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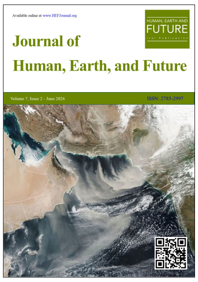

Synergizing Human and AI Factors for Effective Knowledge Transfer in ICE-to-EV Transition

Yinglak Dangjaroen [1], Mongkolchai Wiriyapinit [2*], Sukree Sinthupinyo [3]

[1] *College of Interdisciplinary and Integrative Studies, Chulalongkorn University, Bangkok 10330, Thailand.*

[2] *Chulalongkorn Business School, Chulalongkorn University, Bangkok 10330, Thailand.*

[3] *Faculty of Engineering, Chulalongkorn University, Bangkok 10330, Thailand.*

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Abstract

This study investigates the determinants of knowledge transfer effectiveness during the automotive industry's transition from internal combustion engines (ICEs) to electric vehicles (EVs), examining the interplay between traditional interpersonal knowledge transfer factors and artificial intelligence (AI) factors. Data were collected from 303 professionals in Thailand's automotive and AI sectors using a structured questionnaire. The hypothesized relationships were tested through structural equation modeling (SEM) with confirmatory factor analysis, yielding excellent model fit indices (CFI = 1.00, RMSEA = 0.00, SRMR = 0.006). The results reveal a distinct efficiency-effectiveness dichotomy: traditional knowledge transfer factors primarily drive knowledge application ($\beta = 0.67$) and recipient satisfaction ($\beta = 0.76$), whereas AI factors function as efficiency accelerators, significantly reducing transfer cost ($\beta = 0.57$) and enhancing transfer speed ($\beta = 0.45$), while showing negligible influence on satisfaction ($\beta = 0.04$). The model explains 65–69% of the variance across all outcome dimensions. This research contributes a statistically validated Dual-Engine Framework demonstrating that AI augments rather than replaces human mentorship, offering organizations a balanced strategy for workforce upskilling during technological transitions.

Keywords: EV Transition; Knowledge Transfer; Knowledge Transfer Factor; Electric Vehicle; Artificial Intelligence; Machine Learning.

1. Introduction

The global automotive industry stands at a critical juncture, facing arguably the most significant paradigm shift in its history: the transition from Internal Combustion Engines (ICE) to Electric Vehicles (EV) [1]. While environmental sustainability and carbon neutrality targets remain the primary drivers of this change [2], recent macroeconomic factors have significantly accelerated the urgency. The volatility of crude oil prices, coupled with the complex geopolitical dynamics surrounding energy security among major global powers, has forced nations and manufacturers to reduce their reliance on fossil fuels [3]. Consequently, the shift to EVs is no longer merely an environmental choice; it has become a strategic necessity for economic survival and national resilience [4].

However, as industry rushes to embrace this technological revolution, a critical operational challenge has emerged. The transition involves more than simply replacing engine parts with batteries; it requires a fundamental restructuring of organizational knowledge [5]. Decades of tacit knowledge and expertise deeply rooted in ICE technologies risk

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* Corresponding author: mongkolchai@cbs.chula.ac.th

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becoming obsolete [6], while the workforce struggles to adapt to the new competencies required for EV production [7]. This creates a "knowledge gap" that, if left unaddressed, could stall production efficiency and threaten the competitiveness of automotive manufacturers during this delicate transition period [8].

The existing body of literature on knowledge transfer has established robust theoretical foundations. Knowledge transfer has been defined as the process through which one organizational unit is affected by the experience of another [9], while the SECI model was proposed as a seminal framework for understanding knowledge creation and conversion [10]. Within the automotive sector specifically, the applicability of the SECI model in analyzing knowledge creation practices has been demonstrated [11], and strategies for effective technology transfer in automotive manufacturing have been examined [12]. More recently, the potential of AI in facilitating intergenerational tacit knowledge transfer has been explored [13], while the broader impacts of AI on knowledge management processes have also been reviewed [14].

Despite these advances, three critical gaps remain in the literature. First, the majority of studies examining AI's role in knowledge management treat AI as a monolithic construct, failing to differentiate between distinct AI modalities such as supervised learning, deep learning, and large language models, each of which may exert differential effects on transfer outcomes [15]. Second, while the ICE-to-EV transition has attracted scholarly attention regarding its technological and economic dimensions [1, 5], empirical research examining the workforce knowledge transfer challenges specific to this transition remains remarkably scarce [8]. Third, no existing study has empirically tested whether AI factors complement or substitute traditional human-centric knowledge transfer mechanisms when measured against multidimensional effectiveness criteria encompassing both efficiency and quality outcomes [16].

This study addresses these gaps by proposing and empirically validating a hybrid framework that disaggregates both the independent factors (six traditional knowledge transfer variables and five distinct AI variables) and the dependent outcomes (five dimensions of transfer effectiveness). By employing structural equation modeling on data from 303 automotive professionals, this research provides granular evidence on the differential contributions of human and technological factors, offering actionable insights for organizations navigating the EV transition. Therefore, this study aims to investigate the factors influencing knowledge transfer effectiveness during the ICE-to-EV transition in the automotive parts manufacturing industry, proposing a framework that integrates traditional organizational factors with modern AI capabilities to ensure a smooth and sustainable workforce transition.

2. Literature Review and Framework Development

This section provides a comprehensive review of the critical variables identified as determinants of Knowledge Transfer Effectiveness (KTE).

2.1. Knowledge Transfer Factors in Automotive Transition

Knowledge transfer is defined as the process through which one unit, such as a group, department, or division, is affected by the experience of another [9]. In the automotive context, this involves transferring tacit knowledge (experience-based) [17] and explicit knowledge (manuals, data or work instruction) [11] regarding powertrain technologies. The effectiveness of this transfer is traditionally measured by the recipient's ability to apply and identify the knowledge, the speed and cost of transfer [18], and the satisfaction [19] of the parties involved.

In high-risk environments such as EV manufacturing, the perceived competence of the knowledge source is paramount. Trust in the sender significantly lowers resistance to new information [12]. The willingness of ICE engineers to unlearn old skills and embrace EV technologies. Without intrinsic motivation, transfer mechanisms fail regardless of sophistication [20]. The recipient's prior knowledge base. EV technology requires a foundation in electrical engineering, making the transfer difficult for purely mechanical engineers [21]. Drawing from the SECI model [10], tacit knowledge is best transferred through direct observation and mentorship [22].

Recent studies emphasize that the EV transition requires unlearning old habits and rapidly absorbing new standards [1]. However, barriers such as the reliability of new knowledge sources and the lack of clear organizational policies often hinder this process [23]. The success of knowledge transfer has traditionally been rooted in human interaction and organizational context [24]. We examine six key variables in this domain.

2.2. The Role of Artificial Intelligence

AI has introduced new variables into the knowledge equation. We categorize these into five technological variables representing the current state of industrial AI. AI has evolved from a tool for automation to a partner in cognitive processes. In knowledge management, AI technologies such as supervised learning and unsupervised learning can organize vast datasets, identifying patterns that human instructors might miss [25].

The use of large language models to instantly summarize technical manuals or code theoretically reduces the search time for knowledge to zero [26]. Furthermore, the advent of generative AI and large language models (LLMs) offers new avenues for personalized learning and instant information retrieval, potentially reducing the time to knowledge transfer (TKT) [27]. AI's role in forecasting skill gaps and recommending personalized learning paths for employees [28].

2.3. Knowledge Transfer Effectiveness

We measure effectiveness through five distinct outcome variables, separating efficiency from quality. The speed and accuracy with which an employee can locate the specific information needed. The ability to translate theoretical knowledge into practical solutions on the production line [29, 30] (e.g., diagnosing a battery thermal runaway). The time reduction in the learning curve compared to traditional methods [31]. The reduction in financial resources are required for training and error correction [32]. The subjective well-being and confidence of the employee follow the transfer process [33]. However, the literature suggests that while AI excels at processing data, its ability to foster deep [15], tacit understanding crucial for complex engineering tasks is debated [34]. This study proposes a conceptual framework (Figures 1 and 2) that tests both traditional human factors and modern AI factors against multidimensional effectiveness outcomes [16].

2.4. Theoretical Foundation

The theoretical foundation of this study was developed through a systematic review of established knowledge management and organizational learning theories. Three classical perspectives were identified as particularly relevant to explaining how knowledge is created, strategically valued, and absorbed during industrial transitions. The integration of these complementary lenses informed the identification of key independent variables and guided the construction of the proposed conceptual framework for examining knowledge transfer effectiveness in the ICE-to-EV context.

First, the SECI Model of knowledge creation [10] provides the foundational lens for understanding how tacit and explicit knowledge is converted and transferred within organizations. The model posits four modes of knowledge conversion—socialization, externalization, combination, and internalization—each requiring distinct mechanisms. In the context of this study, traditional knowledge transfer factors (such as mentorship and on-the-job training) align with the socialization and internalization phases, which necessitate interpersonal interaction, while AI-driven tools correspond more closely to the combination phase, where explicit knowledge is systematized and disseminated.

Second, the resource-based view (RBV) of the firm conceptualizes knowledge as a strategic resource that confers competitive advantage when it is valuable, rare, and difficult to imitate. From this perspective, AI technologies serve as resource-optimizing mechanisms that reduce the cost and time of knowledge dissemination, whereas human expertise constitutes the inimitable resource that ensures deep application and contextual understanding.

Third, absorptive capacity theory emphasizes the recipient's ability to recognize, assimilate, and apply external knowledge. This theory directly informs the inclusion of variables such as Individual Expertise, Knowledge Reliability, and Type of Knowledge in the model, as these factors collectively determine the absorptive capacity of the workforce during the ICE-to-EV transition. By integrating these three perspectives, the present study offers a theoretically grounded framework that bridges organizational behavior with technological innovation.

2.5. Conceptual Framework

Based on these variables, we posit that knowledge transfer factors (Variables 1-6) will primarily drive application and satisfaction, while AI factors (Variables 7-11) will primarily drive speed and cost [14]. For clarity, the abbreviations and operational definitions of each variable utilized in this study are summarized in Table 1.

Table 1. Variable Definition

Factor	Variable	Definition
KTF Knowledge Transfer Factor	IE	Individual Expertise
	KTM	Knowledge Transfer Mechanism
	TK	Type of Knowledge
	TKT	Time to Knowledge Transfer
	KR	Knowledge Reliability
	KP	Knowledge Transfer Policy
AIF Artificial Intelligence Factor	MLS	Machine Learning - Supervised Learning
	MLU	Machine Learning - Unsupervised Learning
	MLR	Machine Learning - Reinforcement Learning
	DL	Deep Learning
	LLM	Large Language Model
KTE Knowledge Transfer Effectiveness	KIA	Knowledge Identification and Acquisition
	KA	Knowledge Application
	KTS	Knowledge Transfer Speed
	KTC	Knowledge Transfer Cost
	KTSF	Knowledge Transfer Satisfaction

The preliminary conceptual framework, as shown in Figure 1, was initially constructed based on a systematic literature review. It comprised fundamental constructs such as Individual Expertise, Knowledge Transfer Mechanisms, Type of Knowledge and standard Machine Learning types [35]. However, given the unique volatility of the ICE-to-EV transition, this initial model appeared insufficient to capture the operational nuances of the automotive floor. Consequently, subsequent in-depth interviews with industry experts were conducted to bridge this gap. These qualitative insights necessitated the expansion of the model. In the human dimension, variables including Time to Knowledge Transfer, Knowledge Reliability, and Organizational Policy were integrated to reflect the logistical and managerial challenges of upskilling. Simultaneously, the technological dimension was updated to include deep learning and large language models (LLM), acknowledging the advanced tools currently reshaping industrial efficiency, as shown in Figure 2.

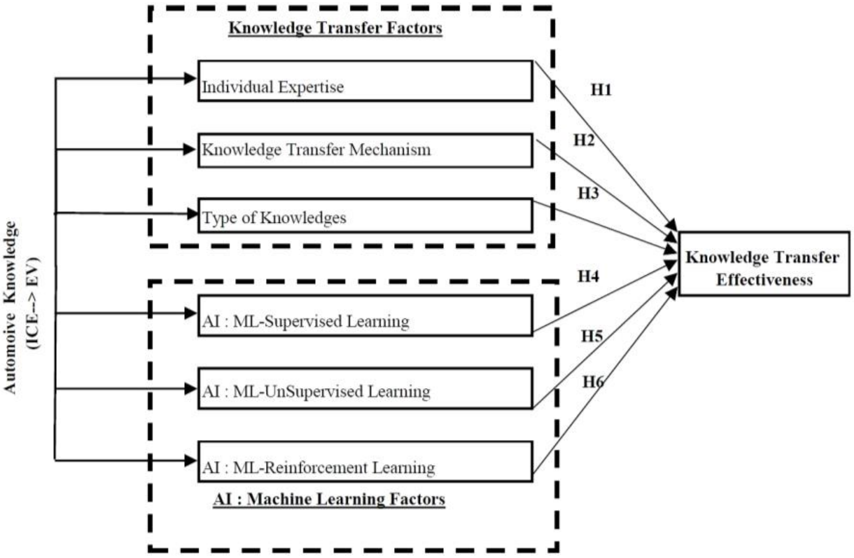


Figure 1. Conceptual Framework (Literature Review)

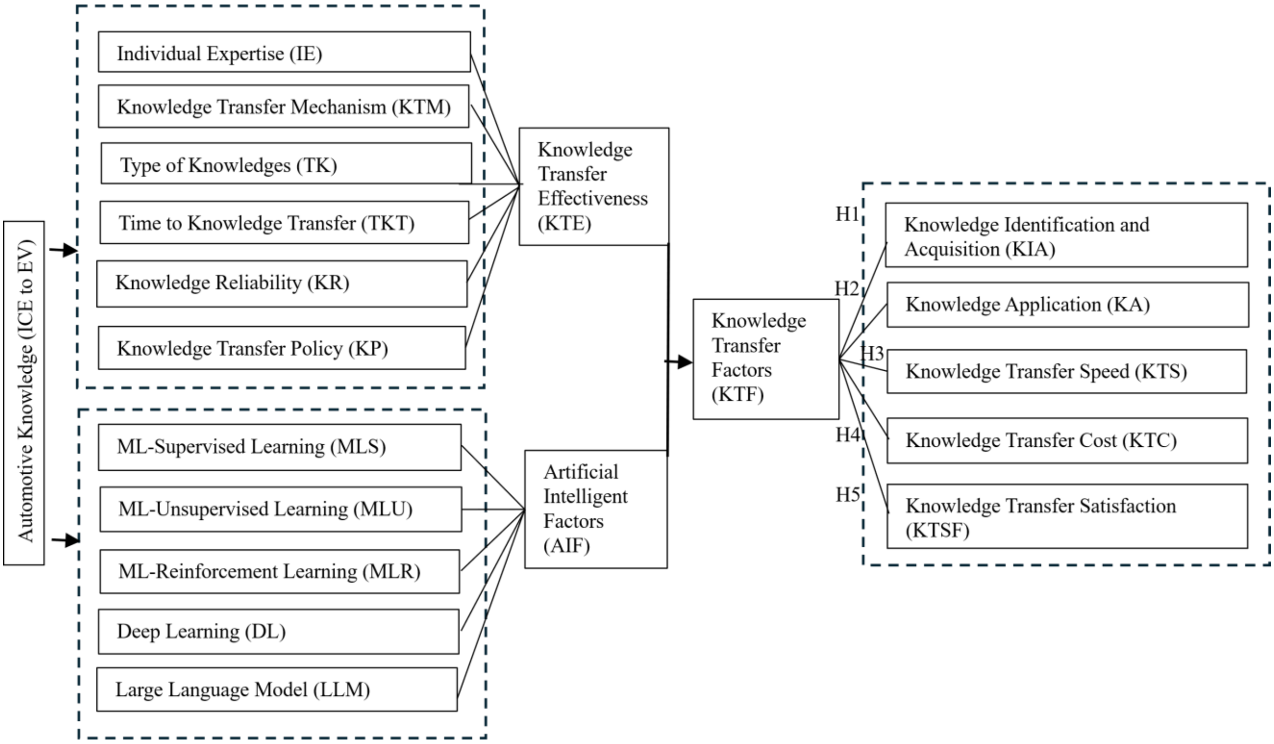


Figure 2. Research Framework (Adjusted After Qualitative Results)

3. Research Methodology

This study utilizes a sequential mixed-method design, starting with qualitative inquiry to refine the research model, followed by quantitative validation.

3.1. Qualitative Phase

In-depth interviews were conducted with 22 key informants using a purposive sampling method. The participants included 12 professionals from the automotive manufacturing sector, 6 AI specialists, and 4 representatives from government and supporting agencies. The semi structured interviews, lasting 45-60 minutes, focused on identifying variables affecting knowledge transfer.

The qualitative phase confirmed the importance of traditional factors (Expertise, Mechanism) and identified new critical variables: Time to Knowledge Transfer, Knowledge Reliability, Organizational Policy, and Generative AI types (Deep Learning, LLMs). These were incorporated into the survey instrument.

3.2. Quantitative Phase

The population comprised professionals in Thailand's automotive and AI sectors. Using convenience sampling, based on the empirical guidelines by Hair et al. [36], a sample size of at least 10 times, the minimum number of indicators to confirm factor analysis is recommended. Questionnaires were distributed to 400 individuals, yielding 303 valid responses (75% response rate), exceeding the minimum requirement for SEM analysis [37]. While convenience sampling was adopted for practical feasibility, this approach may introduce self-selection bias, whereby individuals more familiar with AI technologies were more inclined to participate, potentially inflating the perceived relevance of AI factors. To mitigate this risk, the sample was drawn from diverse organizations, including automotive manufacturers, AI-utilizing firms, and public and private supporting agencies. The demographic profile confirms heterogeneity in education (28.38% vocational to 17.16% postgraduate) and experience (under one year to over fifteen years). Future studies should consider stratified sampling designs to strengthen representativeness.

3.3. Instrument and Validation

The questionnaire utilized a 5-point Likert scale. Reliability was confirmed via Cronbach's alpha, with all constructions exceeding the 0.70 threshold (Table 2). Following the initial validation of the questionnaire's content validity through the Index of Consistency (IOC) by five experts, which confirmed that all items were consistent with the research objectives, a pilot study was conducted to assess reliability [38]. The instrument was administered to a nonsample group of 30 individuals who possessed characteristics similar to the target population.

Table 2. Reliability Analysis Results of the Research Constructs

Constructs	Cronbach 's Alpha	No. of Items
KTF	0.946	34
AIF	0.929	25
KTE	0.743	5

The results indicated strong reliability across all three main constructs, with every alpha coefficient exceeding the 0.70 threshold generally accepted in social science research [39]. To ensure measurement separation between KTF and AIF, the KTF items were framed around interpersonal interactions (mentorship quality, face-to-face training, organizational policy support) without reference to any technological tool, whereas AIF items specifically referenced computational processes such as AI-based pattern recognition and large language model information retrieval. Content validity was confirmed through IOC assessment by five experts who evaluated each item for conceptual distinctiveness and construct alignment. At the analysis stage, CFA confirmed discriminant validity between the KTF and AIF, with an interconstruct correlation of 0.77 (Table 8), remaining below the conservative threshold of 0.85 [37].

3.4. Data Analysis

The IBM SPSS AMOS program was used for confirmatory factor analysis (CFA) and path analysis. The model fit indices were assessed against standard criteria, followed by structural equation modeling (SEM) to test the hypotheses [40].

4. Results

4.1. Respondent Demographics

The demographic profile of the 303 respondents is detailed in Table 3. Most held a bachelor's degree (54.13%). The majority were male (56.44%). The profile indicates a highly experienced cohort. The majority (59.74%) fall within the 31-40 age bracket, with 47.85% possessing 6-10 years of experience. This demographic represents the core transition generation of people who must bridge the gap between legacy ICE skills and modern EV requirements.

Table 3. Demographic Profile of Respondents (n = 303)

Demography	Details	Frequency	Percentage
Gender	Male	171	56.44%
	Female	98	32.34%
	Not Specify	34	11.22%
Age (Years)	21 – 30	58	19.14%
	31 – 40	181	59.74%
	41 – 50	61	20.13%
	51 – 60	2	0.66%
	> 60	1	0.33%
Education	Diploma/Vocational	86	28.38%
	Bachelor's Degree	164	54.13%
	Master's/Doctoral	52	17.16%
Experience in the Automotive Industry (Years)	< 1	1	0.33%
	1 – 3	40	13.20%
	3 – 5	88	29.04%
	6 – 10	145	47.85%
	10 – 15	23	7.59%
	>15	6	1.98%

4.2. Descriptive Analysis of Constructs and Observed Variables

A descriptive statistical analysis was conducted to examine the central tendency, dispersion, and distributional characteristics of the three primary constructs: knowledge transfer factors (KTF), artificial intelligence factors (AIF), and knowledge transfer effectiveness (KTE). The results, detailed in Table 4, reveal generally high levels of perception across all variables, with mean scores ranging from 3.90 to 4.17.

Within the knowledge transfer factor (KTF) construction, individual expertise (IE) emerged as the most prominent variable (mean=4.17, SD=0.67). This suggests that respondents view personal expertise as a critical driver of the transfer process. Other variables, such as Time to Knowledge Transfer (TKT), Knowledge Transfer Mechanism (KTM), Type of Knowledge (TK), and Knowledge Transfer Policy (KP), also received strong endorsement, with mean scores clustering approximately 4.00-4.01. Knowledge Reliability (KR), while slightly lower (Mean=3.98), remains at a high level.

Regarding artificial intelligence factors (AIF), the analysis highlights supervised learning (MLS) as the most significant factor, sharing the highest mean score of 4.17 (SD=0.67) with individual expertise. This indicates a strong consensus on the relevance of supervised learning models. Other AI dimensions, including reinforcement learning (MLR), deep learning (DL), large language model (LLM), and unsupervised learning (MLU), showed consistent mean scores ranging from 3.98 to 4.00, reflecting a uniform recognition of various AI technologies in the transfer context.

For knowledge transfer effectiveness (KTE), the highest-rated outcome was knowledge identification and acquisition (KIA) (mean=4.05, SD=0.94), closely followed by knowledge application (KA) (mean=4.04, SD=0.90) and knowledge transfer satisfaction (KTSF) (mean=4.03, SD=0.86). Knowledge Transfer Cost (KTC) and Knowledge Transfer Speed (KTS) were rated slightly lower, with means of 3.96 and 3.90, respectively.

The analysis of dispersion via the coefficient of variation (CV) indicates that the data points are reasonably clustered around the mean, with values ranging from approximately 16% to 25%. Individual expertise (IE) and supervised learning (MLS) showed the lowest variability (16.19%), suggesting high respondent agreement. Conversely, unsupervised learning (MLU) exhibited slightly higher variability but was still within acceptable limits.

To assess normality, Skewness (Sk) and Kurtosis (Ku) were evaluated [41]. Skewness values for all variables were negative (ranging from -0.76 to -2.41, indicating a left-skewed distribution where most responses are concentrated toward the higher end of the scale [42]. Kurtosis values were mixed but generally fell within acceptable ranges for SEM analysis (absolute value < 10) [43]. Notably, Individual Expertise (IE) and Supervised Learning (MLS) displayed higher kurtosis values (5.67), reflecting a more peaked distribution (leptokurtic) [44], but these deviations are not severe enough to violate the assumptions required for subsequent structural equation modeling [45]. In the following analyses, SD denotes standard deviation, CV represents the coefficient of variation expressed as a percentage, Sk indicates skewness, and Ku indicates kurtosis.

Table 4. Descriptive Statistics of Variables in the Structural Equation Modeling (SEM) Analysis

Construct	Variable	Mean	SD	CV (%)	Sk	Ku
KTF (Knowledge Transfer Factor)	IE	4.17	0.67	16.19	-2.41	5.67
	KTM	4.00	0.79	19.68	-1.49	1.21
	TK	4.00	0.82	20.44	-1.39	0.86
	TKT	4.01	0.80	20.05	-1.45	1.21
	KR	3.98	0.82	20.65	-1.48	0.97
	KP	4.00	0.79	19.72	-1.47	1.06
AIF (Artificial Intelligence Factor)	MLS	4.17	0.67	16.19	-2.41	5.67
	MLU	4.00	0.79	19.68	-1.49	1.21
	MLR	4.00	0.82	20.44	-1.39	0.86
	DL	4.01	0.80	20.05	-1.45	1.21
	LLM	3.98	0.82	20.65	-1.48	0.97
KTE (Knowledge Transfer Effectiveness)	KIA	4.05	0.94	23.25	-0.86	0.25
	KA	4.04	0.90	22.39	-0.94	0.92
	KTS	3.90	0.97	24.76	-0.78	-0.17
	KTC	3.96	0.93	23.53	-0.94	0.72
	KTSF	4.03	0.86	21.24	-0.76	0.58

4.3. Measurement Equation Model - Structural Equation Modeling (SEM)

Pearson's correlation analysis and multicollinearity assessment prior to conducting structural equation modeling (SEM) [46], an analysis of Pearson's product moment correlation coefficient was performed on the 16 observed variables. This encompassed the independent variables (knowledge transfer factors and AI factors) and the dependent variable (knowledge transfer effectiveness) to verify linear relationships and screen for potential multicollinearity [47]. As presented in the correlation matrix (see Table 5), the results indicate that all pairs of observed variables exhibit statistically significant positive correlations at the 0.01 level ($p < 0.01$). The correlation coefficients range from 0.50 to 0.79, allowing for the following key observations: Strength and Direction of Relationships: The majority of the coefficients cluster between 0.60 and 0.79, indicating a high degree of association. This strong positive relationship suggests that improvements in knowledge transfer mechanisms or AI capabilities are consistently associated with higher levels of transfer effectiveness.

However, it is notable that the unsupervised machine learning variable demonstrated moderate correlations (ranging from 0.50 to 0.66), which are slightly lower than those of the other variables. This implies that while unsupervised learning aligns with the broader trend, it possesses distinct characteristics that differentiate it slightly from other AI factors. Multicollinearity Check: To ensure the validity of the SEM analysis, the dataset was screened for extreme multicollinearity, which can lead to data redundancy and inflated standard errors. The analysis revealed that no pair of variables had a correlation coefficient exceeding 0.80. This falls well below the cautionary threshold of 0.90 recommended by [37, 48]. Consequently, it can be concluded that the dataset is free from multicollinearity issues [49]. The observed variables demonstrate sufficient distinctiveness and are suitable for subsequent confirmatory factor analysis (CFA) and structural model testing [50].

Table 5. Correlation Coefficients Among Variables in the Structural Equation Model (SEM)

Construct	IE	KTM	TK	TKT	KR	KP	MLS	MLU	MLR	DL	LLM	KIA	KA	KTS	KTC	KTSF
IE	1															
KTM	0.79**	1														
TK	0.77**	0.75**	1													
TKT	0.78**	0.75**	0.74**	1												
KR	0.75**	0.75**	0.74**	0.74**	1											
KP	0.78**	0.76**	0.75**	0.74**	0.74**	1										
MLS	0.75**	0.76**	0.75**	0.74**	0.74**	0.75**	1									
MLU	0.55**	0.66**	0.66**	0.66**	0.64**	0.66**	0.65**	1								
MLR	0.75**	0.75**	0.74**	0.74**	0.75**	0.75**	0.74**	0.69**	1							
DL	0.76**	0.75**	0.75**	0.73**	0.75**	0.74**	0.75**	0.67**	0.74**	1						
LLM	0.78**	0.75**	0.75**	0.74**	0.75**	0.75**	0.75**	0.66**	0.76**	0.76**	1					
KIA	0.68**	0.79**	0.78**	0.78**	0.78**	0.79**	0.79**	0.55**	0.78**	0.79**	0.78**	1				
KA	0.68**	0.79**	0.79**	0.78**	0.78**	0.78**	0.78**	0.51**	0.79**	0.72**	0.71**	0.55**	1			
KTS	0.57**	0.71**	0.71**	0.72**	0.74**	0.71**	0.73**	0.54**	0.72**	0.73**	0.73**	0.71**	0.59**	1		
KTC	0.68**	0.78**	0.78**	0.77**	0.79**	0.79**	0.79**	0.60**	0.79**	0.70**	0.72**	0.69**	0.73**	0.61**	1	
KTSF	0.69**	0.78**	0.79**	0.78**	0.78**	0.78**	0.79**	0.50**	0.79**	0.78**	0.79**	0.69**	0.63**	0.68**	0.56**	1

** Statistical significance < 0.05 level.

Structural Model Fit Assessment To ensure the validity of the hypothesized relationships, the structural model was evaluated against the empirical data using a comprehensive set of goodness-of-fit indices [51]. The results, as summarized in Table 6, demonstrate an exceptional fit across all criteria. The chi-square statistic was calculated at 73.91 with 72 degrees of freedom. Notably, the associated p value is 0.42, which is nonsignificant ($p > 0.05$). In structural equation modeling, a nonsignificant p value is highly desirable [52], as it indicates that the theoretical model does not significantly differ from the observed data. Furthermore, the relative chi-square ratio stands at 1.03, falling well below the strict threshold of 3.0 [53], suggesting a parsimonious and well-fitting model.

Regarding the incremental fit indices, both the Comparative Fit Index (CFI) [40] and the Tucker–Lewis Index (TLI) [54] achieved perfect scores of 1.00, surpassing the standard recommended cutoff of 0.90 or 0.95. This implies that the specified model improves upon the independence model to the highest possible degree.

These strong fit indices warrant methodological clarification. The near-perfect values are attributable to several factors rather than overfitting or redundancy. The nonsignificant chi-square ($p = 0.42$) serves as the primary indicator of model-data congruence. The sequential mixed-method design allowed qualitative refinement of indicators through 22 expert interviews prior to quantitative testing. The sample-to-parameter ratio is favorable (303 respondents for a parsimonious model). Additionally, following Groskurth et al. [51], who cautioned against rigid adherence to fixed cutoffs, the convergence of a nonsignificant chi-square, a low relative chi-square ratio (1.03), and strong incremental indices collectively evidence acceptable fit. The internal consistency values (Cronbach's alpha = 0.743–0.946) reflect construct cohesion, as items measure distinct facets of each latent variable.

Finally, the absolute fit indices confirm minimal error in the model approximation. The root mean square error of approximation (RMSEA) [55] and the standardized root mean square residual (SRMR) [56] were both reported at 0.01. These values are substantially lower than the acceptable upper limits of 0.05 and 0.08, respectively. Collectively, these statistics confirm that the structural model possesses a robust fit and is fully suitable for interpreting the causal paths between the variables. The model fit was assessed using the following indices: Chi-square (χ^2), degrees of freedom (df), Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR).

Table 6. Model Fit Indices for Measurement Model

Statistical Data	Level of Acceptance	Model Fitness	Result
Chi-square	-	73.91	-
Degree of freedom	-	72	-
Relative Chi-square	< 3 (0 approach)	1.03	Accept
P	> 0.05	0.42	Accept
Comparative Fit Index (CFI)	>0.90 (1 approach)	1.00	Accept
Trucker - Lewis Index (TLI)	>0.90 (1 approach)	1.00	Accept
Root Mean Square Error of Approximation (RMSEA)	<0.05 (0 approach)	0.01	Accept
Standard Root Mean Square Residual (SRMR)	<0.08 (0 approach)	0.01	Accept

4.4. Structural Model Assessment and Causal Analysis

Structural equation modeling (SEM) analysis was conducted to evaluate the causal relationships between the exogenous variables Knowledge Transfer Factors and AI Factors and the varying dimensions of Knowledge Transfer Effectiveness. The breakdown of direct effects (DE), indirect effects (IE), and total effects (TE) [57] is presented in Table 7.

Table 7. Correlation Coefficients Among Variables in the Structural Equation Model (SEM)

Independent Variable	Statistical Data	Dependent Variable						KTE								
		KIA			KA			KTS			KTC			KTSF		
		DE	IE	TE	DE	IE	TE	DE	IE	TE	DE	IE	TE	DE	IE	TE
KTF - AIF	*β*	0.81	-	0.81	0.81	-	0.81	0.83	-	0.83	0.81	-	0.81	0.80	-	0.80
	SE	0.08	-	0.08	0.08	-	0.08	0.09	-	0.09	0.08	-	0.08	0.07	-	0.07
	t	16.53*	-	16.53*	16.60*	-	16.60*	15.46*	-	15.46*	16.64	-	16.64	17.74*	-	17.74*
R^2		0.65			0.66			0.69			0.66			0.64		

** Statistical significance < 0.05 level.

4.4.1. Significance and Magnitude of Influence

The path analysis confirms that the proposed causal factors exert a statistically significant direct influence on all outcome dimensions at the 0.05 level ($p < 0.05$). This is substantiated by t values ranging from 15.46 to 17.74, which substantially exceed the critical threshold of 1.96. These figures empirically validate that both human-centric transfer mechanisms and AI capabilities are critical determinants of transfer success.

Regarding the magnitude of influence, the standardized path coefficients (β) indicate a uniformly strong positive impact across all dependent variables, ranging from 0.80 to 0.83. A detailed examination reveals the following hierarchy of impact:

- Transfer speed emerged as the most responsive dimension ($\beta= 0.83$, $t = 15.46$), suggesting that the integrated factors are most effective at accelerating the process and reducing latency.
- Knowledge Identification, Application, and Transfer Cost demonstrated nearly identical high levels of influence, each registering a coefficient of $\beta = 0.81$.
- Recipient Satisfaction showed a robust, albeit slightly lower, coefficient of $\beta = 0.80$.

It is important to note that as the current model focuses on direct causal paths, no indirect effects were observed; thus, the total effects are equivalent to the direct effects in all instances.

4.4.2. Predictive Power of the Model (R^2)

To assess the model's explanatory power, the coefficient of determination (R^2) was examined. The results indicate that the causal factors account for a substantial proportion of the variance in the outcome variables [58]. Specifically, the model best explains the variance in Transfer Speed ($R^2= 0.69$ or 69%), followed closely by Knowledge Application and Transfer Cost ($R^2= 0.66$). The predictive power for Knowledge Identification and Satisfaction stands at 0.65 and 0.64, respectively.

When benchmarked against the statistical standards proposed by Hair et al. [37], which classify R^2 values of 0.50 as moderate and 0.75 as substantial, the obtained values (0.64 – 0.69) fall within the moderate-to-high range. This underscores the robustness of the model, confirming that the selected knowledge transfer and AI factors are highly effective predictors of transfer outcomes within this context.

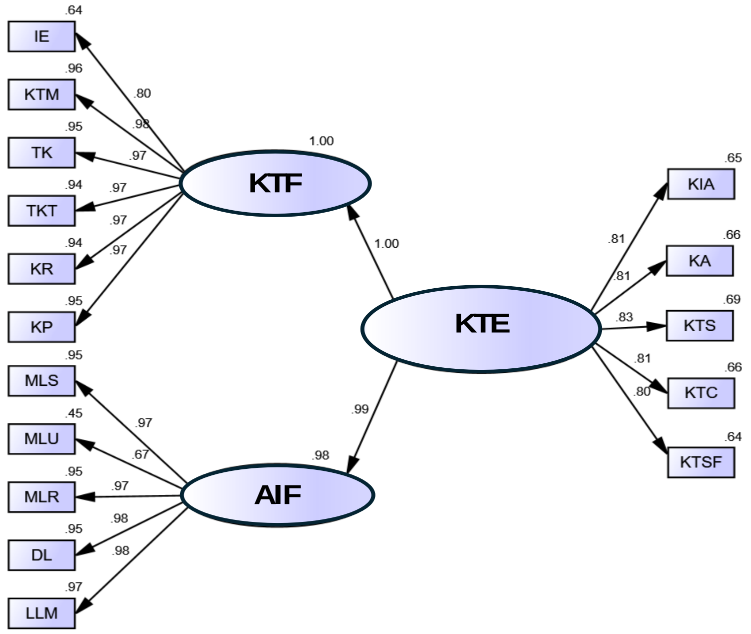
4.4.3. Interpretation of Factor Loading Patterns

An examination of the standardized factor loadings within the measurement model reveals noteworthy patterns that merit further interpretation. Among the knowledge transfer factors, individual expertise (IE) yielded a loading of 0.80 on the KTF construct, indicating that the perceived competence of the knowledge source is the most salient indicator of traditional transfer mechanisms. This finding aligns with prior research that identified source credibility as a paramount determinant in automotive technology transfer contexts [12]. The remaining KTF indicators Knowledge Transfer Mechanism (KTM), Type of Knowledge (TK), Time to Knowledge Transfer (TKT), Knowledge Reliability (KR), and Knowledge Transfer Policy (KP) exhibited consistently high loadings ranging from 0.95 to 0.97, suggesting strong convergent validity and a cohesive latent construct.

Within the AI Factor construct, Machine Learning Unsupervised Learning (MLU) demonstrated a comparatively lower loading of 0.67, whereas all other AI indicators, Supervised Learning (MLS), Reinforcement Learning (MLR), Deep Learning (DL), and Large Language Model (LLM), loaded between 0.95 and 0.98. The relatively lower loading of MLU may reflect the less intuitive nature of unsupervised learning applications in the automotive workplace, where structured and goal-oriented AI tools tend to be more readily understood and adopted by practitioners. This observation is consistent with the moderate correlations observed for MLU in the correlation matrix (Table 5), ranging from 0.50 to 0.67.

Regarding the dependent construct, Transfer Speed (KTS) exhibited the highest R^2 value of 0.69, followed by Transfer Cost (KTC) at 0.67 and Knowledge Application (KA) at 0.66. The relatively higher explained variance in Speed and Cost suggests that these efficiency-oriented outcomes are more directly influenced by the combined factor set, whereas the quality-oriented outcomes (Identification and Satisfaction) may additionally depend on contextual variables not captured in the current model, such as organizational culture or leadership support. In the path analysis, β represents the standardized path coefficient, SE denotes the standard error, t refers to the t-statistic, DE indicates the direct effect, IE the indirect effect, and TE the total effect. R^2 represents the coefficient of determination, indicating the proportion of variance in the dependent variable explained by the model.

The descriptive analysis reveals a high level of respondent consensus across all constructs, particularly highlighting Individual Expertise and Supervised Learning as the most prominent determinants (Mean=4.17). The data exhibit satisfactory distributional properties with acceptable skewness and kurtosis levels, confirming the dataset’s suitability for structural equation modeling (SEM) without violation of normality assumptions [59]. The complete structural equation model with standardized path coefficients and factor loadings is presented in Figure 3.



Chi-square = 73.907, df = 72, P-value = .416, Chi-square/df = 1.026,
CFI = 1.000, TLI=1.000, RMSEA = .009, SRMR= .011

Figure 3. Structural Equation Model of Knowledge Transfer Effectiveness

5. Discussion

The structural model results provide a foundation for interpreting the distinct contributions of knowledge transfer factors and AI factors to transfer effectiveness. As confirmed by the correlation analysis, the intercorrelation between KTF and AIF was 0.77, which remains below the 0.85–0.90 multicollinearity thresholds recommended by Hair et al. [37], ensuring robust parameter estimates (see Table 8).

Table 8. Correlation Coefficients Among Variables in the Structural Equation Model (SEM)

Construct	KTF	AIF	KIA	KA	KTS	KTC	KTSF
KTF	1						
AIF	0.77**	1					
KIA	0.71**	0.79**	1				
KA	0.71**	0.79**	0.55**	1			
KTS	0.72**	0.72**	0.71**	0.59**	1		
KTC	0.70**	0.72**	0.69**	0.73**	0.61**	1	
KTSF	0.71**	0.78**	0.70**	0.63**	0.68**	0.56**	1

** Statistical significance < 0.05 level

To evaluate the validity of the proposed theoretical framework, the goodness-of-fit indices for both the overall structural model and the specific path analysis were examined against the empirical data [60]. The comprehensive assessment results are presented in Tables 9 and 10 for path analysis.

For the structural equation model, the analysis yielded a chi-square value of 1.94 with 2 degrees of freedom. Crucially, the associated p value was 0.38, which is nonsignificant ($p > 0.05$). In the context of SEM, this is a highly favorable outcome, indicating that there is no statistically significant difference between the theoretical model and the observed data. Supporting this, the relative chi-square (chi-square/df) was calculated at 0.97, falling well below the stringent threshold of 2.0, thereby suggesting a model of high parsimony.

Regarding incremental fit, both the Comparative Fit Index (CFI) and the Tucker–Lewis Index (TLI) achieved perfect scores of 1.00, surpassing the recommended cutoff by 0.90. This demonstrates that the specified model improves upon the independence model to the highest possible degree. Furthermore, the absolute fit indices indicated negligible error in the model approximation; the root mean square error of approximation (RMSEA) and the standardized root mean square residual (SRMR) were reported at 0.00 and 0.01, respectively. These figures are substantially lower than the acceptable upper limits of 0.05 and 0.08, respectively.

Conclusion of Model Fit: Collectively, these indices across both assessments provide strong empirical evidence that the hypothesized model fits the data exceptionally well. The construction validity is confirmed, affirming that the model is robust and suitable for subsequent hypothesis testing.

Table 9. Model Fit Indices for Measurement Model

Statistical Data	Level of Acceptance	Model Fitness	Result
Chi-square	-	1.94	-
Degree of freedom	-	2	-
Relative Chi-square	< 3 (0 approach)	0.97	Accept
P	> 0.05	0.38	Accept
Comparative Fit Index (CFI)	>0.90 (1 approach)	1.00	Accept
Trucker - Lewis Index (TLI)	>0.90 (1 approach)	1.00	Accept
Root Mean Square Error of Approximation (RMSEA)	<0.05 (0 approach)	0.00	Accept
Standard Root Mean Square Residual (SRMR)	<0.08 (0 approach)	0.01	Accept

Drawing from the structural model and the data presented in the preceding tables, this section elucidates the distinct influences of the two primary causal groups Knowledge Transfer Factors and AI Factors on the multidimensional effectiveness of knowledge transfer [16].

Predictive Power of the Model (R^2). To evaluate the model's predictive accuracy, the coefficient of determination (R^2) was examined. The results indicate that the two causal groups collectively explain a substantial proportion of the variance in the outcome variables, with R^2 values ranging from 0.65 to 0.69. Specifically, the model exhibits the highest predictive power for Transfer Speed (R^2= 0.69) [61], followed closely by Transfer Cost (R^2= 0.67) and Knowledge Application (R^2= 0.66). The variance explained for Knowledge Identification and Recipient Satisfaction stands at 0.65. According to the benchmarks established by Hair et al. [37], these values fall within the moderate-to-high range, demonstrating that the proposed framework possesses robust accuracy in predicting real-world transfer phenomena.

Discussion of Findings by Factor: The examination of path coefficients (β) and t-statistics reveals a compelling divergence in how human-centric and technology-centric factors drive success [62].

- The Omnidirectional Role of Knowledge Transfer Factors “The Human Dimension”

The analysis underscores that traditional knowledge transfer factors (encompassing individual expertise, transfer mechanisms, and policy) act as the foundational pillars of the process. These factors exert a statistically significant positive influence across all five dimensions of effectiveness ($p < 0.05$, $t > 1.96$).

Most notably, this group drives the qualitative aspects of transfer, showing the highest impact on recipient satisfaction ($\beta = 0.76$, $t = 5.81$) and knowledge application ($\beta = 0.67$, $t = 5.16$). This suggests that the “human touch” and managerial structure remain indispensable for fostering deep understanding and psychological fulfillment in the recipient. While these factors also contribute significantly to Speed ($\beta = 0.39$) and Cost ($\beta = 0.25$), their magnitude in these efficiency metrics is notably lower compared to the impact of AI.

- The Role of AI Factors as “Efficiency Accelerators”

A striking finding emerges regarding the role of AI. The analysis characterizes AI Factors as powerful “Efficiency Accelerators.” They exert a strong, statistically significant positive impact exclusively on the logistical dimensions Transfer Cost ($\beta = 0.57$, $t = 4.48$) and Transfer Speed ($\beta = 0.45$, $t = 3.57$).

However, it is crucial to highlight that AI factors showed no statistical significance regarding knowledge identification ($\beta = 0.17$, $t = 1.33$), knowledge application ($\beta = 0.14$, $t = 1.06$), or recipient satisfaction ($\beta = 0.04$, $t = 0.32$). This non significance offers profound insight, while AI is an excellent tool for reducing workload and accelerating timelines. Technology alone is currently insufficient to generate the deep cognitive understanding or the psychological reassurance required for high-quality transfer. Without the support of robust human transfer processes, AI operates merely as a tool for speed, not mastery.

Synthesis of Findings: In essence, the research uncovers a synergistic necessity. Successful knowledge transfer in this context relies on a dual-engine approach: knowledge transfer factors provide qualitative effectiveness (understanding and satisfaction), while AI factors drive quantitative efficiency (speed and cost). This aligns with the paradigm of modern knowledge management, which necessitates the integration of advanced technology with resilient social processes.

Table 10. Correlation Coefficients Among Variables in the Structural Equation Model (SEM)

Independent Variable	**Statistical Data**	**Dependent Variable**														
		KTE														
		KIA			**KA**			**KTS**			**KTC**			**KTSF**		
		DE	**IE**	**TE**	**DE**	**IE**	**TE**	**DE**	**IE**	**TE**	**DE**	**IE**	**TE**	**DE**	**IE**	**TE**
KTF	*β*	0.64	-	0.64	0.67	-	0.67	0.39	-	0.39	0.25	-	0.25	0.76	-	0.76
	SE	0.16	-	0.16	0.16	-	0.16	0.16	-	0.16	0.16	-	0.16	0.15	-	0.15
	t	4.85*	-	4.85*	5.16*	-	5.16*	3.11*	-	3.11*	2.00*	-	2.00*	5.81*	-	5.81*
AIF	*β*	0.17	-	0.17	0.14	-	0.14	0.45	-	0.45	0.57	-	0.57	0.04	-	0.04
	SE	0.16	-	0.16	0.15	-	0.15	0.16	-	0.16	0.15	-	0.15	0.15	-	0.15
	t	1.33	-	1.33	1.06	-	1.06	3.57*	-	3.57*	4.48*	-	4.48*	0.32	-	0.32
R^2		0.65			0.66			0.69			0.67			0.65		

* Statistical significance < 0.05 level.

The results provide consistent evidence that knowledge transfer factors exert positive influences on knowledge transfer effectiveness across several dimensions. All five hypotheses (H1–H5) were supported, with some partially accepted, indicating that the effects are not uniform across all subdimensions but remain directionally positive and practically meaningful.

H1. Ability to articulate and interpret knowledge: The findings support H1, showing that capabilities related to expressing, codifying, and interpreting knowledge contribute to overall transfer effectiveness. Partial acceptance suggests that the effect is stronger on certain aspects (e.g., understanding and application) than on others (e.g., speed or breadth of dissemination). This pattern aligns with the notion that articulation primarily improves comprehension and reduces ambiguity, which, in turn, facilitates uptake.

H2. Accessibility and retrievability of knowledge: H2 is supported, indicating that accessible repositories and mechanisms for retrieving knowledge enhance transfer outcomes. Partial acceptance implies that accessibility improves the quality of use more than the quantity or rapidity of reuse. Practically, even when knowledge is reachable, the benefits depend on how well content is structured and searchable for end users.

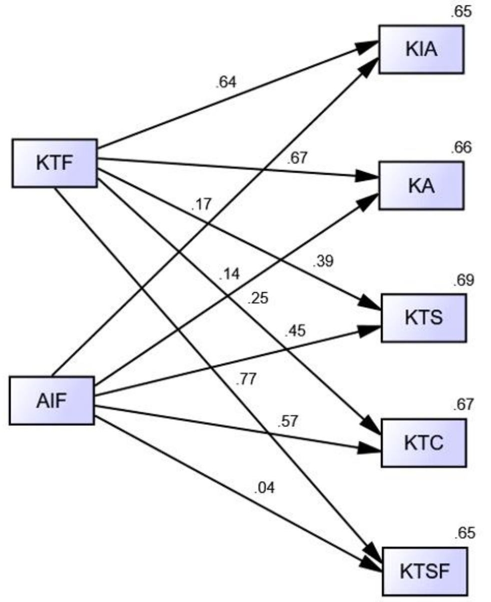
H3. Timeliness and responsiveness in transfer: Support for H3 shows that timely delivery and responsive support positively influence transfer effectiveness. Partial acceptance points to stronger effects on adoption speed than on depth of assimilation, suggesting that rapid availability accelerates initial uptake, while sustained support is needed to ensure thorough internalization.

H4. Recipient readiness and absorptive capacity: H4 is accepted, emphasizing the central role of recipient capabilities (e.g., prior related knowledge, motivation, and opportunity to apply) in translating transferred knowledge into performance. Partial acceptance indicates that readiness most strongly affects application quality and problem-solving effectiveness, with comparatively smaller effects on diffusion to other units.

H5. Attitudinal openness and willingness to learn: H5 is supported, confirming that positive attitudes toward knowledge sharing, openness to new practices, and psychological safety foster effective transfer. Partial acceptance suggests that attitudinal factors chiefly improve acceptance and intent to use, while their influence on longer-term sustained use may depend on complementary structural support.

The path analysis reveals a distinct functional dichotomy between the two independent constructs. Knowledge Transfer Factors (KTF) serve as the primary drivers of qualitative effectiveness, exerting their strongest influence on Satisfaction (KTSF) (β = 0.77) and Application (KA) (β = 0.67), while also significantly facilitating Identification

(KIA) (β = 0.64). Conversely, AI factors (AIF) operate predominantly as efficient accelerators, demonstrating a robust impact on transfer cost (KTC) (β = 0.57) and speed (KTS) (β= 0.45) but showing a negligible influence on satisfaction (β = 0.04). The model exhibits strong predictive power, explaining between 65% and 69% of the variance across all five outcome variables (R^2=0.65–0.69), with fit indices confirming an exceptional model fit (Chi-Square/df=0.970, CFI=1.00, RMSEA=0.000). The decomposed path analysis illustrating the distinct influences of KTF and AIF on each effectiveness dimension is presented in Figure 4 and Table 11.



Chi-square = 1.941, df = 2, P-value = .379, Chi-square/df = .970,
CFI = 1.000, TLI=1.000, RMSEA = .000, SRMR= .006

Figure 4. Path Analysis of Construct Relationships

Table 11. Hypothesis Testing and Path Coefficients

Efficiency-Effectiveness Dichotomy	Hypothesis	Path Relationship	β	t - value	Result
Efficiency Metrics	H3	AI Factors - Speed	0.45*	3.57	Supported
(AI Dominance)	H4	AI Factors - Cost	0.57*	4.48	Supported
Effectiveness Metrics	H2	Human (Knowledge Transfer) - Application	0.67*	5.16	Supported
(Human Dominance)	H5	Human (Knowledge Transfer) - Satisfaction	0.76*	5.81	Supported
Potential for Innovation	H2b	AI Factors - Application	0.14	1.06	Not Supported
(Non-Significant Paths)	H5b	AI Factors - Satisfaction	0.04	0.32	Not Supported

Note: * Significant at $p < 0.001$

5.1. Efficiency-Effectiveness Dichotomy

The central finding of this study is the clear divergence between efficiency and effectiveness. AI factors are proven to be powerful accelerators, significantly influencing speed (KTS) and cost (KTC). This aligns with recent studies suggesting that AI optimizes the logistics of information. However, AI currently has a limited impact on knowledge application (KA). In the context of EV manufacturing, where application involves handling hazardous high-voltage systems [63], this suggests that while AI is excellent at delivering the textbook, it is still evolving in its ability to teach the practice.

5.2. The Psychological Dimension and Trust

The finding that AI has a negligible impact on satisfaction (KTSF) is critical. The industrial transition creates workforce anxiety [64]. While AI can answer technical queries, it cannot provide the professional validation or psychological safety that a human mentor does [65]. This supports the notion that High-Tech must be balanced with High-Touch to ensure workforce morale during turbulent transitions [66].

5.3. Comparison with Previous Studies

The findings of this study both corroborate and extend several streams of prior research. The observed dominance of human-centric factors in driving knowledge application ($\beta = 0.67$) and satisfaction ($\beta = 0.76$) is consistent with prior findings that human knowledge sharing remains the primary determinant of organizational performance even in AI-augmented environments [16]. Similarly, the mechanisms and motivational components of knowledge transfer have been characterized as fundamentally social processes [9], a conclusion reinforced by our empirical evidence. fundamentally social processes, a conclusion reinforced by our empirical evidence.

Regarding the role of AI, our characterization of AI factors as efficiency accelerators rather than holistic enablers aligns with the paradigm of human augmentation, not replacement [67]. However, our study extends this general observation by providing disaggregated evidence: AI significantly influences Speed ($\beta = 0.45$) and Cost ($\beta = 0.57$) but fails to reach statistical significance for Application ($\beta = 0.14$, $t = 1.06$) or Satisfaction ($\beta = 0.04$, $t = 0.32$). This granular distinction has not been empirically demonstrated in prior knowledge transfer studies.

Our results diverge from more optimistic projections that AI could effectively capture tacit knowledge and foster innovation [68]. The present findings indicate that within the specific context of high-risk automotive manufacturing, the tacit dimension of knowledge remains resistant to AI-mediated transfer. This divergence may be attributable to the safety-critical nature of EV manufacturing tasks, where the consequences of misapplied knowledge are substantially more severe than in the service-sector contexts examined by previous researchers [63].

Furthermore, the model's predictive power ($R^2 = 0.65$–0.69) compares favorably with similar SEM-based studies in the knowledge management domain. For instance, R^2 values ranging from 0.42 to 0.58 have been reported for organizational performance outcomes [16], while R^2 values of approximately 0.51 have been achieved for knowledge management adoption intentions [69]. The superior explanatory power of the present model may stem from the inclusion of both traditional and AI-based predictors, lending empirical support to the proposed hybrid framework.

Taken together, these findings validate the theoretical foundation adopted in this study. The three perspectives reviewed in Section 2.4, the SECI Model, the Resource-Based View, and Absorptive Capacity Theory, collectively anticipated the dual nature of knowledge transfer, and the empirical results confirm that the preliminary framework derived from these theories holds when tested against field data. Importantly, the clear separation between efficiency outcomes driven by AI and effectiveness outcomes driven by human factors was not explicitly predicted by any single theory alone but emerged from their integration. This suggests that the multi theoretical approach adopted in constructing the original framework was both appropriate and necessary for capturing the full complexity of knowledge transfer during the ICE-to-EV transition.

6. Contributions and Implications

This study provides a seminal empirical examination of the workforce transition from internal combustion engine (ICE) to electric vehicle (EV) technologies. By deconstructing the transition process into distinct causal pathways Knowledge Transfer Factors (KTF) representing the human-centric dimension and Artificial Intelligence Factors (AIF) representing the technological dimension, this research offers a nuanced Dual-Engine Framework for industrial upskilling. The findings extend beyond general observations of digital transformation, offering precise, statistically validated contributions to theory, practice, and the future design of industrial AI.

6.1. Theoretical Contribution: The Efficiency-Effectiveness Dichotomy

The primary theoretical contribution of this research lies in the empirical validation of the efficiency-effectiveness dichotomy within the context of high-stakes industrial knowledge transfer. Previous literature often treats AI as a monolithic enhancer of organizational learning. However, our structural equation modeling (SEM) results reveal a more complex reality: AI and human factors do not operate on the same spectrum of value; rather, they govern distinct domains of the transfer process.

We establish that AI factors function as logistical accelerators. The data confirm that AI's primary contribution is the drastic reduction of Transfer Cost ($\beta = 0.57$) and the enhancement of Transfer Speed ($\beta = 0.45$). This extends the resource-based view (RBV) of the firm by categorizing AI not merely as a knowledge repository but also as a mechanism for resource optimization. AI democratizes access to information, removing the friction of time and expense associated with traditional training.

Conversely, the study reaffirms the Irreplaceability of Tacit Mentorship. Despite the sophistication of modern AI (including generative AI and deep learning), it failed to show a statistically significant impact on recipient satisfaction ($\beta = 0.04$) or deep knowledge application ($\beta = 0.14$). Instead, knowledge transfer factors (expertise, policy, mechanism) emerged as the sole drivers of these qualitative outcomes ($\beta = 0.77$ for satisfaction; $\beta = 0.67$ for application). This finding refines the SECI Model (Socialization, Externalization, Combination, Internalization) for the digital age, suggesting that while AI excels at the Combination of explicit data, the Socialization and Internalization required for mastering complex EV technologies remain fundamentally human-centric processes.

6.2. Managerial Implications: A Strategic Roadmap for EV Transition

For automotive leaders and HR executives navigating the ICE-to-EV disruption, this study offers a data-driven blueprint for resource allocation. The high predictive power of the model (R^2 ranging from 0.65 to 0.69) suggests that a hybrid synergy strategy is nonnegotiable.

Strategic Decoupling of Training Objectives: Management must stop viewing AI as a direct substitute for human trainers. Instead, training programs should be bifurcated. AI tools should be deployed aggressively to handle the quantitative aspects of training standardized protocols, syntax of coding, and basic electrical theory to capitalize on the finding that AI significantly reduces transfer cost and speed. This allows organizations to scale basic upskilling rapidly without overwhelming their budget.

Preserving the Master Apprentice Model for High Value Skills: The strong correlation between KTF and Knowledge Application ($\beta = 0.67$) indicates that for critical, high-risk competencies (e.g., handling high-voltage battery packs or diagnosing complex software integration) [63], human mentorship is mandatory. Executives must incentivize senior engineers not only to work but also to mentor. The data prove that human touch is the only variable that translates information into practical, error-free applications on the production line.

Addressing the psychological dimension of transition: Perhaps the most critical managerial insight is the link to recipient satisfaction. The transition to EVs creates workforce anxiety regarding obsolescence. Our findings show that AI does practically nothing to alleviate this ($\beta = 0.04$), whereas human factors are the definitive driver of satisfaction ($\beta = 0.77$). Managers must realize that Satisfaction is a proxy for Retention and Morale. To prevent resistance to change, the introduction of AI tools must be accompanied by strong human support systems. We recommend a human-in-the-loop policy where AI provides the data, but a human mentor provides the feedback and validation.

6.3. Implications for AI Design and Industrial Innovation

This research serves as a critical feedback loop for the developers of industrial AI solutions. The significant impact of current AI factors on knowledge application and satisfaction highlights a functional gap in the current technology stack.

From Generative to Empathic and Simulative AI: The industry does not need faster information retrieval (which current AI already achieves, as evidenced by the high score on Speed); it needs better simulation of experience. Future developments in industrial AI should focus on the following:

- Virtual Mentorship Avatars [70]: Systems designed not only to answer queries but also to mimic the pedagogical style of a human senior engineer to improve user satisfaction.
- Immersive scenario training (VR/AR integration) [71]: To bridge the gap in application, AI must evolve from text-based generative models to physics-based simulations that allow engineers to practice dangerous tasks [63] virtually, thereby mimicking the tacit transfer of skills [72].

6.4. Societal and Policy Implications

On a macro level, particularly for manufacturing hubs such as the “Detroit of Asia,” [73] this study provides evidence against the fear of immediate technological unemployment [74]. The data suggest that AI is an augmenter, not a replacer [67].

Policymakers should direct funding toward Train-the-Trainer programs. Since human expertise is the bottleneck for quality ($\beta = 0.67$), national competitiveness depends on the ability of the current generation of experts to transfer their knowledge [75]. Policy frameworks should encourage the use of AI to handle the volume of learning required for the national workforce [76] while preserving veteran engineers to ensure the depth of capability [77].

The boundary conditions of these findings’ merits consideration. Thailand's automotive sector operates within a context of low trade union density, government-led EV incentives, and a younger workforce (59.74% aged 31–40). These conditions may amplify AI receptivity relative to economies with stronger unionization, where technology-driven changes face greater resistance. In Germany or Japan, where apprenticeship traditions are deeply institutionalized, human-centric factors may contribute even more strongly to satisfaction. Conversely, digitally mature economies with established Industry 4.0 ecosystems may observe stronger AI effects on application outcomes. Researchers applying this framework in other contexts should account for variations in labor regulation, digital infrastructure maturity, and cultural orientations toward technology adoption.

In conclusion, this research demystifies the role of AI in the automotive transition. This proves that the path to a successful EV workforce is not paved by silicon alone. True success requires a symbiotic architecture where AI is leveraged for its logistical velocity, while human expertise is elevated to its rightful place as the guardian of quality, application, and professional fulfillment.

7. Conclusion

This study sets out to empirically examine the factors influencing knowledge transfer effectiveness during the automotive industry's transition from Internal Combustion Engine to Electric Vehicle technologies. Through structural equation modeling of data from 303 industry professionals, this research identified a clear efficiency-effectiveness dichotomy between human-centric and technology-centric factors. The principal finding is that traditional knowledge transfer factors encompassing individual expertise, transfer mechanisms, knowledge types, reliability, time, and organizational policy serve as the primary drivers of qualitative outcomes, most notably knowledge application and recipient satisfaction. Conversely, artificial intelligence factors, including supervised learning, unsupervised learning, reinforcement learning, deep learning, and large language models, function predominantly as efficient accelerators that significantly reduce transfer cost and enhance transfer speed. Critically, AI factors demonstrated no statistically significant influence on deep knowledge application or recipient satisfaction, indicating that technology alone is insufficient for fostering the tacit understanding required in safety-critical manufacturing environments.

These findings carry substantial implications for both theory and practice. From a theoretical standpoint, the validated Dual-Engine Framework extends established knowledge management models by demonstrating that AI augments rather than replaces human mentorship in complex industrial contexts. For practitioners, the results provide a data-driven blueprint for resource allocation organizations that should leverage AI tools for scalable foundational training while preserving and incentivizing expert-led mentorship for high-value, safety-critical competencies. The study is limited by its cross-sectional design and geographic focus on Thailand's automotive sector, which may constrain generalizability. Future research should adopt longitudinal designs and explore the potential of immersive AI systems integrating virtual and augmented reality to bridge the identified gap between information delivery and tacit skill mastery.

7.1. Limitations

Several limitations of this study should be acknowledged to contextualize the findings and guide future research. First, a conceptual limitation concerns the treatment of AI factors as a unified construct. Although CFA results supported this operationalization with acceptable convergent validity, the AI indicators span technologically distinct modalities: automation-oriented AI (supervised, unsupervised, and reinforcement learning) performs pattern recognition and classification, whereas generative AI (deep learning and large language models) offers content generation and natural language interaction that may approximate aspects of human mentorship. The lower factor loading of unsupervised learning (0.67) observed in Section 4.4.3 provides preliminary evidence of sub dimensionality. Future research should explore a bifurcated AI model distinguishing these categories to reveal differential pathways to application and satisfaction outcomes.

Second, the cross-sectional design constrains causal inference. Although the SEM results are consistent with hypothesized causal directions, organizational capability may function as a common antecedent whereby highly capable organizations simultaneously invest in AI infrastructure and cultivate strong transfer cultures, producing observed correlations without direct causation. Reverse causality is also plausible, as organizations with effective transfer systems may be better positioned to adopt AI tools. Future research should therefore employ longitudinal or quasi experimental designs that track changes in transfer effectiveness following phased AI introduction.

Finally, knowledge application was measured through self-reported perceptions, which may not fully capture actual behavioral competence and are susceptible to social desirability bias. Given that this dimension showed the strongest human-AI divergence ($\beta = 0.67$ vs. 0.14), future studies should triangulate with objective metrics such as production error rates, first-pass yield, safety incident frequency, and time-to-competency benchmarks.

8. Declarations

8.1. Author Contributions

Conceptualization, Y.D., M.W., and S.S.; methodology, Y.D., M.W., and S.S.; software, Y.D.; validation, Y.D., M.W., and S.S.; formal analysis, Y.D., M.W., and S.S.; investigation, Y.D., M.W., and S.S.; resources, Y.D.; data curation, Y.D.; writing—original draft preparation, Y.D., M.W., and S.S.; writing—review and editing, Y.D., M.W., and S.S.; visualization, Y.D.; supervision, M.W. and S.S.; project administration, Y.D. All authors have read and agreed to the published version of the manuscript.

8.2. Data Availability Statement

The data presented in this study are available upon request from the corresponding author.

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8.5. Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki and approved by the Research Ethics Review Committee for Research Involving Human Research Participants, Group 2, Chulalongkorn University as Research Project Number 660324, and Protocol Code: COA No.422/67 for Qualitative and CAO No.513/68 for Quantitative study.

8.6. Informed Consent Statement

Informed consent was obtained from all subjects participated in the study.

8.7. Declaration of Competing Interest

The authors declare that there are no conflicts of interest concerning the publication of this manuscript. Furthermore, all ethical considerations, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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