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Enhancing New Product Development Performance in the Automotive Industry: The Role of Design Changes, Virtual Manufacturing, Supplier Readiness, and Workforce Competency

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KEYWORDS

New Product Development, Design Changes, Virtual Manufacturing, Supplier Readiness, Workforce Competency, Structural Equation Modeling

ABSTRACT

New Product Development (NPD) is a critical factor for success in the automotive industry, influencing market competitiveness and innovation. This study examines the impact of design iterations & changes (DI), virtual manufacturing readiness (VMR), supplier process readiness (SPR), and people skills & competencies (PSC) on New Product Development Performance (NPDP). A structured survey was conducted among 258 professionals in the automotive sector, and data were analyzed using Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM). The results confirm that excessive design iterations negatively impact NPD performance, while virtual manufacturing, supplier readiness, and workforce competency significantly enhance NPD outcomes. The study offers theoretical contributions to NPD literature and practical insights for manufacturers aiming to optimize product development cycles.

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1. INTRODUCTION

In the fast-paced automotive industry, New Product Development (NPD) plays a crucial role in maintaining market relevance and competitive advantage (Cooper, 2019). The speed and efficiency of NPD determine an organization's ability to respond to evolving consumer demands, technological advancements, and regulatory changes (Eisenhardt & Tabrizi, 1995). However, various internal and external factors contribute to delays and inefficiencies in the NPD process.

Among these factors, design iterations & changes (DI), virtual manufacturing readiness (VMR), supplier process readiness (SPR), and people skills & competencies (PSC) have been identified as key influencers in determining NPD performance (NPDP) (Krishnan & Ulrich, 2001). While virtual prototyping and supplier collaboration have been recognized for their positive impact on development speed, excessive design modifications are often cited as a major bottleneck (Thomke & Fujimoto, 2000). Additionally, a skilled workforce enhances cross-functional collaboration, ensuring a smoother development process (Goffin & Koners, 2011).

Despite the significance of these factors, empirical research on their combined impact using structural equation modeling (SEM) remains limited. This study addresses this gap by developing and testing a comprehensive model that examines how DI, VMR, SPR, and PSC influence NPDP in the automotive industry.

Research Objectives

1. To assess the negative impact of design iterations & changes on NPD performance.
2. To evaluate the positive influence of virtual manufacturing readiness, supplier process readiness, and workforce competency on NPD performance.

3. To provide practical recommendations for optimizing the NPD process in the automotive sector.

2. LITERATURE REVIEW

2.1 New Product Development Performance (NPDP) – Dependent Variable

NPDP is a measure of how efficiently and successfully a company develops and launches new products (Griffin, 1997). It includes aspects like development speed, cost efficiency, and market success (Calantone & Di Benedetto, 2000). Previous studies highlight that a streamlined NPD process reduces time-to-market and enhances product quality (Langerak & Hultink, 2006).

2.2.1. People Skills & Competencies (PSC) – Positive Impact

A highly skilled workforce reduces inefficiencies, enhances cross-functional collaboration, and accelerates problem-solving (Goffin & Koners, 2011). Studies highlight that NPD success is heavily dependent on knowledge transfer and training initiatives (Brown & Eisenhardt, 1995).

H1: People Skills & Competencies positively affect NPD Performance.

2.2.2. Supplier Process Readiness (SPR) – Positive Impact

Strong supplier involvement enhances procurement efficiency, quality assurance, and production scalability (Handfield & Bechtel, 2002). Firms that engage suppliers early in NPD experience fewer disruptions and faster time-to-market (Wasti & Liker, 1997).

H2: Supplier Process Readiness positively affects NPD Performance.

2.2.3 Virtual Manufacturing Readiness (VMR) – Positive Impact

Virtual manufacturing tools, such as simulation software, digital twins, and virtual prototyping, significantly reduce development time and costs (Rosen et al., 2015). Research suggests that companies integrating digital tools achieve faster prototyping and problem resolution (Mourtzis et al., 2014).

H3: Virtual Manufacturing Readiness positively affects NPD Performance.

2.2.4. Design Iterations & Changes (DI) – Negative Impact

Frequent design modifications during NPD create delays, increase costs, and disrupt the supply chain (Clark & Fujimoto, 1991). Studies indicate that uncontrolled design iterations extend development cycles (Krishnan & Ulrich, 2001). Conversely, minimizing late-stage changes improves efficiency (Thomke & Fujimoto, 2000).

H4: Design Iterations & Changes negatively affect NPD Performance.

3. RESEARCH METHODOLOGY

This study employs a quantitative research approach to examine the influence of design iterations & changes (DI), virtual manufacturing readiness (VMR), supplier process readiness (SPR), and people skills & competencies (PSC) on New Product Development Performance (NPDP) in the automotive industry. A structured survey methodology was adopted to collect data from professionals involved in the NPD process across various automotive firms. The study follows a deductive research design, beginning with the formulation of hypotheses based on existing literature, followed by empirical validation through statistical analysis.

The target population for this research comprised professionals engaged in different phases of the NPD cycle, including design engineers, supply chain managers, manufacturing specialists, and quality assurance professionals from automobile industry. A total of 258 valid responses were obtained through a structured questionnaire. A purposive sampling technique was employed to ensure that participants possessed relevant expertise in NPD activities. The questionnaire utilized a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) to measure the constructs.

4. DATA ANALYSIS AND RESULTS:

4.1 Detail of respondents

Table 1: Demographics (N=258)

Demographic Variable	**Category**	**Frequency (N)**	**Percentage (%)**
Gender	Male	182	70.5%
	Female	70	27.1%

	Other/Prefer not to say	6	2.3%
Age Group	20-30 years	76	29.5%
	31-40 years	98	38.0%
	41-50 years	56	21.7%
	51 years & above	28	10.9%
Job Role	Design Engineer	80	31.0%
	Supply Chain Manager	60	23.3%
	Manufacturing Specialist	54	20.9%
	Quality Assurance	40	15.5%
	Other	24	9.3%
Years of Experience	0-5 years	66	25.6%
	6-10 years	78	30.2%
	11-15 years	64	24.8%
	16 years & above	50	19.4%
Education Level	Diploma	38	14.7%
	Bachelor's Degree	122	47.3%
	Master's Degree	80	31.0%
	PhD	18	7.0%

Source: Primary data

Table 4.1 presents the demographic profile of the respondents (N=258), offering insights into their gender, age group, job role, years of experience, and education level. The sample is predominantly male (70.5%), with females comprising 27.1%, and a small percentage (2.3%) identifying as other or preferring not to disclose their gender. The age distribution shows that the majority of respondents (38.0%) fall within the 31-40 years range, followed by 29.5% in the 20-30 years category, 21.7% in the 41-50 years group, and 10.9% aged 51 years and above. In terms of job roles, Design Engineers constitute the largest group (31.0%), followed by Supply Chain Managers (23.3%), Manufacturing Specialists (20.9%), and Quality Assurance professionals (15.5%), while 9.3% hold other roles. Regarding work experience, 30.2% have 6-10 years of experience, 25.6% have 0-5 years, 24.8% have 11-15 years, and 19.4% have 16 or more years. The educational background of the respondents indicates that nearly half (47.3%) hold a Bachelor's degree, while 31.0% have a Master's degree, 14.7% possess a Diploma, and 7.0% have a PhD.

4.2. Normality:

The dataset's suitability for further statistical analysis was assessed for normality through the evaluation of skewness and kurtosis as primary statistical indicators. According to Hair et al. (2019), skewness and kurtosis values should fall within ±2, suggesting that the data distribution remains largely consistent with normality. The findings in Table 2 indicate that all skewness and kurtosis values are within the specified threshold, thus fulfilling the normality assumption. The standard deviations for all items exceed 0.5, indicating that the responses demonstrate adequate variability and are normally distributed.

4.3 Exploratory Factor Analysis:

EFA was conducted to identify the underlying factor structure of the constructs related to New Product Development Performance (NPDP). The primary objective of this analysis was to assess the dimensionality of the constructs, determine factor loadings for each measurement item, and ensure that the observed variables correspond to their respective theoretical dimensions. Prior to performing EFA, the Kaiser-Meyer-Olkin (KMO) test for sampling adequacy was applied, yielding a KMO statistic of 0.915. This value exceeds the recommended threshold of 0.60 (Kaiser, 1974), indicating that the dataset is suitable for factor analysis. Additionally, Bartlett's test of sphericity was statistically significant at $p < 0.001$, confirming the appropriateness of the dataset for factor extraction.

Figure A: Sree plot for five factors

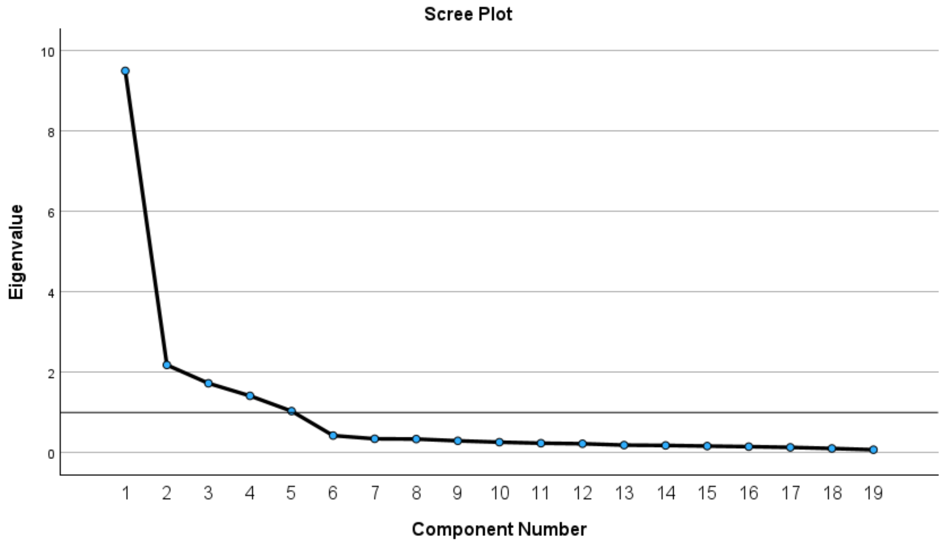

Table A: KMO

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.915
Bartlett's Test of Sphericity	Approx. Chi-Square	4602.767
	df	171
	Sig.	<.001

The factor extraction process was conducted using Principal Component Analysis (PCA) with varimax rotation to facilitate better differentiation between factors. The analysis extracted five distinct factors, based on the criterion that Eigenvalues exceeded 1, accounting for 83.526% of the total variance explained. This strong explanatory power indicates that the extracted factors effectively capture the essential dimensions of the measured constructs. The results confirmed the robustness of the factor structure and ensured that each item loaded appropriately onto its intended latent construct. The five extracted factors correspond to Design Iterations & Changes (DI), Virtual Manufacturing Readiness (VMR), Supplier Process Readiness (SPR), People Skills & Competencies (PSC), and New Product Development Performance (NPDP), aligning with theoretical expectations.

The factor loadings for all items exceeded 0.70, which is the established threshold for construct validity (Hair et al., 2019). The details of descriptive statistics, including mean, standard deviation, skewness, and kurtosis, are presented in Table 2. These findings indicate that the measurement items exhibit strong factor loadings, ensuring the reliability of the underlying constructs for further analysis.

Table B: Total variance explained

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.161	37.691	37.691	7.161	37.691	37.691	3.384	17.811	17.811
2	2.456	12.929	50.620	2.456	12.929	50.620	3.196	16.823	34.634
3	2.284	12.020	62.640	2.284	12.020	62.640	3.101	16.321	50.954
4	1.972	10.378	73.018	1.972	10.378	73.018	3.063	16.122	67.076
5	1.475	7.766	80.783	1.475	7.766	80.783	2.604	13.707	80.783
6	.462	2.432	83.216						
7	.429	2.259	85.475						
8	.378	1.989	87.464						
9	.347	1.828	89.291						
10	.326	1.717	91.008						
11	.312	1.641	92.650						
12	.287	1.511	94.161						
13	.239	1.256	95.417						
14	.203	1.066	96.483						
15	.171	.899	97.382						
16	.158	.829	98.211						
17	.145	.763	98.975						
18	.126	.662	99.636						
19	.069	.364	100.000						

Extraction Method: Principal Component Analysis.

Table 2: Descriptives, Scale Items and Factor Loadings

Items	Loadings	Mean	Standard deviations	Skewness	Kurtois
q1	.837	3.58	.843	-.729	.249
q2	.815	3.78	1.032	-.688	-.073
q3	.862	3.66	1.002	-.444	-.485
q4	.776	3.64	.889	-.875	.692
q5	.878	3.60	1.133	-.501	-.264
q6	.782	3.59	.971	-.136	-.627
q7	.800	3.44	1.050	-.586	.227
q8	.858	3.61	1.132	-.547	-.227
q9	.899	3.35	1.042	-.664	.160
q10	.796	3.41	.951	-.374	.078
q11	.829	3.45	1.021	-.603	-.001
q12	.876	3.37	1.037	-.583	.067
q13	.848	2.78	1.207	.071	-.819
q14	.865	2.81	1.142	.133	-.477
q15	.861	2.90	1.140	.032	-.387
q16	.815	3.32	1.194	-.629	-.780
q17	.801	3.52	1.270	-.615	-.795

q18	.838	3.40	1.300	-.621	-.798
q19	.805	3.21	1.181	-.641	-.784

Source: Primary survey

4.4 Measurement Model (Confirmatory Factor Analysis - CFA)

Following EFA, Confirmatory Factor Analysis (CFA) was conducted to validate the measurement model by assessing construct reliability and validity. The model fit was evaluated using multiple fit indices, which demonstrated that the model exhibited a robust fit to the data. The Normed Fit Index (NFI = 0.948), Tucker-Lewis Index (TLI = 0.972), and Comparative Fit Index (CFI = 0.977) all exceeded the recommended threshold of 0.90, indicating strong model adequacy (Hu & Bentler, 1999). Additionally, the Root Mean Square Error of Approximation (RMSEA) was 0.054, which is well within the acceptable range of <0.08, further confirming model validity.

The chi-square test yielded a value of $\chi^2 = 247.156$ with 142 degrees of freedom, leading to a normed chi-square value (χ^2/df) of 1.741. This value falls within the acceptable range of $1 < \chi^2/df < 3$, suggesting a well-fitted model. These results confirm that the measurement model exhibits strong construct validity and is suitable for further hypothesis testing using Structural Equation Modeling (SEM).

4.5 Reliability and Validity of Research Constructs

To assess the reliability and validity of the research constructs, Cronbach's alpha and Composite Reliability (CR) were computed to evaluate internal consistency, while Average Variance Extracted (AVE) was used to establish convergent validity. Discriminant validity was examined by comparing AVE values with Maximum Shared Variances (MSV) to ensure that each construct was distinct from others. The results confirm that all CR values exceed 0.70, indicating strong internal consistency, while AVE values are above the threshold of 0.50, supporting convergent validity (Fornell & Larcker, 1981). Additionally, the MSV values are lower than the AVEs, confirming that each construct maintains discriminant validity.

Figure 1: NPDP measurement model

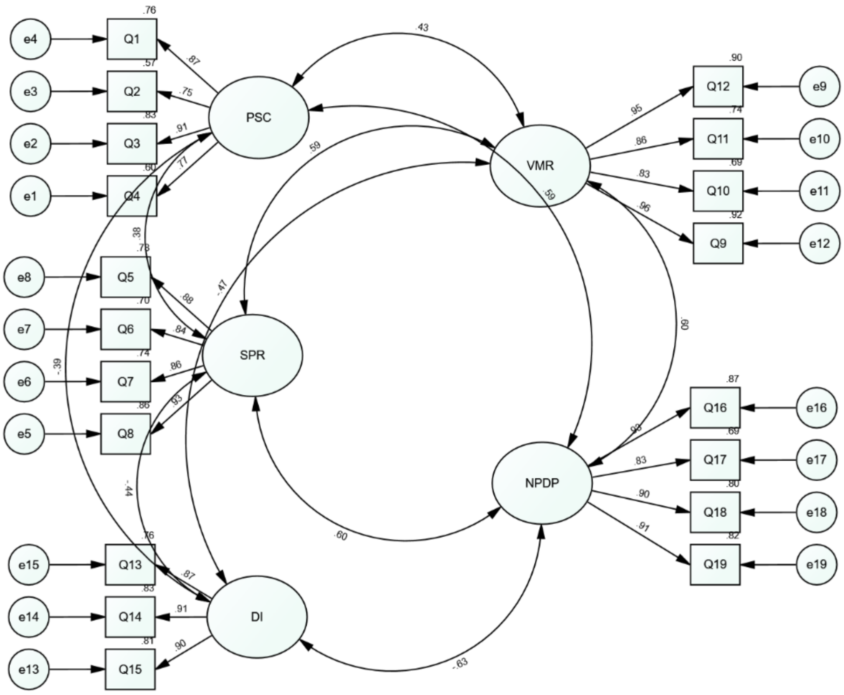

Table 3. Reliability and Validity

	CR	AVE	MSV	DI	PSC	SPR	VMR	NPDP
DI	0.924	0.801	0.399	0.895				
PSC	0.898	0.688	0.352	-0.386	0.830			
SPR	0.931	0.772	0.362	-0.443	0.377	0.879		
VMR	0.945	0.812	0.365	-0.470	0.425	0.586	0.901	
NPDP	0.940	0.797	0.399	-0.632	0.593	0.602	0.604	0.893

4.6 Hypotheses testing using SEM model

To test the hypothesized relationships between Design Iterations & Changes (DI), Virtual Manufacturing Readiness (VMR), Supplier Process Readiness (SPR), People Skills & Competencies (PSC), and New Product Development Performance (NPDP), Structural Equation Modeling (SEM) was employed. The Maximum Likelihood Estimation (MLE) method was used due to its robustness in handling complex relationships between latent constructs (Blunch, 2013). The SEM analysis evaluated the significance of path coefficients, standardized regression weights (β), critical ratios (CR/T), p-values, and standard errors (SE). Following established statistical guidelines, hypotheses were considered supported if the p-value was below 0.05 and the T-value exceeded 1.96 (Hair et al., 2019).

As presented in Table 4, the results indicate that People Skills & Competencies (PSC) have a significant positive effect on New Product Development Performance (NPDP), with a standardized regression coefficient of $\beta = 0.370$, $p = 0.000$, $T = 6.473$, confirming H1. Similarly, Supplier Process Readiness (SPR) positively influences NPDP, as evidenced by $\beta = 0.302$, $p = 0.000$, $T = 5.661$, supporting H2. Additionally, Virtual Manufacturing Readiness (VMR) has a significant positive impact on NPDP (β = 0.254, p = 0.000, T = 4.852), thereby validating H3.

Conversely, Design Iterations & Changes (DI) exhibit a significant negative impact on NPDP (β = -0.404, p = 0.000, T = -7.350), confirming H4. These results indicate that while virtual manufacturing capabilities, supplier readiness, and skilled workforce positively contribute to enhancing NPD performance, excessive design modifications act as a critical bottleneck in the product development process.

Explained Variance (R^2) and Model Strength

The model's coefficient of determination (R^2) for NPDP was 0.46, indicating that DI, VMR, SPR, and PSC together explain 46% of the variance in New Product Development Performance. Among the predictors, Design Iterations & Changes had the strongest negative effect, whereas People Skills & Competencies emerged as the strongest positive determinant of NPDP. This suggests that while improving virtual manufacturing readiness and supplier coordination can enhance NPD efficiency, minimizing unnecessary design revisions is crucial to preventing project delays.

Figure 2: SEM model for Investment decision

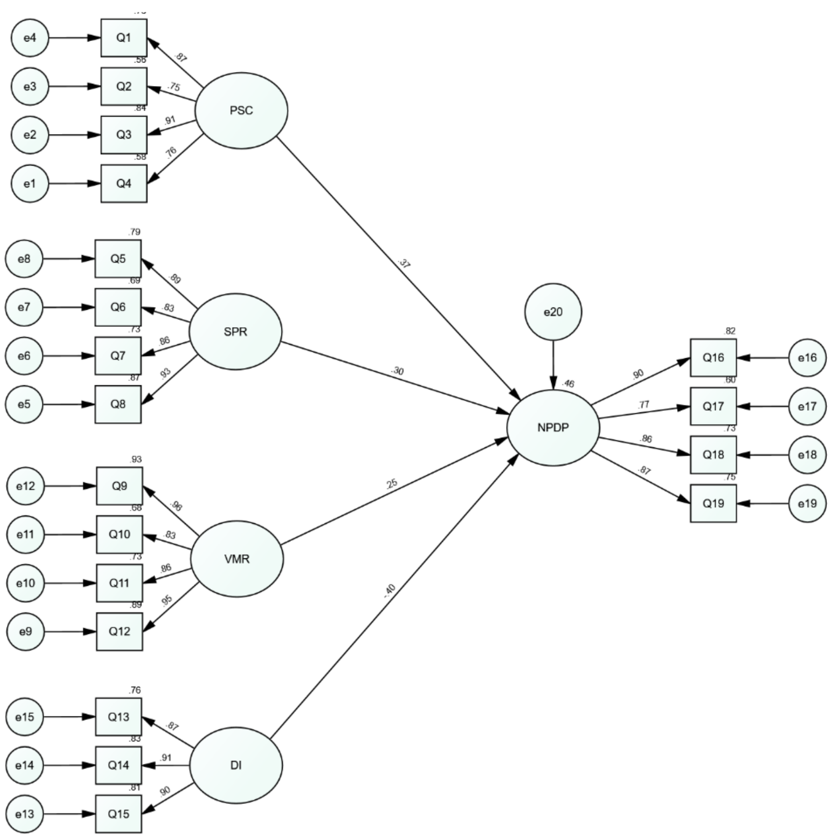

Table 4: Path coefficients for hypothesis results

Hypothesis	Path	S.E.	C.R./T	P	(β)	Decision
H1	People Skills & Competencies (PSC) → New Product Development Performance (NPDP)	.076	6.473	0.000	.370	Supported
H2	Supplier Process Readiness (SPR) → New Product Development Performance (NPDP)	.046	5.661	0.000	.302	Supported
H3	Virtual Manufacturing Readiness (VMR) → New Product Development Performance (NPDP)	.048	4.852	0.000	.254	Supported
H4	Design Iterations & Changes (DI) → New Product Development Performance (NPDP)	.049	-7.350	0.000	-.404	Supported

5. DISCUSSION

The results of this study provide empirical support for the proposed framework, highlighting the critical role of virtual manufacturing, supplier readiness, and workforce competency in optimizing new product development (NPD) performance in the automotive sector. However, the findings also underscore the detrimental impact of excessive design iterations on the efficiency of the NPD process.

5.1 The Role of People Skills & Competencies in NPD Performance

The findings demonstrate that People Skills & Competencies (PSC) significantly enhance NPD performance. This aligns with prior research suggesting that a well-trained, knowledgeable workforce reduces inefficiencies, enhances problem-solving, and accelerates project completion (Goffin & Koners, 2011). Companies investing in employee training, cross-functional collaboration, and digital tool adoption are better positioned to streamline their NPD processes (Brown & Eisenhardt, 1995). The positive relationship between PSC and NPDP emphasizes the need for organizations to develop human capital through continuous learning and technical skill development to enhance product development efficiency.

5.2 Supplier Process Readiness as a Key Enabler of NPD

The study also confirms that Supplier Process Readiness (SPR) positively impacts NPDP, reinforcing the importance of early supplier involvement in the development cycle. These results are consistent with the findings of Handfield & Bechtel (2002) and Wasti & Liker (1997), which suggest that strong supplier integration reduces manufacturing disruptions and accelerates time-to-market. The ability of suppliers to align with design specifications, production schedules, and quality requirements is critical to ensuring seamless execution in NPD. Companies should prioritize collaborative planning, supplier training, and digital integration to further enhance supply chain coordination.

5.3 The Positive Influence of Virtual Manufacturing Readiness

The study further establishes that Virtual Manufacturing Readiness (VMR) is a significant driver of NPD performance. The adoption of simulation software, digital twins, and virtual prototyping has been shown to reduce reliance on physical prototypes, accelerate design validation, and improve manufacturability (Rosen et al., 2015; Mourtzis et al., 2014). Organizations that leverage virtual tools for early-stage testing and process optimization can significantly reduce product development cycles and minimize costly rework. These findings highlight the strategic importance of Industry 4.0 technologies in driving manufacturing efficiency and NPD success.

5.4 The Negative Impact of Design Iterations & Changes on NPD Performance

The results reveal that Design Iterations & Changes (DI) negatively influence NPD performance, indicating that frequent modifications and late-stage design changes are key bottlenecks in the product development cycle. These findings are in line with prior studies by Clark & Fujimoto (1991) and Krishnan & Ulrich (2001), which emphasize that uncontrolled design iterations increase costs, prolong development timelines, and disrupt production planning. While iterative design improvements are necessary, excessive changes—particularly in later stages—can lead to inefficiencies, supply chain disruptions, and increased project risks. Automotive firms must adopt a structured approach to design revisions, emphasizing early-stage design validation, concurrent engineering, and modular standardization to mitigate unnecessary delays.

5.5 Practical Implications

The findings of this study offer valuable practical insights for automotive manufacturers and NPD managers. First, organizations should invest in upskilling employees and fostering cross-functional collaboration to enhance workforce competency. Second, strengthening supplier partnerships and integrating suppliers early in the development process can reduce procurement-related delays and improve production scalability. Third, leveraging digital tools such as virtual reality labs, digital twins, and real-time simulation software can optimize the NPD process by reducing physical testing time and enhancing design efficiency. Finally, companies must implement rigorous change management strategies to control unnecessary design modifications and prevent costly rework.

These recommendations align with broader industry trends emphasizing lean product development, agile methodologies, and digital transformation as key enablers of faster, more efficient NPD cycles.

5.6 Limitations and Future Research Directions

While this study provides robust insights, it has certain limitations. First, the cross-sectional nature of the data limits the ability to assess causal relationships over time. Future research should employ longitudinal studies to track how these factors evolve across different stages of the NPD lifecycle. Second, this study focuses on the automotive industry, and its findings may not be fully generalizable to other manufacturing sectors. Future studies could explore sector-specific variations in NPD performance. Third, additional variables such as technological innovation, organizational culture, and regulatory compliance could be incorporated into future models to provide a more comprehensive understanding of NPD success factors.

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