GenAI adoption for KM in other countries and sectors [4], [11], yet there is limited scholarly attention on how GenAI can be adopted to enhance KM practices within the South African context—particularly within the automotive industry, where competitive pressure and operational complexity are high. This represents a clear research gap: while GenAI is widely discussed as a general-purpose capability, there is insufficient empirical and conceptual clarity on the specific factors that influence its adoption for KM in South Africa's automotive sector. Without such context-specific understanding, decision-makers risk relying on generic adoption assumptions that may not hold under local constraints such as skills availability, legacy systems, governance maturity, organisational culture, and readiness for change.

This study addresses that gap by identifying the critical factors that determine GenAI adoption for improving KM practices in South Africa's automotive sector. The novelty of the study lies in its explicit focus on a) GenAI specifically (rather than AI broadly), b) KM practices as the adoption target (rather than production automation alone), and c) the South African automotive context, which remains under-researched despite its economic importance. In doing so, the study develops a conceptual model that consolidates and organises the key adoption factors relevant to this setting and links them to GenAI-enabled KM outcomes. The study is guided by the following research question: What factors determine the adoption of GenAI to improve KM practices in the South African automotive industry?

The study makes both theoretical and practical contributions. Theoretically, it (1) addresses a critical gap in understanding GenAI's role in enhancing KM practices in South Africa's automotive sector, (2) proposes a context-specific conceptual model that identifies critical factors influencing adoption while highlighting relevant GenAI tools and capabilities, and (3) contributes original insights to the limited body of knowledge on GenAI adoption frameworks tailored to the automotive sector. Practically, the study (1) supports managers, KM professionals, and cross-functional leaders in making informed decisions about adopting GenAI solutions for KM improvement, (2) provides guidance that can assist the automotive industry—and other organisations pursuing similar transitions—in integrating GenAI into daily knowledge processes, and (3) highlights implementation considerations that are directly pertinent to successful GenAI deployment, including readiness, governance, and alignment with organisational needs.

The remainder of this study is structured as follows: Section 2 presents the research method, Section 3 reports the findings and discussion, and Section 4 concludes the study.

2. METHODS

A quantitative design was adopted for this study as the most suitable approach due to the main goal of this research: to identify key factors that impact the adoption of GenAI to improve KM practices in the South African automotive sector. Since the variables are definitely known in existing literature, the study aimed at statistical generalizability as opposed to exploration depth. Thus, the quantitative study offers empirical rigor and internal validity that is needed to test the hypotheses without the confounding effects of qualitative interpretation [12]; [13]. A quantitative research design is a precise design to assess phenomena using accurate measurements [14]. The respondents' interest in participating in the study was high, providing confidence in their day-to-day practical use of Gen AI. Additionally, the survey included a question on the respondent's familiarity with GenAI, which showed that the overwhelming majority (90.1%) reported familiarity, with only 9.9% indicating a lack of familiarity detailed in Table 2. Figure 1 presents the Research process flow diagram outlining the research methods used in the study.

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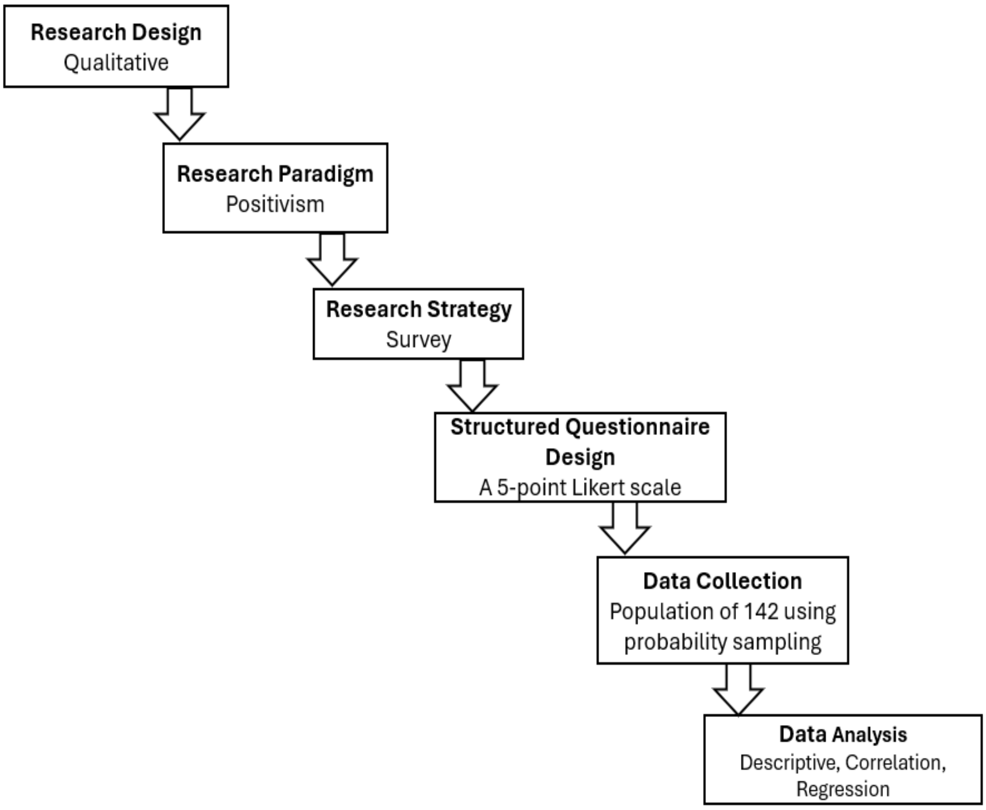

Figure1. Research process flow diagram (Researcher)

2.1. Data Collection

The quantitative research collected numerical data through a structured and quantitative questionnaire containing closed-ended questions to determine variables affecting the implementation of GenAI. On the other hand, [15] proposed that closed-ended questionnaires make it possible to effectively gather a lot of quantitative data from a wide range of participants in a short amount of time. A 5-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree" was used to collect responses. Since this research aimed to identify the factors influencing the adoption of GenAI to enhance KM, the questionnaire surveys were distributed via Google Forms to individuals in the automotive industry and have integrated GenAI into their daily work and are knowledgeable about KM practices within their organizations. The questionnaire survey was organized into three main sections: Section One collected biographical information from participants. Section Two focused on participants' background knowledge of GenAI and KM practices. Finally, Section Three included the specific questionnaire items. Ethical approval was obtained from the university's research ethics committee prior to data collection, and all participants provided consent to participate in the survey.

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2.2. Sampling

A probability sampling technique was applied in this study. The purpose of using probability sampling is to generalize research results [16]. Probability sampling, also known as random sampling, is often used in quantitative research [17]. In this research, a simple random sampling method was used to sample out participants to be used in the questionnaire survey. The sample size for this study was 140, determined using the [18] formula for calculating sample size based on the population of 220; however, 142 responses were ultimately collected. Individuals who have integrated GenAI into their daily work and are aware of KM procedures in their organization comprised the study's targeted population. The categories of respondents in terms of participants are presented in Table 1.

Table 1: Respondents' Categories

Respondents	Position/Job Title	Department	Amount
Category 1	IT operations specialist	IT Infrastructure & Operations	44
Category 2	Software engineer	Software/Application Development	49
Category 3	KM analyst	AI department	9
Category 4	Manager	IT	16
Category 5	Other	Other	24

2.3. Data Analysis

The software to generate both descriptive and inferential statistics was an inclusive data analysis tool known as Statistical Package of Social Science (SPSS) [19]. The first step in the analysis is descriptive statistics, which helps in the discovery of absolute numbers that assist researchers in gathering information on several variables and identifying the trends. Descriptive statistics were used to summarize variables, from demographics to general developments in GenAI adoption. According to [20], inferential analysis supports the complex studies by depicting the relationship between various variables and making predictions, and generalizations. Pearson's correlation was used to assess the linear relationship between the adoption of GenAI and the following constructs: Perceived Usefulness, Perceived Enjoyment, Perceived Ease of Use, Compatibility, Competition Intensity, Organizational Size, Normative Pressure, Mimetic Pressure, Coercive Pressure, FATAA, and KM Practices. Regression analysis was conducted in this study after the correlation analysis, with separate analyses performed for each adoption level. Individual independent variables were tested against the GenAI adoption factors, treated as the dependent variable. Regression analysis was performed by framework and construct.

2.4. Underpinned theoretical models

This study applied the PPAO Adoption Model [21], the TOEG Adoption Model [22], and the IEO Adoption Model [23] to determine aspects that positively impact the GenAI adoption to improve KM practices. The PPAO Adoption Model aimed at making the complicated process through which innovators and entrepreneurs pass when adopting GenAI technology clear [22]. The model employed 10 factors to analyze the impact of the adoption of GenAI, but only three factors were identified to have a positive influence on the adoption of GenAI by the entrepreneur; these factors include perceived enjoyment, perceived usefulness, and perceived ease of use, which constitute the Technology Acceptance Model (TAM). Figure 2 shows the PPAO Adoption Model [22].

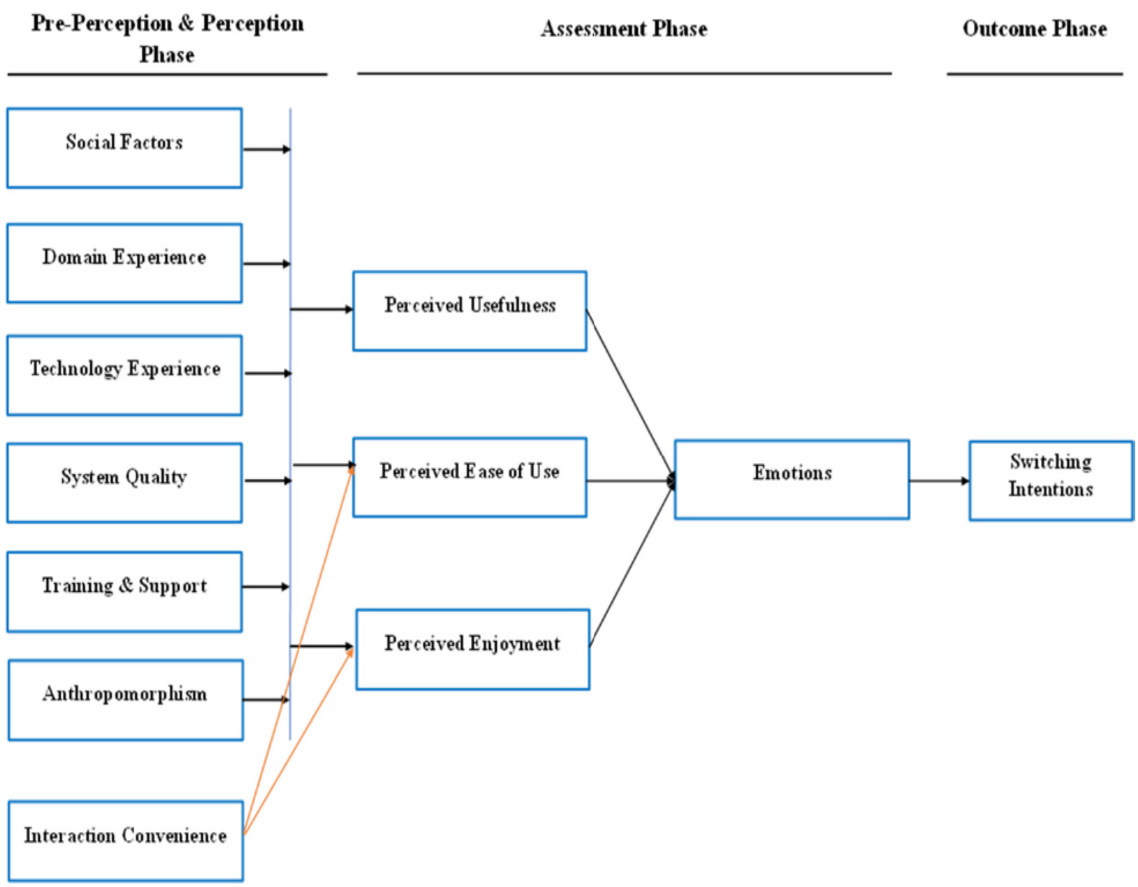

Figure 2. PPAO Adoption Model [21]

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The TOEG adoption model was developed by [23] and outlines nine factors that influence GenAI technology adoption, derived from a combination of constructs from the Diffusion of Innovation (DOI), Technology Organization, Environment (TOE), and Institutional Theory (INST) [23]. However, only three factors—compatibility, competition intensity, and organizational size—significantly impact GenAI adoption. Figure 3 illustrates the TOEG Adoption model by [23].

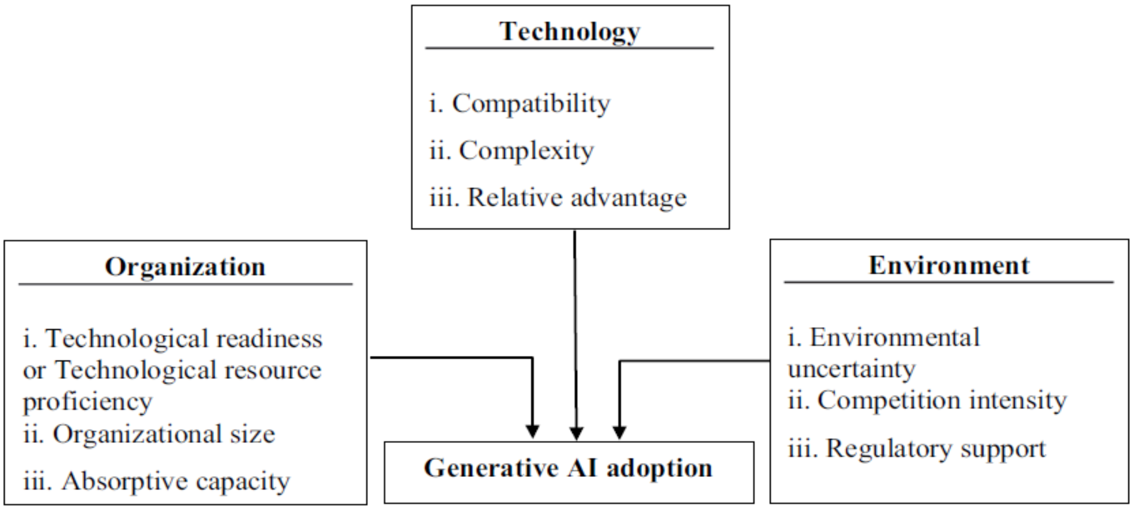

Figure 3. TOEG Adoption model [22]

Moreover, [24] created the IEO model to study the impacts of environmental elements on the technology adoption and the performance of an organization. The institutional pressure theory (Coercive, Normative, Mimetic forces) and FATAA theory of ethics (Fairness, Accountability, Transparency, Accuracy, Autonomy) were used in the model to determine which factors can influence the adoption of GenAI [24]. This model discovered that purpose of accountability, transparency, accuracy, autonomy, coercive, normative, and mimetic pressures have a positive impact on the adoption of GenAI in IT organizations. The IED Adoption Model, which is put forward by [24], is shown in Figure 4.

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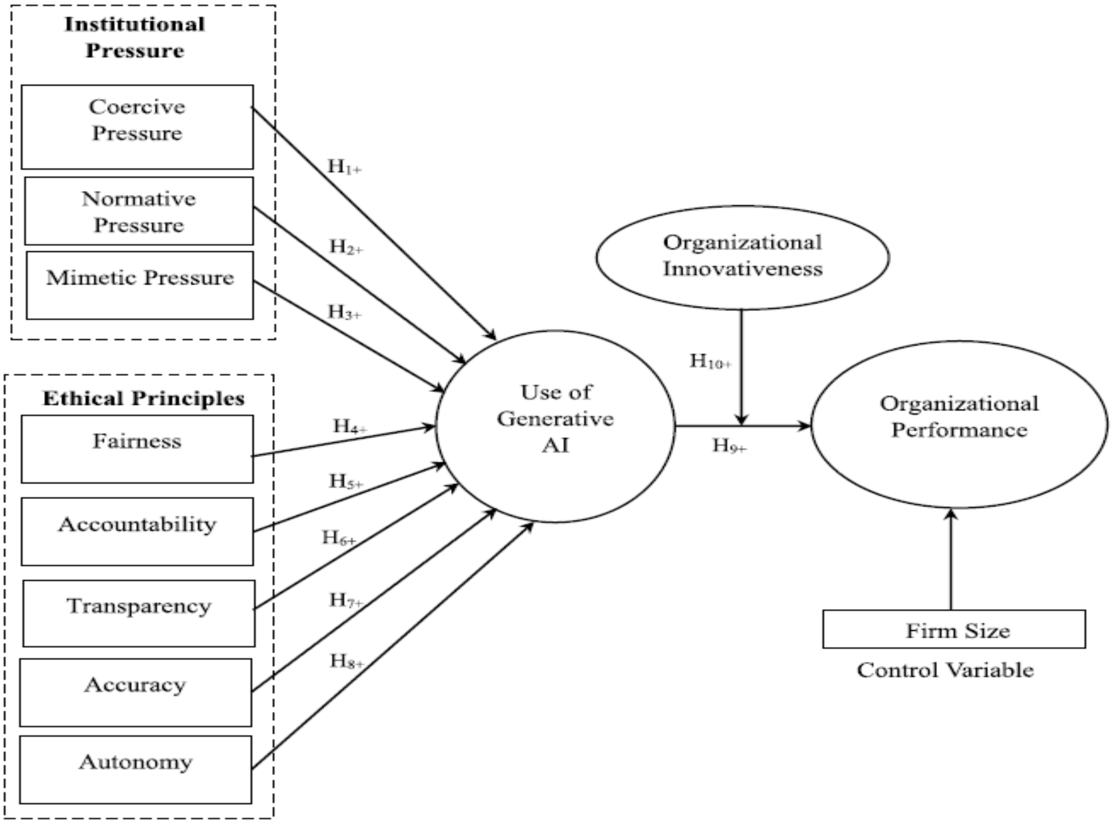

Figure 4. IEO Adoption Model [23]

3. RESULTS AND DISCUSSION

3.1. Respondent Profile

This section presents and interprets the findings of this study stemming from the key objective: (i) determining the factors influencing the adoption of GenAI. Based on the response rate, 142 of 220 participants completed the questionnaire, yielding an average response rate of 64.5%. Descriptive statistics, correlation, and regression analysis were used to evaluate the findings statistically. The results were critically discussed within the study's conceptual and theoretical framework. Table 2 presents the demographic characteristics of the study participants. Of the 142 responses, 38% of participants held a bachelor's degree, with 23.2% each for a national diploma and an honours degree. Furthermore, participants with a Master's degree accounted for 9.2%, while doctoral degree holders made up 1.4%. The "other" category accounted for 4.9% of participants. In terms of position status, IT specialists represented the highest percentage at 65.5%. KM professionals accounted for 6.3%, while department managers comprised 11.3% of the participants. Lastly, participants in other positions accounted for 16.9% of the total. In addition, years of experience were also observed. The largest group, comprising 51.4% of participants, had 1-10 years of experience. 35.2% of participants reported having 11 to 20 years of experience, while 7% had 21 to 30 years of experience in their current roles. Additionally, the findings indicated that 6.3% of participants had less than one year of experience.

Table 2. Respondents' Demographic Information

Demographics	Category	Frequency	Percentage
Qualifications	National Diploma	33	23.2
	Bachelor's Degree	54	38.0
	Honours Degree	33	23.2
	Master's Degree	13	9.2
	Doctoral Degree	2	1.4
	Other	7	4.9
Position/Job title	IT Specialist	93	65.5
	KM Professional	9	6.3
	Department Manager	16	11.3
	Other	24	16.9
Years of experience	Less than 1 year	9	6.3
	1-10 years	73	51.4
	11-20 years	50	35.2
	21-30 years	10	7.0

Table 3 presents the background of the study participants. An overwhelming majority of participants (90.1%) reported familiarity with GenAI, with only 9.9% indicating a lack of familiarity. While 89.4% of participants reported familiarity with KM practices, a smaller proportion (10.6%) reported less familiarity.

Table 3. Participant's background information

	Yes %	No %
GenAI familiarity	90.1	9.9
KM practices familiarity	89.4	10.6

3.2. Reliability Testing

The reliability analysis of the constructs in Table 4 shows strong consistency, with Cronbach's Alpha for each construct exceeding 0.700. Therefore, these constructs are deemed reliable and appropriate for evaluating the adoption of GenAI in KM practices within a South African setting.

Table 4. Reliability Analysis

Construct	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
GenAI Tools (GAITOOLS)	0.850	0.852	5
Perceived Usefulness (PU)	0.838	0.842	3
Perceived Ease of Use (PEOU)	0.888	0.890	3
Perceived Enjoyment (PE)	0.886	0.885	3
Compatibility (COMP)	0.875	0.875	3
Competition Intensity (CI)	0.839	0.843	3
Organisational Size (ORG_SIZE)	0.797	0.797	3
Coercive pressure (COER_P)	0.828	0.831	3
Normative pressure (NORM_P)	0.871	0.873	3
Mimetic pressure (MIM_P)	0.881	0.884	3
KM Practices (KM_PR)	0.847	0.852	4
FATAA Ethical Principles	0.858	0.860	5
GenAI Model (GAIM)	0.889	0.890	4

3.3. Correlations and Regression Analysis

Table 5 presents the study's findings on the Pearson correlation of the constructs. The GenAI Adoption (GAI), which represented adoption outcomes, strongly correlated with all variables in the study. The strongest connections were on PE at a value of .708, PU at a value of .676, MIM_P at a value of .652, and COMP at a value of .631. The correlation analysis confirmed that the adoption of GenAI was significantly influenced by PU, PEOU, PE and COMP, CI, and MIM_P. All correlations were significant at $p < 0.001$, highlighting the robustness of the results and confirming that GenAI adoption results from an interaction among technological characteristics, organizational resources, and institutional forces.

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Table 5. Correlations of Constructs

Variables	Measure	GAITOOLS	PU	PEOU	PE	COMP	CI	ORG_SIZE	COER_P	NORM_P	MIM_P	FATAA	KM_PR	GAIM
GAITOOLS	P	1												
PU	P	.628**	1											
PEOU	P	.551**	.738**	1										
PE	P	.508**	.703**	.692**	1									
COMP	P	.388**	.515**	.592**	.580**	1								
CI	P	.465**	.610**	.622**	.619**	.689**	1							
ORG_SIZE	P	.374**	.506**	.523**	.570**	.679**	.690**	1						
COER_P	P	.262**	.372**	.358**	.382**	.532**	.578**	.523**	1					
NORM_P	P	.356**	.518**	.400**	.584**	.584**	.557**	.539**	.563**	1				
MIM_P	P	.405**	.555**	.525**	.623**	.635**	.643**	.593**	.557**	.695**	1			
FATAA	P	.562**	.549**	.450**	.458**	.470**	.499**	.445**	.343**	.458**	.487**	1		
KM_PR	P	.614**	.490**	.433**	.470**	.439**	.463**	.357**	.320**	.495**	.516**	.553**	1	
GAIM	P	.453**	.676**	.599**	.708**	.631**	.609**	.589**	.495**	.605**	.652**	.536**	.467**	1

**. Correlation is significant at the 0.01 level (2-tailed).

Table 6 shows that the adjusted R Square value of .624 in the model summary indicates that KM_PR, COER_P, PEOU, FATAA, ORG_SIZE, NORM_P, GAITOOLS, COMP, PE, MIM_P, CI, and PU together explain about 62.4% of the variation in GenAI adoption for KM. This suggests that these predictors account for more than half of the observed changes in GenAI adoption, indicating strong explanatory power and a good fit to the data. The statistical significance of GenAI adoption is strongly supported by the p-value ($p < 0.001$), which falls below the conventional 0.05 threshold. This p-value signifies that the relationship observed in the regression model is unlikely to have occurred by random chance, with a probability of less than 0.1. Subsequently, it confirms that the combined influence of the predictors on GenAI adoption is meaningful and that the model is valid for explaining variations in the outcome.

Table 6. Multiple Regression Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.810a	.656	.624	.465	.656	20.501	12	129	<.001

a. Predictors: (Constant), KM_PR, COER_P, PEOU, FATAA, ORG_SIZE, NORM_P, GAITOOLS, COMP, PE, MIM_P, CI, PU

b. Dependent Variable: GAIM

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Table 7 presents the coefficients for each independent variable, with the GenAI adoption treated as the dependent variable. Regression analysis was performed for each framework and construct, which were adapted to identify GenAI adoption factors. GAITOOLS were found to have a statistically significant positive influence on GenAI adoption. The standardized Beta coefficients of 0.453 in the table indicate a moderately strong positive association between GAITOOLS and GenAI adoption. A p-value of < 0.001 confirms the high significance of this relationship, surpassing the standard 0.05 significance level. Therefore, the hypothesis that GAITOOLS have a significant influence on GenAI adoption is strongly supported.

The PPOA Framework illustrates how PU, PEOU, and PE influence the GenAI adoption. The standardized Beta coefficients in the table indicate the relative strength and direction of the relationships between PU, PEOU, and PE and GenAI adoption. The results show that PE had the strongest influence on GenAI adoption, with a standardized Beta value of 0.443, suggesting a strong relationship. PU follows with a Beta value of 0.326, indicating a moderate positive effect. In contrast, PEOU had a very low Beta value of 0.052, suggesting that it has little to no influence on GenAI adoption in this model.

The TEOG Framework illustrates how COMP, CI, and ORG_SIZE influence GenAI adoption. The standardized Beta coefficients revealed the individual influence of COMP, CI, and ORG_SIZE on GenAI adoption, within the TEOG framework. COMP arose as the most influential factor, with a Beta value of 0.327, indicating a moderate positive relationship with GenAI adoption. CI was the next strongest predictor, showing a positive relationship with a Beta value of .25. Finally, ORG_SIZE demonstrated a weaker but still positive effect, with a Beta value of .194. Within this framework, COMP ($p < 0.001$), CI ($p = 0.009$), and ORG_SIZE ($p = 0.038$) all demonstrated a statistically significant positive influence on GenAI adoption, as their p-values fall below the conventional 0.05 threshold. This suggests that COMP, CI, and ORG_SIZE significantly influence GenAI adoption within the TEOG-specific framework.

The IEO Framework illustrates how COER_P, NORM_P, and MIM_P influence GenAI adoption. The standardized Beta coefficients revealed the individual influence of COER_P, NORM_P, and MIM_P on GenAI adoption, within the IEO framework. MIM_P occurred as the most influential factor, with a Beta value of .408, indicating a strong positive

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relationship with GenAI adoption. NORM_P followed with a Beta value of 0.249, demonstrating a moderate positive effect with GenAI adoption. Conversely, COER_P exhibited the least influence, with a Beta value of .128, indicating only a minor impact on GenAI adoption. This implies that its practical impact is assumed to be insignificant when making decisions. Moreover, within this framework, NORM_P ($p = 0.006$) and MIM_P ($p < 0.001$) demonstrated a statistically significant positive influence on GenAI adoption, as their p-values fall below the standard .05 threshold. Contrary to COER_P, which was not found to be statistically significant ($p = 0.102$), indicating that it does not meaningfully influence GenAI adoption within the IEO framework.

FATAA was found to have a statistically significant positive influence on GenAI adoption. The standardized Beta coefficient in the table signifies the strength and direction of the connection between FATAA and GenAI adoption. With a Beta value of 0.536, a strong positive relationship is evident, indicating that as FATAA increases, GenAI adoption also rises significantly. A p-value of < 0.001 confirms the high significance of this relationship, as it is well below the standard 0.05 significance level. Therefore, the hypothesis that FATAA significantly influences GenAI adoption is strongly supported.

KM_PR was found to have a statistically significant positive influence on GenAI adoption. The standardized Beta coefficient of 0.467 indicates a moderately strong, positive relationship with GenAI adoption. A p-value of < 0.001 confirms the high significance of this relationship, exceeding the standard 0.05 significance level. Therefore, the hypothesis that KM_PR significantly influences the GenAI adoption model is strongly supported.

Table 7. Coefficient of each model

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
GenAI Tools	(Constant)	2.197	0.358		6.132	<.001
	GAITOOLS	0.494	0.082	0.453	6.016	<.001
PPOA Framework	(Constant)	1.458	0.221		6.595	<.001
	PU	0.263	0.073	0.326	3.601	<.001
	PEOU	0.043	0.074	0.052	0.582	0.562
	PE	0.398	0.076	0.443	5.231	<.001

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Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
TEOG framework	(Constant)	1.875	0.226		8.277	<.001
	COMP	0.262	0.074	0.327	3.532	<.001
	CI	0.205	0.077	0.25	2.663	0.009
	ORG_SIZE	0.146	0.07	0.194	2.093	0.038
IEO Framework	(Constant)	1.92	0.219		8.753	<.001
	COER_P	0.092	0.056	0.128	1.648	0.102
	NORM_P	0.2	0.072	0.249	2.791	0.006
	MIM_P	0.329	0.072	0.408	4.583	<.001
FATAA Ethical Principles	(Constant)	2.345	0.269		8.721	<.001
	FATAA	0.48	0.064	0.536	7.51	<.001
KM Practices	(Constant)	2.256	0.335		6.727	<.001
	KM_PR	0.472	0.075	0.467	6.253	<.001

In summary, the top 5 predictors of GenAI adoption are presented in Table 8.

Table 8. Top five predictors of GenAI adoption

Rank	Predictors	Beta values	Interpretation
1	FATAA	0.536	Strongest predictor
2	KM Practices	0.467	Very strong predictor
3	GenAI Tools	0.453	Very strong predictor
4	Perceive Enjoyment	0.443	Strong predictor
5	Mimetic Pressure	0.408	Strong predictor

The results of the hypothesis tests in Table 9 show that most predictors across the different frameworks significantly explain GenAI adoption, with only two exceptions. Specifically, GenAI Tools (H1), Perceived Usefulness (H2), Perceived Enjoyment (H4), Compatibility (H5), Competition Intensity (H6), Organizational Size (H7), Normative Pressure (H9), Mimetic Pressure (H10), FATAA (H11), and KM Practices (H12) all exhibit strong, positive statistical significance ($p < 0.05$). In contrast, Perceived Ease of Use (H3) and Coercive Pressure (H8) were discovered to be non-significant, indicating they do not have a significant effect on the outcome. Overall, the results support most of the proposed relationships, highlight the importance of the identified constructs, and suggest that ease of use and coercive pressures may not be key drivers in this context.

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Table 9. Hypothesis testing

Hypothesis	Results	Action
H1: GenAI Tools (capabilities for KM) are a positive factor influencing the adoption of GenAI to enhance KM in the South African automotive sector.	P=<0.001<0.05	Supported
H2: Perceived Usefulness is a positive factor influencing the adoption of GenAI for enhancing KM in the South African automotive sector.	P=<0.001<0.05	Supported
H3: Perceived Ease of Use is a positive factor influencing the adoption of GenAI for enhancing KM in the South African automotive sector.	P=0.562>0.05	Not Supported
H4: Perceived Enjoyment is a positive factor influencing the adoption of GenAI for enhancing KM in the South African automotive sector.	P=<0.001<0.05	Supported
H5: Compatibility is a positive factor influencing the adoption of GenAI for enhancing KM in the South African automotive sector.	P=<0.001<0.05	Supported
H6: Competition intensity is a positive factor influencing the adoption of GenAI for enhancing KM in the South African automotive sector.	P=0.009<0.05	Supported
H7: Organisational size is a positive factor influencing the adoption of GenAI for enhancing KM in the South African automotive sector.	P=0.038<0.05	Supported
H8: Coercive pressure is a positive factor influencing the adoption of GenAI to enhance KM in the South African automotive sector.	P=0.102>0.05	Not Supported
H9: Normative pressure is a positive factor influencing the adoption of GenAI to enhance KM in the South African automotive sector.	P=0.006<0.05	Supported
H10: Mimetic is a positive factor influencing the adoption of GenAI to enhance KM in the South African automotive sector.	P=<0.001<0.05	Supported

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Hypothesis	Results	Action
H11: FATAA ethical principles are positive factors influencing the adoption of GenAI to enhance KM in the South African automotive sector.	P=<0.001<0.05	Supported
H12: KM Practices are positive factors influencing GenAI to enhance KM in the South African automotive sector.	P=<0.001<0.05	Supported

3.4. Discussion

This study set out to examine the factors influencing the adoption of Generative AI (GenAI) to improve knowledge management (KM) practices in South Africa's automotive sector. Overall, the findings indicate that GenAI adoption is not driven by a single condition, but rather by a combined effect of technological readiness, user perceptions, organisational and environmental pressures, institutional forces, and—most strongly—ethical governance and KM maturity. The strength of the overall model provides confidence in this conclusion: the predictors jointly explained a substantial proportion of variance in GenAI adoption (Adjusted $R^2 = 0.624$; $p < 0.001$), indicating that the integrated conceptual approach captures meaningful and context-relevant determinants of adoption.

The regression results show that GenAI tools (GAITOOLS) are a strong and statistically significant predictor of adoption ($\beta = 0.453$, $p < 0.001$), supporting H1. This suggests that adoption in the South African automotive context is strongly associated with the availability and perceived adequacy of GenAI capabilities for KM tasks—such as knowledge capture, retrieval, summarisation, and support for routine problem-solving. In practical terms, this implies that organisations are more likely to adopt GenAI when they have access to usable tools, supporting infrastructure, and relevant functionalities that clearly align with KM needs. This finding is consistent with the argument that technological availability and capability are foundational conditions for adoption because they reduce implementation uncertainty and increase the perceived feasibility of integrating GenAI into everyday knowledge processes [24]. In a sector challenged by skills constraints, fast technological change, and operational pressures, tangible tool capability appears to serve as a "proof point" that GenAI can deliver value in real workflows rather than remaining a conceptual innovation.

Within the PPOA framework, Perceived Usefulness (PU) and Perceived Enjoyment (PE) were both significant predictors of GenAI adoption, supporting H2 and H4 (PU: $\beta = 0.326$, $p < 0.001$; PE: $\beta = 0.443$, $p < 0.001$). These results reinforce the idea that adoption decisions are strongly shaped by whether users believe GenAI improves their job performance (usefulness) and whether the experience of interacting with GenAI is positive and engaging (enjoyment). The finding for usefulness aligns with established technology adoption literature that identifies performance expectancy as a core driver of uptake [25]. In KM settings specifically, usefulness may reflect GenAI's ability to reduce time spent searching for knowledge, improve the quality and speed of decision-making, and enable consistent responses to recurring operational issues.

Notably, Perceived Enjoyment ($\beta = 0.443$) emerged as one of the strongest adoption drivers in the study (ranked fourth overall), suggesting that affective experience is not merely an added benefit but a meaningful adoption lever. This supports prior work showing that positive emotional experiences can strengthen intention to use GenAI and shape favourable attitudes toward its continued adoption [22]. In practice, users may be more willing to embed GenAI into their daily KM routines when the interaction feels intuitive, responsive, and rewarding—especially in knowledge-intensive environments where employees may already be overloaded and sceptical of new systems.

In contrast, Perceived Ease of Use (PEOU) was not significant ($\beta = 0.052$, $p = 0.562$), leading to the rejection of H3. This result suggests that, in this context, ease-of-use may be less decisive than usefulness and engagement. There are several plausible interpretations grounded in the study setting and sample characteristics. First, the respondent profile is dominated by IT specialists and technically oriented roles, who may be less sensitive to usability barriers because they are accustomed to adopting complex digital tools. Second, automotive organisations often implement technologies through structured processes (training, support structures, integration into existing systems), which can reduce the relative importance of "ease" as an initial adoption condition. Third, when competitive or organisational pressure to innovate is high, users may tolerate usability challenges if the tool is perceived as valuable and effective. In short, ease-of-use may still matter at the implementation level, but it does not appear to be a primary determinant of adoption intention once usefulness and experience are accounted for.

The TEOG framework results show that Compatibility (COMP), Competition Intensity (CI), and Organisational Size (ORG_SIZE) are all significant predictors of adoption—supporting H5, H6, and H7 (COMP: $\beta = 0.327$, $p < 0.001$; CI: $\beta = 0.250$, $p = 0.009$; ORG_SIZE: $\beta = 0.194$, $p = 0.038$). Among these, compatibility is the strongest TEOG predictor, implying that adoption is more likely when GenAI aligns with existing processes, values, workflows, data practices, and KM routines. This reinforces prior findings that compatibility is a central organisational driver of GenAI adoption because it reduces disruption and lowers implementation complexity [23]. In the automotive sector—where operations are often highly standardised—technologies that integrate smoothly with established systems, documentation practices, and quality processes are more readily accepted.

Competition intensity also plays a meaningful role. The positive relationship ($\beta = 0.250$) suggests that organisations facing stronger competitive pressure are more likely to adopt GenAI for KM as a strategic response to innovation demands. This aligns with the view that competitive environments accelerate technology uptake because firms seek productivity gains, faster problem-solving, and knowledge-driven differentiation to keep pace with peers and rivals [23]. Organisational size has a weaker but significant influence, which is consistent with the argument that larger organisations often have greater resource capacity—financial, infrastructural, and human—to absorb adoption costs and manage implementation risk [26]. This result suggests that size-related capability (e.g., budgets, IT governance, change management capacity) may support adoption even if it is not the main driver.

The IEO framework results indicate that institutional pressures shape GenAI adoption in nuanced ways. Normative pressure ($\beta = 0.249$, $p = 0.006$) and mimetic pressure ($\beta = 0.408$, $p < 0.001$) significantly predicted adoption, supporting H9 and H10. Mimetic pressure, in particular, emerged as one of the strongest predictors overall (ranked fifth), indicating that organisations are strongly influenced by the desire to emulate successful peers and align with perceived industry best practices. This aligns with the interpretation that organisations adopt GenAI partly to avoid falling behind—especially when competitors or benchmark firms signal value through visible success stories and performance gains [27]. Normative pressure also matters, suggesting that professional expectations, industry standards, and shared beliefs about "modern" digital capability influence adoption

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decisions, particularly in sectors where technology leadership is increasingly linked to legitimacy.

However, coercive pressure was not significant (β = 0.128, p = 0.102), resulting in rejection of H8. This implies that direct mandates or forceful external requirements may not be the primary mechanism driving adoption in this context. This finding resonates with prior research suggesting that mimetic and normative pressures often exert greater influence than coercive forces in emerging technological domains—especially when regulatory frameworks are still developing or when adoption is driven by strategic choice rather than compliance [27]. In practical terms, GenAI adoption for KM in South Africa's automotive sector may currently be shaped more by competitive imitation and professional norms than by strict regulatory or customer-imposed requirements.

Two of the strongest predictors of adoption were FATAA ethical principles and existing KM practices, supporting H11 and H12. FATAA showed the strongest effect of all variables (β = 0.536, p < 0.001), while KM practices also demonstrated a highly significant and strong relationship with adoption (β = 0.467, p < 0.001). These results suggest that GenAI adoption for KM is strongly enabled when organisations have (1) robust ethical and governance orientations (fairness, accountability, transparency, accuracy, autonomy) and (2) established KM routines and structures capable of absorbing GenAI into daily knowledge processes.

The dominance of FATAA as the top predictor provides an important insight for GenAI adoption in knowledge-sensitive environments: trust, governance, and responsible use are not "afterthoughts"—they appear central to adoption decisions. This finding is consistent with the view that ethical principles positively influence GenAI adoption by reducing perceived risk, increasing trust, and strengthening organisational confidence in responsible deployment [24]. In KM contexts where GenAI interacts with internal documents, technical procedures, and potentially sensitive operational knowledge, concerns about accuracy, accountability, and transparency can directly affect whether users and leaders accept or resist adoption.

Similarly, the strong influence of KM practices indicates that GenAI adoption is more likely where KM is already valued and operationalised. Organisations with mature KM processes—such as documentation standards, knowledge repositories, communities of practice, and structured learning mechanisms—are better positioned to integrate GenAI effectively. This supports the argument that KM capabilities constitute tactical assets that enable organisations to exploit new technologies more successfully [7]. Put simply, GenAI does not replace KM maturity; rather, it leverages and amplifies it. Without structured KM practices, GenAI may lack the organisational "landing zone" needed for meaningful integration and sustainable use.

When the strongest predictors are considered together (FATAA, KM practices, GenAI tools, perceived enjoyment, and mimetic pressure), the adoption story becomes clearer: GenAI adoption for KM in South Africa's automotive sector is most likely when organisations (1) build ethical assurance and governance, (2) strengthen KM readiness, (3) provide capable GenAI tools aligned to KM tasks, (4) ensure positive user experience, and (5) respond strategically to peer-driven competitive signals. This reinforces the central conclusion that adoption is multi-dimensional and requires both "hard" enablers (tools, resources, fit) and "soft" enablers (trust, norms, experience, institutional legitimacy).

Finally, the correlation patterns strengthen these interpretations: GenAI adoption (GAIM) showed strong associations with perceived enjoyment, perceived usefulness, mimetic pressure, and compatibility—indicating that positive user experience, performance value, peer influence, and organisational fit operate together as a reinforcing system rather than isolated effects. The overall empirical picture therefore supports the study's integrated framing: GenAI adoption for KM in this sector is shaped by a combined readiness logic (KM maturity + ethical governance), an acceptance logic (usefulness + enjoyment), and a legitimacy/strategy logic (fit + competition + institutional imitation).

4. CONCLUSION

The study investigated the factors influencing Generative AI (GenAI) adoption for enhancing knowledge management (KM) practices in South Africa's automotive sector. Using an integrated adoption perspective, the findings show that GenAI adoption is shaped by a combination of technological, individual, organisational, institutional, and ethical determinants rather than a single driver. The regression model demonstrated strong explanatory power (Adjusted $R^2 = 0.624$, $p < 0.001$).

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Results indicate that ethical and KM readiness are central to adoption. FATAA ethical principles were the strongest predictor (β = 0.536, p < 0.001), followed by existing KM practices (β = 0.467, p < 0.001) and GenAI tool capability (β = 0.453, p < 0.001). User perceptions also significantly influenced adoption, with perceived enjoyment (β = 0.443, p < 0.001) and perceived usefulness (β = 0.326, p < 0.001) supporting the salience of affective and performance-based evaluations. Compatibility (β = 0.327, p < 0.001), competition intensity (β = 0.250, p = 0.009), and organisational size (β = 0.194, p = 0.038) further confirm the role of organisational fit and capacity. Institutional forces were also significant, particularly mimetic pressure (β = 0.408, p < 0.001) and normative pressure (β = 0.249, p = 0.006), whereas perceived ease of use (β = 0.052, p = 0.562) and coercive pressure (β = 0.128, p = 0.102) were not significant in this context.

The study contributes by extending GenAI–KM adoption evidence to an under-researched South African automotive setting and by validating a context-specific model that foregrounds ethical governance, KM maturity, and institutional imitation as key adoption mechanisms. A key limitation is the restricted contextual scope and cross-sectional design. Future research should test the model across multiple firms and sectors, incorporate post-adoption outcomes (e.g., satisfaction and continuance intention), and examine governance issues related to privacy, security, and responsible GenAI use.

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