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RESEARCH ARTICLE

Bridging development and operations: A model to improve new product innovation practices and manufacturing readiness

Madurakavi Deivanayakan*

ASM Front-End Manufacturing Singapore Pte Ltd, Manager II - Technical Projects, Postal code: 737860, Singapore

Abstract – In today's ever-changing competitive markets, organizations need to stay competitive to maintain their market position, which sets the expectation of flexibility towards new technology adoption and the introduction of products that are coupled with innovation and consistency. The focus is not just on a timely market launch. Factors such as product development cycle time, meeting quality expectations, manufacturing readiness, and a solid execution plan to achieve product cost targets determine the success of new product releases. Though other factors may define New Product Introduction (NPI) success, this research is primarily focused on bridging development and operations within an organization to analyze and improve innovation practices during new product development and identify the key factors for successful NPI. From the literature, four factors were identified: collaborating with operations early in development phases, establishing an NPI team, using digital methods, and an organizational support environment. Various hypotheses were developed based on the literature and tested through a questionnaire survey. The collected data were analyzed. Findings and recommendations are shared to enhance the success rate of new product development and introduction, as well as product technical documentation and training efficiency.

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1. Introduction

In this competitive world, innovative features and product uniqueness are helping companies keep their offerings distinct from those of other brands. To develop a highly innovative product, firms also need to invest heavily in brainstorming and process development. If an organization can maintain its high margin and revenue for an extended period compared to its rivals, it is in a sustainable competitive landscape. Every organization aims to achieve this through the performance of its business. Leaders of many businesses recognize this approach of regularly launching new products to achieve a competitive advantage [1]. Past studies and industry reports highlight that organizations are increasing their budgets for research and development activities, and the contribution of small-scale industries to innovations is also increasing year by year [2-3]. Developing a product is often an expensive and time-consuming process. In industrialized and developing countries, new product success rates are trending downward [3-5]. While customers expect the new product to be delivered faster, organizations focus on reducing their development cycle time to align with customer expectations for faster market release [6]. Safety, reliability, quality, delivery, cost, and flexibility are the primary objectives of operations [7], whether a new product is being launched or an existing product is being upgraded. A company will fail to meet its operational objectives if it is not adequately prepared with scaling plans for manufacturing readiness using advanced approaches, ensuring consistent, high-quality manufacturing to meet time-to-market requirements [8]. Awareness among employees of the manufacturing strategy and support from top management are important factors to be considered [9]. However, from a product technical documentation and training (TDT) efficiency point of view, literature reviews highlight four key areas, namely early operations engagement, Methods of Technical Product Documentation (TPD), Establishing NPI transition team, Training plan, and environmental factors of the organization, and are analyzed in detail towards NPD success in terms of Product TDT perspective.

Strategies covering portfolio management, research, project environment, processes, commercialization, performance evaluation, and organizational culture were suggested across various literature for new product success. However, factors such as financial constraints, the lapse of staff training, a lack of strategic planning, and the failure to integrate the latest technology developments pose challenges to adopting NPI [10]. Such efforts require support from top management and commitment. Aspects positively influencing such NPI success include developing competitive strategies, staff training, supplier development, and the organization's culture and structure, among others. Staff training plays a crucial role, with a significant impact on NPI success in any manufacturing organization [8]. Inadequately drafted procedures will not only create confusion on the shop floor but also lead to quality adherence failure in meeting product requirements, especially during new product development. To ensure a new product is successfully implemented, an organization must invest substantially in staff training, providing proper work instructions and a supporting competency framework [8, 11]. Considering these emerging challenges, this research primarily focuses on identifying and proposing key activities across the NPD, product transfer to operations, and volume manufacturing stages of the product life cycle. The emphasis is on enhancing product technical documentation and manufacturing personnel training to achieve operational objectives effectively. This is particularly critical during the qualification phases of a new product, where time-to-market and scaling requirements coincide.

- RO1: To determine how efficiently product TDT contributes to NPI success, establishing them as dependent variables
- RO2: To categorize the key factors influencing the efficiency of product TDT as independent variables

*CORRESPONDING AUTHOR | Madurakavi Deivanayakan | ✉ dmkavi2007@gmail.com

- RO3: To explore the relationship between these key factors and the efficiency of product technical documentation and training with correlation analysis

In this paper, Section 2 presents a literature review of independent and dependent variables from empirical studies and references that serve as the basis for the proposed framework. Section 3 outlines the research methodology, which includes a structured questionnaire. The analysis of the collected data and the questionnaire feedback is presented in Section 4. Finally, the recommendations, along with their limitations, are discussed in Section 5.

2. Literature Review

The NPD process typically faces primary challenges, including the absence of a clear product development strategy aligned with broader business objectives, low-priority development activities, and misinterpretation of customer requirements, all of which increase the likelihood of product launch failure. The next level of problems is associated with the product development process, including a lack of focus and standardized procedures, issues with organizational environments, failure to learn from past mistakes, ineffective communication, and the absence of project milestones and cost control [12, 13]. The above issues in product development and introduction help establish this research's problem statement and identify the key elements of product TDT from literature reviews and primary research.

2.1 New product introduction in assembly and test manufacturing

New Product Development refers to activities from generating ideas to their commercialization, whereas New Product Introduction (NPI) extends beyond commercialization to include product launch, volume production, and associated marketing support. According to various studies, product development is described as a concurrent process that involves creating, refining, and adapting both product designs and production systems [14]. This process typically includes stages such as product and product systems development, engineering prototypes, pilot production (Alpha), pre-series production (Beta), and finally, volume ramp-up [15, 16].

2.2 Efficient Product TDT for NPI Success

Design reviews focused on manufacturability should be concurrent to ensure effective collaboration among departments, such as the design team and production and engineering teams. In such a scenario, the team has the opportunity to listen to the voice of manufacturing engineering, which could be addressed well ahead of time during the design phase. If this approach is not followed right from the beginning, the manufacturer will provide feedback on the proposed design changes during product transfer for validation. It is usually a long list of design change proposals from the operations side to address manufacturability issues. Not all firms commit resources to address all design change proposals, as this was not expected at all. During product development, key performance indicators typically include cost, productivity, time, and quality. Cost and productivity are generally assessed based on the total hours spent developing, building, testing, and installing the product. Quality is evaluated by metrics related to design non-conformances, such as the number of project phases completed within the given timeframe without deviations. The time from idea generation to final production is called the cycle time; all organizations aim to minimize it [10]. Several studies have identified training operations staff during product transfer as a key activity. An important objective during the NPD process is to establish a cross-functional system for effective coordination to achieve a balanced fit in the initial efforts to mitigate the gap. This refers to the alignment between the product design created by the design team and the manufacturing expectations at operations [17]. The hypotheses were framed as:

- Hypothesis 1: Efficient product TDT is significantly correlated with the success of new product development

2.3 Key Factors of Efficient TPD and Training

2.3.1 Early collaboration with operations

Early involvement of suppliers and manufacturers and frequent communication with them play a critical role by influencing design decisions and enabling the timely preparation of raw materials. This approach enhances manufacturing flexibility by reducing the overall cycle time for new product development [18]. Failing to integrate operations throughout the NPD lifecycle means missing the benefits of implementing design-for-manufacturing principles. Apart from this, failing to assign experienced engineers to NPD activities can negatively impact additional resource training during the volume ramp-up phase. These selected individuals must remain involved over an extended period [19] to ensure that the expertise gained during development is leveraged to maximize operational efficiency, including during prototype and initial build development. Losing such knowledge would require extra effort, cost, and time to rebuild with the retraining of another member of staff who was not exposed to design iterations. Without proper planning for operations collaboration in developing the TDT product, new product development projects are more likely to face significant risks [20]. Research indicates that involving suppliers through formal agreements positively contributes to NPI success. To strengthen this collaboration, such agreements should be tied to performance outcomes, encouraging suppliers to meet targets while fostering a win-win relationship that eliminates unnecessary conflicts. While benefits like long-standing relationships, easy access to common knowledge, increased focus on NPI scope, and enhanced coordination are qualitative factors that are hard to quantify, they provide lasting positive effects on the overall performance of new product introduction. Early collaboration enables suppliers to plan accordingly through capacity planning and expansion, securing materials, and, if needed, upgrading processes to meet upcoming NPI requirements. Additionally, many firms support their suppliers by sharing tooling or investing in jigs/fixtures to maintain at suppliers' sites to meet volume demand [21]. Based on the above findings, the hypothesis is proposed.

- Hypothesis 2: Early operations collaboration is significantly correlated to efficient product technical documentation & training.

2.3.2 Establishing NPI transition team

Formal training will facilitate the overall organizational performance [22]. A study across 74 companies found that larger organizations with dedicated training budgets are more likely to provide product-specific training than smaller firms [19]. Adapting to the new technologies required for manufacturing new products reflects an organization's financial commitment to its training and development budget [23]. Whenever design and manufacturing activities occur at different locations, either design or manufacturing engineers typically need to travel back and forth until all plans are finalized [24]. An effective approach to involving design engineers in the new product manufacturing site allows designers to gain knowledge and understanding of manufacturing systems' limitations and capabilities, which are likely to be the same for both new and existing products. By establishing an NPI transition team in this way, designers develop a strong understanding of potential design-for-manufacturing challenges in advance, enabling them to make more informed decisions in the design of future NPD and to compensate for the overlooked mistakes of operations staff at the early phases of development [13, 25].

Based on the above findings, the hypothesis is proposed.

- Hypothesis 3: Establishing an NPI transition team is significantly correlated with efficient product TDT.

2.3.3 Digital methods usage

From the perspective of product TDT, a manufacturing plan is a structured sequence of activities that estimates the labor hours required to carry out the tasks based on the product's design [26]. It also includes all stages of planning through final testing, focusing on detailed planning at each stage to reduce the risks associated with planned activities. The plan also involves evaluating the necessary tools, jigs, and fixtures required for product assembly and testing [27]. A comprehensive training program will develop the confidence to carry out tasks successfully. Key activities during the initial phase include identifying the detailed procedures for various assemblies, developing and validating them, and training additional resources to finalize and release the documentation, which helps boost production [13]. The above-mentioned procedures are created using 3D visuals or video to aid manufacturing staff in visualizing the criticality and complexity of sub-assemblies or parts, enabling the minimization of errors. Based on such validation outcomes, engineering change orders are created to capture and communicate the design changes to manufacturing for implementation. The use of CAD software and 3D modeling helps streamline this process by enabling review and approval steps that reduce errors downstream and potential delays [17]. Reviewing design information and assembly instructions using 3D models effectively allows product visualization, which can sometimes compensate for limited opportunities to develop physical prototypes. This approach also facilitates efficient communication of information to the other side of the design [28].

- H_4: Digital methods usage is significantly correlated to efficient product technical documentation & training.

2.3.4 Organization environment

Collaborating with external suppliers during product design can enhance NPD flexibility. However, it is important to recognize that relying on external partners, such as suppliers, to manage changes to technical documentation, such as drawings or component specifications, can be challenging [29]. Therefore, implementing a structured change management and communication plan becomes crucial, with a plan outlining clear strategies for addressing design errors and incorporating improvements [25]. It is also essential to ensure that these updates are implemented swiftly, with effective communication to both manufacturing teams and suppliers [30], thereby supporting time-to-market goals during the NPD phase. Allocation and sharing of assets, such as customer requirements and technology information, utilizing common communication platforms, serves as a key differentiator in strengthening supplier relationships, which, in turn, positively impacts new product development outcomes. Additional considerations include providing access to physical assets such as tooling, information systems integration, and staff engagement mechanisms during the NPI process. While factors such as top management commitment may not directly influence immediate results, they play a crucial role in fostering an aligned organizational culture that encourages open communication and detailed information sharing for mutual benefit [21]. On the other hand, several barriers may hinder the adoption of advanced manufacturing technologies, including budget constraints, insufficient competency, insufficient training, and management's reluctance to commit to long-term infrastructure investment [10].

- H_5: Organization environment is significantly correlated to efficient product technical documentation & training.

A conceptual framework for achieving efficient product technical documentation and training to support successful NPD has been developed based on insights from various literature sources and proposed hypotheses. This framework is illustrated in Figure 1. The five hypotheses proposed will be evaluated with a questionnaire-based quantitative survey, with findings discussed in the subsequent sections. Based on these literature reviews, the Product TDT framework is tailored for the capital equipment industry, as depicted in Figure 1.

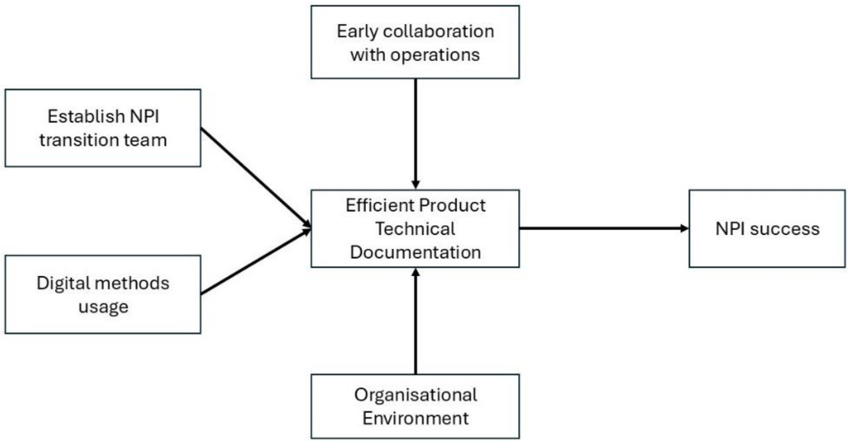

Figure 1. Proposed framework

3. Materials and Methods

A survey research methodology was adopted, using convenience sampling. To explore and evaluate the study's objectives, a self-administered questionnaire was designed. The constructs and variables used in the questionnaire were carefully extracted from the relevant literature. Following the development of the questionnaire, its face validity was tested. The questionnaire has been shown to the author's colleagues to identify duplicate and ambiguous items. To increase the response rate, the questionnaire was prepared in Google Docs and made accessible to all participants in the study. Previous studies have noted that closed-ended questions offer respondents comfort and allow them to answer the questions more quickly. The respondent must tick the appropriate answer from the five possible options given in the questions. This kind of question is easy to answer and, in general, allows for better analysis to obtain data without missing answers, making it the most suitable way to gather data [31-32]. To present the preliminary survey results, various descriptive statistics techniques have been used. The T-test, pie chart, and descriptive tables provide a frequency count for each variable type, helping us understand the importance and contribution of each variable. To explore the relationship between groups, the T-test and ANOVA have been used.

3.1 Questionnaire Design

Previous studies have noted that the questionnaire should be kept as short as possible to elicit more responses and be structured. The questionnaire for this study has been divided into two sections (See Appendix 1). Section 1 provides details on the variables and target items of the NPI. The second is demographic data collection, which gives us the profile of respondents contacted for the study. The first section collects opinions on research topics, independent variables, and dependent variables related to successful NPI and its related questions. A five-point Likert scale was used to collect responses, with 5 indicating strong agreement and 1 indicating strong disagreement. Section 2 demographic details were collected using the nominal and ordinal scales.

3.2 Distribution and Data Collection Planning

The questionnaire used in this study is divided into two components. The first component consists of items related to variables, and the second component consists of the respondents' demographic details. To facilitate distribution, the questionnaire was prepared in Google Forms. Along with the questionnaire, details about the author and the objectives of the study were included in the message so that respondents are aware of the study's objectives, and guidelines were also attached to help respondents complete the questionnaire without any problems. The questionnaire is simple, without jargon; access is granted to respondents via the link in the message, and it does not require any special tool or technique.

3.3 Sampling and Data Access

To collect data for the study, two NPI-focused companies were selected. The method adopted was a non-probability convenience sampling technique [33]. The reason for choosing these companies is their reputations, business, scopes, and access to employees' contacts in both companies. The author's personal and professional network has been used to contact the management of these two companies to get consent to collect the data from their employees. Based on the profiles, employees working in the NPI and research and development activities have been selected for the data collection process. To keep the company's information confidential, we have masked the company's details. From this section onwards, they are referred to as Company ABC and Company XYZ. Both companies are involved in the assembly and testing of newly developed products. The European business ABC manufactures semiconductor wafer fabs, and the XYZ company assembles the devices using the product output from the wafer fabs. Approximately 2000 employees work across both companies, of whom 1200 hold managerial-level designations. Out of 1200 people, based on their availability and profile suitability, we have shortlisted 450 employees for the survey.

4. Results and Discussion

This section presents the results. In this section, we aim to examine the relationships among multiple variables by analyzing their correlations. Before proceeding with the analysis, all prerequisites were met, and the mean and standard deviation were verified.

4.1 Descriptive Statistics of the Questionnaire

4.1.1 Profile of respondents

The data presented in Figure 2 summarises the profile of the employees contacted in this study. Based on the preliminary analysis, approximately half of the respondents have an average experience of less than 5 years. 23% of the respondents have more than 5 years and less than 10 years of experience, and more than 29% of the respondents have an average of 11 years. Among the respondents, those with less than 5 years of experience have also been working in NPI and assembly operations. Even though 48% of respondents have less than 5 years of experience, their feedback was included in the analysis based on their qualifications, expertise, and working conditions.

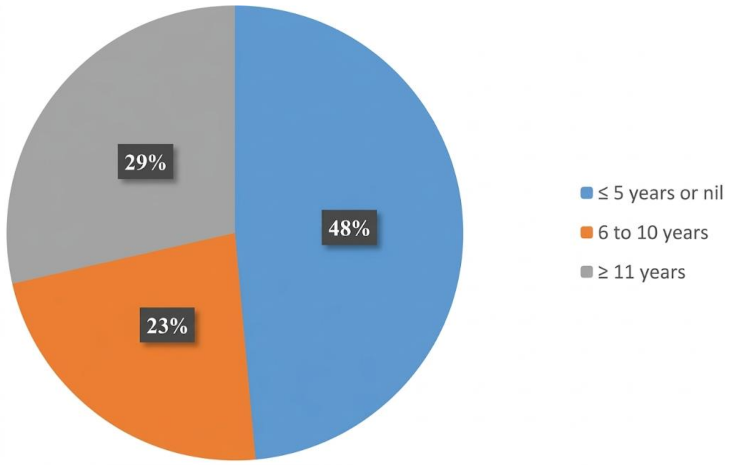

Figure 2. Years of experience in the equipment firm

4.1.2 Descriptive Statistics

The descriptive statistics are provided in Table 1. Provide key information about the data collected. The mean responses across all variables are above 4 on a 5-point Likert scale, indicating that most respondents have responded to the items as either agree or strongly agree. Also, lower standard deviation values indicate a consistent response over the items in the self-administered questionnaire. The highest skewness was observed for the items associated with the “operations engagement” variable. This suggests that respondents generally agree or strongly agree regarding the presence of a supportive environment, active operations engagement, effective NPI transition teams, and efficient training and TPD processes. Digital Methods Use, although still positively rated, shows the comparatively lowest mean, indicating it may be slightly less developed than the other areas. Finally, we are confident that the data have no missing values, and the standard error of skewness was small, indicating that the data are normally distributed without error. After the preliminary descriptive statistics, next, we aim to test the relationship between the variables using ANOVA.

Table 1. Descriptive statistics of items in the questionnaire

Measure	Supporting Environment	Digital Methods Use	NPI Transition Team	Operations Engagement	Efficient TPD and Training
Number of Valid Responses	105	105	105	105	105
Number of Missing Responses	0	0	0	0	0
Mean	4.53	4.39	4.60	4.51	4.57
Standard Deviation	0.500	0.562	0.495	0.522	0.500
Skewness	-0.176	-0.181	-0.374	-0.306	-0.254
Std. Error of Skewness	0.238	0.238	0.238	0.238	0.238
Minimum Value	4	3	4	3	4
Maximum Value	5	5	5	5	5

4.2 Independent Samples T-Test

A t-test is usually used to compare the means of two groups and test for significant differences. This test statistically tests the difference between the two groups, and the results are shown in Table 2. In this section, we compare the significant differences between the variables “digital methods use” and “current industry of work”. The collected data were checked for normality, skewness, and missing values.

- H_0: There is no significant difference between 'digital methods usage' and "current industry of work".
- H_1: There is a significant difference between 'digital methods usage' and "current industry of work".

Table 2. Independent samples T-test results

Assumption of Equal Variances	Levene's Test (*F*)	Sig. (*p*)	*t*-value	*df*	Sig. (2-tailed)	Mean Difference	Std. Error	95% Confidence Interval
Variances Assumed	0.216	0.643	0.166	103	0.868	-0.010	0.060	[-0.128, 0.109]
Variances Not Assumed			0.166	94.822	0.868	-0.010	0.060	[-0.129, 0.109]

According to Table 2, the p-value (2-tailed) is greater than 0.05; we did not have sufficient evidence to reject the null hypothesis. The p-value indicates that we are accepting the null hypothesis. That means these two groups have similar characteristics. We aim to test the difference between these two groups using a one-way ANOVA. ANOVA tests the significance of differences between two groups by using variance as an estimate of the measurement error.

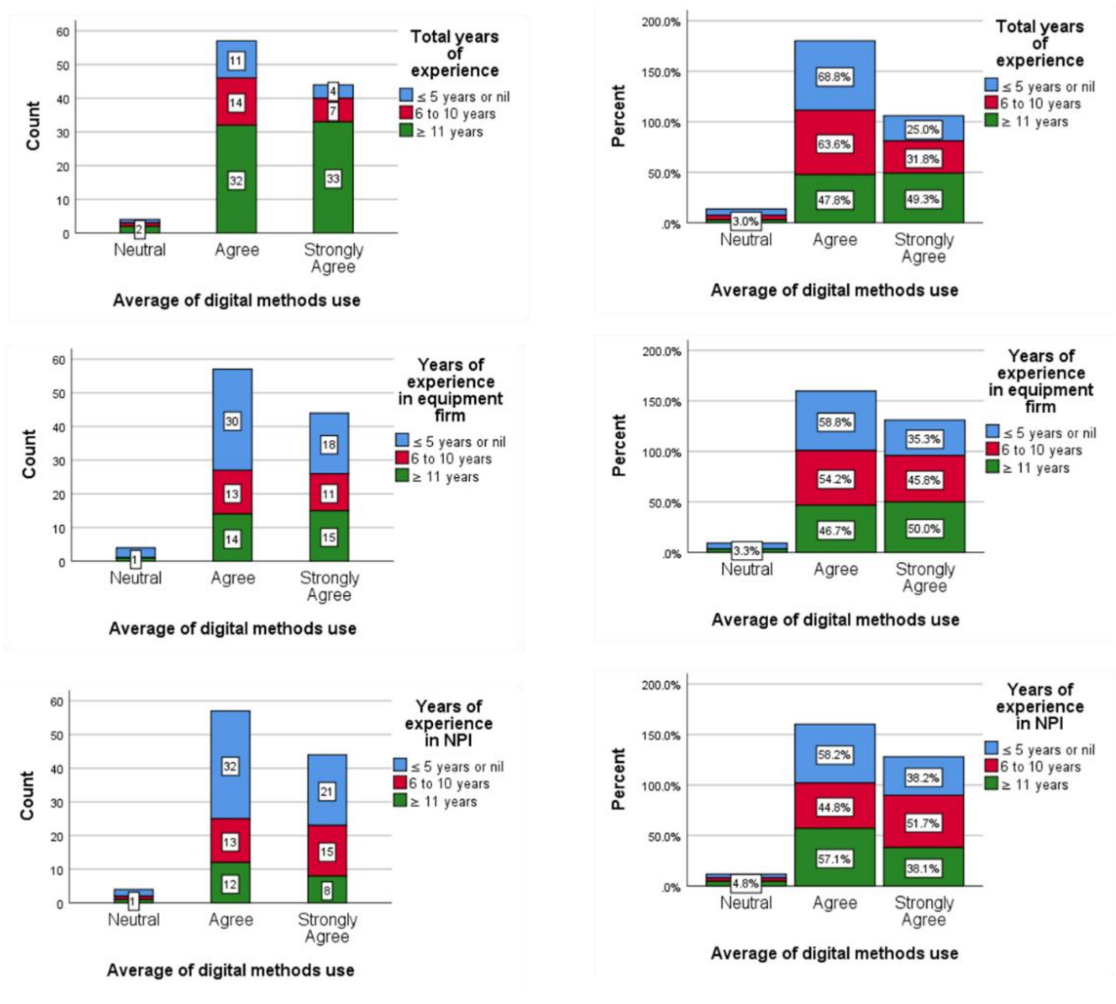

Figure. 3 Descriptive stacked bar chart of variables

The descriptive statistics are provided in Figure 3, which shows the proportion of years of experience vs. digital-methods usage. From this, work-related factors (experience) show significant differences compared to digital methods. Since each experience group has a different level of association with digital methods, we aim to identify which age group has the highest association with digital methods. Employees with 5 years or less experience contribute the highest proportion within the Agree category, while those with 11 or more years of experience are more represented in the Strongly Agree category. This suggests that although digital methods are broadly accepted, more experienced employees tend to show stronger endorsement and greater confidence in their use. In contrast, neutral responses are minimal across groups, indicating very little uncertainty or resistance toward the use of digital methods. Overall, the results reflect a positive, experience-strengthening adoption of digital methods within the organization.

4.3 One-Way ANOVA

- H0: The perception of the use of "digital methods usage" is not affected by "years of experience in business equipment."
- H1: At least one category in the "years of experience in equipment firm" group has a different perception of "digital methods usage."

The *p*-value of 0.307 is greater than the significance level of 0.05; therefore, we do not have sufficient evidence to reject the null hypothesis. According to Table 3, the null hypothesis is accepted, indicating that there is no difference between the digital methods and years of experience. So, we can infer that years of experience do not significantly affect the usage of digital methods.

Table 3. One-way ANOVA test

Source of Variation	Sum of Squares	df	Mean Square	F-value	Sig. (p-value)
Between Groups	0.750	2	0.376	1.194	0.307
Within Groups	32.014	102	0.35		
Total	32.758	104			

4.4 Reliability

Reliability tests are used to assess the consistency of the questionnaire, measuring whether it yields the same results over time and whether its items are correlated (see Table 4). Table 5, the Case Processing Summary, tells us that 105 samples were analyzed in total. Additionally, Table 6, the Inter-Item Correlation Matrix, shows that all correlations are positive, indicating that the items assess a common underlying construct. Cronbach's Alpha reliability statistics in Table 5 show a value of 0.744, which is > 0.7 according to DeVellis R.F., and the scale has very good internal consistency, making it acceptable to continue this research analysis [30].

Table 4. Case summary for reliability

Case Processing Summary			
		N	%
Cases	Valid	105	100.0
	Excluded	0	0.0
	Total	105	100.0

Table 5. Reliability statistics

Cronbach's Alpha	No of Items
0.744	5

Table 6. Inter-item correlation matrix

	Supporting Environment	Digital Methods Use	NPI Transition Team	Operations Engagement	Efficient TPD and Training
Supporting Environment	1.000	0.321	0.282	0.408	0.426
Digital Methods Use	0.321	1.000	0.294	0.367	0.462
NPI Transition Team	0.282	0.294	1.000	0.359	0.361
Operations Engagement	0.408	0.367	0.359	1.000	0.414
Efficient TPD and Training	0.426	0.462	0.361	0.414	1.000

4.5 Correlations and Multiple Regression

This study uses a standard multiple regression analysis to examine how four factors relate to the main outcome, effective TPD and training.

- Checking the assumptions
- Multicollinearity

Multicollinearity is used to check whether the independent variables are highly correlated with one another. If multicollinearity exists, it will create a problem in estimating the effects of independent variables on the dependent variables. In this study, the dependent variable is "NPI success," and the remaining factors are independent variables.

Table 7. Correlation of all variables

Variables	1. Supporting Environment	2. Digital Methods Use	3. NPI Transition Team	4. Operations Engagement	5. Efficient TPD and Training
Supporting Environment	1.000	0.423**	0.435**	0.541**	0.410**
Digital Methods Use		1.000	0.377**	0.435**	0.450**
NPI Transition Team			1.000	0.529**	0.387**
Operations Engagement				1.000	0.437**
Efficient TPD and Training					1.000

Irrespective of dependent and independent variables, the Pearson correlation among each variable is shown in Table 7. The dependent variable 'Efficient TDP and training,' with a correlation value of more than 0.3, preferably shows a relationship with the independent variable, such as 'NPI transition team', 'supporting environment', 'operation engagement', or 'Digital method use'. Here, the maximum and minimum Pearson correlation regarding the dependent variable is 0.387 for 'Transition team,' and 0.45 for 'Digital methods use, both of which are greater than 0.3. Meanwhile, the correlation among the independent variables is all within an acceptable range below 0.7. Here, the maximum and minimum correlations among the independent variables range from 0.41 to 0.541, which falls within the acceptable limit of 0.7. No variables need to be removed or combined, as all variables fall within the acceptable correlation range.

Table 8. Coefficient

Predictor Variable	Standardized Beta	Std. Error	*t*-value	Significance (*p*)	Tolerance	VIF
(Constant)	–	–	3.265	0.002	–	–
Mean of Operations Engagement	0.166	0.105	1.574	0.119	0.577	1.734
Mean of NPI Transition Team	0.135	0.103	1.302	0.196	0.674	1.485
Mean of Digital Methods Use	0.223	0.082	2.717	0.008	0.744	1.343
Mean of Supporting Environment	0.147	0.104	1.421	0.158	0.645	1.551

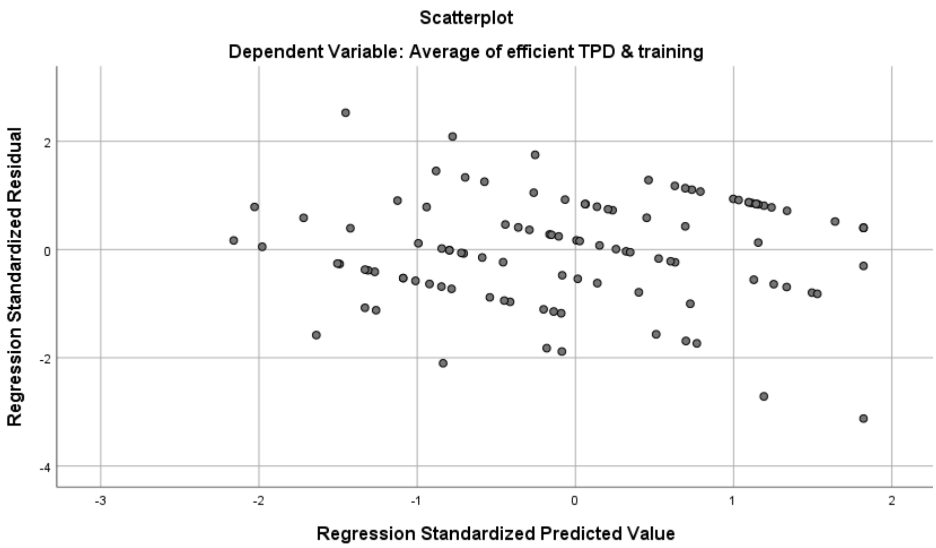

Figure 4. Regression scatter plot

Collinearity tests are used in multiple regression analysis to detect multicollinearity that may not be apparent in the correlation matrix. The "Coefficients" display these diagnostic findings (Table 8). Strong correlations between a given variable and the other independent variables are indicated by tolerance values below 0.1, which may signal multicollinearity. For each predictor, tolerance is computed as follows: 1 minus R-squared. Another indicator is the

Variance Inflation Factor (VIF), which is the reciprocal of tolerance; a VIF value greater than 10 generally indicates significant multicollinearity issues [29]. There is no multicollinearity in the dataset, as indicated by the tolerance and VIF values. In Figure 4, we test for normality using a P-P plot. So, it helps us to understand that the data does not have any deviation or skewness. The data does not have any outliers.

4.6 Correlation Analysis – Evaluation of Individual Variables

Correlation analysis helps to identify how closely two variables are related. The hypotheses presented in Section 2 are now empirically tested using correlation analysis.

- H0: There is no correlation between efficient TPD and training and NPI success factors
- H1: There is a significant relationship between efficient TPD and training and NPI success factors

NPI's success is often affected by multiple factors, leading to a focus on crucial areas for improvement. Some of those factors include focus on quality enhancement, market readiness, how quickly firms meet the market demand, and how the supply chain network helps to reach the market quickly [12, 17]. To test the hypothesis, the relationship between the above-mentioned variables is tested using correlation analysis. Since the outcome is measured using multiple metrics, the results in Table 9 provide statistical support for testing the relationship between variables. At a 1% significance level, we have enough evidence to reject the null hypothesis. With statistical evidence, we can say that there is a relationship between operational engagement and Efficient TPD and training.

Table 9. Correlation

Outcome Measures	Correlation Coefficient (r)	Significance Level (p-value)
Time-to-market reduction	0.660**	0.000
Enhancement in manufacturing quality	0.604**	0.000
Minimization of operational waste and rework costs	0.677**	0.000
Accelerated ramp-up after qualification	0.734**	0.000

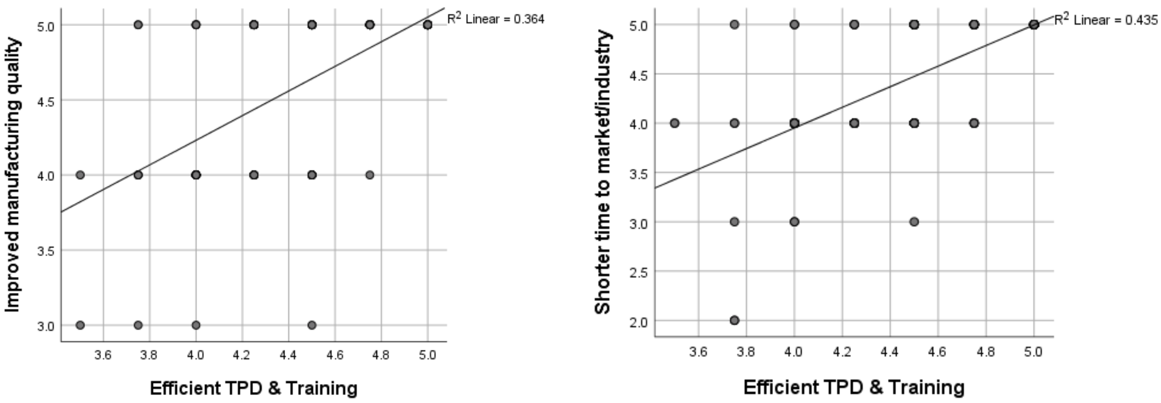

Figure 5. Scatter plot

Efficient TPD and training and NPI success factors have a positive, linear, and very strong correlation, as indicated by the Pearson correlation value (*r*), which is 0.604 (the minimum for improved manufacturing quality) and 0.734 (the maximum for a faster volume ramp-up). The scatter plot charts in Figure 5 are another way to depict these. Thus, effective training and TPD will result in NPI success. The same conclusions were noted, with opportunities for performance improvement adversely affected by information gaps and missing documentation during the NPD process. In addition to causing unnecessary delays in customer deliveries and quality problems, failing to complete technical product documentation in the early phases of new product development will result in productivity losses during the ramp-up stage [17]. To guarantee a successful product outcome, Adler [18] also highlights that training manufacturing staff during the development of new products is identified as a key activity in various research studies, coordinated with interdepartmental resources.

4.6.1 Operations engagement vs efficient TPD and training

- H_0: Effective TPD and training do not significantly correlate with operations engagement.
- H_1: Effective TPD and training are significantly correlated with operational engagement.

Taking the attained *p*-value of ≤0.05 into consideration, reject the null hypothesis H_0 and accept the alternative hypothesis H_1 at 1% significance level. This statistical evidence is shown in Table 10, which uncovered the significant relationship between operational engagement and Efficient TPD and training. The r value indicates a positive relationship between TPD and operational engagement; the strength of the relationship is moderate. Therefore, it is evident that operational engagement positively influences TPD and training, thereby enabling a successful NPI. This association supports the claim that regular interaction and communication with manufacturers and suppliers of highly skilled engineers and technicians will have a positive impact on the design-stage decision-making process, thereby increasing operational flexibility and making materials available for initial processing at the plant during the NPD [18]. Notably, in a survey of 83 respondents, 78 opined that through proper training, the workers feel that they are skilled enough to carry out a job with confidence, which is essential towards successful NPI, is reflected and can be observed from the early stages, starting from the concept development to the improvement of competitive advantage via increasing the product performance [20]. Although the designers would prioritize the functionality of the product, skilled manufacturing engineers and technicians would concentrate on the product's manufacturability, advise designers of potential design impact scenarios, and suggest ways to improve the design [17] to shorten cycle time, reduce product/service costs, prevent late changes, and improve communications, and guarantee that the product performance not only satisfies functionality but also meets manufacturing and serviceability requirements for NPI success [31].

Table 10. Pearson correlation

Correlations		
		Operations engagement
Average of efficient TPD and training	Pearson Correlation	.437**
	Sig. (2-tailed)	0.000
	N	105

4.6.2 New product introduction transition team establishment vs TPD and training

- H_0: The formation of an NPI transition team does not affect the efficiency of technical product documentation and training.
- H_1: The formation of an NPI transition team has a significant impact on the efficiency of technical product documentation and training.

Table 11 indicates that the p-value (Sig. 2-tailed) for the relationship between the NPI transition team and the effectiveness of training and technical product documentation is 0.000. Since this value is below the 0.05 threshold at a 1% level of significance, the H_0 is rejected in favor of the H_1. This suggests a significant link between establishing an NPI transition team and improved TPD and training outcomes. As shown in Figure 5, the Pearson correlation coefficient (r = 0.387) reflects a positive, linear, and moderately strong association. Hence, forming an NPI transition team contributes positively to effective TPD and training, which supports the success of NPI initiatives. This is further supported by the remarks made by [25], which state that the design engineers or manufacturing staff who are expected to receive and impart knowledge of the designed product to manufacturing must co-locate at the initial manufacturing site where controlled builds will take place until the design is perfected and set in stone for mass production. This idea of creating a transition team was also highlighted by [19], who stated that one of the best ways to address problems with the initial or prototype manufacturing of new products is to create an NPI transition team. This team can provide workaround solutions and execute change orders more quickly after design non-conformances are identified. To assist skilled technicians on the transition team in training additional technicians for volume manufacturing, the transition team not only builds prototypes but also conducts design reviews during initial manufacturing and creates work instructions [14].

Table 11. Pearson correlation

Correlations		
		NPI transition team
Average of efficient TPD and training	Pearson Correlation	.387**
	Sig. (2-tailed)	0.000
	N	105
**. Correlation is significant at the 0.01 level (2-tailed).		

4.6.3 Digital methods usage vs efficient TPD and training

- H_0: The use of digital methods has no significant connection with the efficiency of technical product documentation and training.
- H_1: The use of digital methods is significantly related to the efficiency of technical product documentation and training.

From Table 12, for a two-tailed test, the p-value is ≤ 0.05; we have sufficient evidence to reject the null hypothesis and accept the alternative hypothesis, which states that there is a relationship between the variables mentioned above. As seen in Figure 6, the $r = 0.450$ indicates a positive, linear, and moderately strong relationship between the use of digital methods and effective TPD and training. Thus, the use of digital methods will have a positive impact on training and TPD, facilitating NPI success. Our analysis supports the notion that quantitative checklists and paperless soft copy procedures are superior methods for handling technical product documentation [24]. This relationship is possible because training costs, training manuals, and awareness of the product life cycle help workers gain knowledge of the NPI procedure, which, in the long run, increases the efficiency of process management [34]. Previous studies in the domain also highlighted that training and the sharing of information across the network will help all stakeholders associated with the business, ensuring the right information is passed from the idea stage to the final production stage [35].

Table 12. Pearson correlation

Variables	Correlation Coefficient (r)	Significance (p-value)
Digital Methods Usage × Efficient TPD and Training	0.450**	0.000

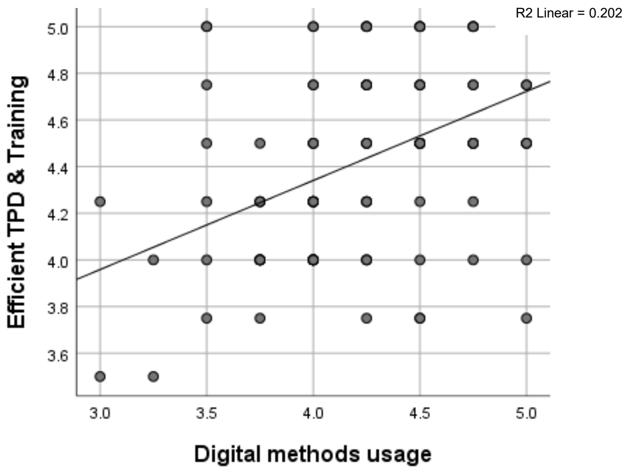

Figure 6. Plot showing the linear relationship between the variables

The use of digital models, such as 3D models and CAD drawings, for product assembly is already being proposed to lower training costs, speed up ramp-up time, and shorten the product life cycle [35]. These digital instructions are also used in virtual training, and the data can be easily stored and shared over a network [33], allowing both designers and manufacturing teams to access the information without difficulty.

4.6.4 Supporting organizational environment vs efficient TPD and training

- H_0: There is no correlation between supporting organizational environment and efficient technical product, documentation, and training
- H_1: There is a significant relationship between a supportive organizational environment and efficient technical product documentation and training.

Table 13 shows that the p-value (Sig 2-tailed) for training score and efficient TPD versus supporting organizational environment is 0.000. At a 1% significance level, accept H1 and reject H0 since the p-value is less than 0.05. This implies that effective TPD and training are related to a supportive organizational environment. As illustrated in Table 13, the Pearson correlation value (r) = 0.410 indicates a positive, linear, and moderately strong relationship between the supporting organizational environment and effective TPD and training. The aforementioned findings support the idea that, even though it is impossible to prevent frequent changes during the development of new product structures, a clear change management infrastructure must be made available so that manufacturers and suppliers can comprehend the changes in technical product documentation in detail and set up internal training efficiently to increase the flexibility of the new product [29]. The production environment can be made more efficient through continuous improvement, but to focus on operational improvements rather than development-process-related improvements, lessons learned during the new product development process must be documented and reviewed frequently [36-38]. Top management's unwavering focus on assessing the status of new product technical documentation and training will allow the associated activities to be given priority and the necessary resources, which will not only facilitate an aligned culture across departments with open communication and detailed information sharing but also contribute to the success of new products [21]. With an r value of 0.45, "digital methods usage" has the highest individual correlation with any independent variable. As a result, the coefficient of determination (COD) = r^2 is equal to 0.2025. Accordingly, TPD and training rating are directly linked to a 20.25 percent change in the values in "digital methods usage."

Table 13. Pearson correlation

Correlations		
		Supporting environment
Average of efficient TPD and training	Pearson Correlation	.410**
	Sig. (2-tailed)	0
	N	105

4.6.5 Regression Model

Based on the Pearson correlation values presented in Table 14, a multiple linear regression model for the dependent variable TPD and training was developed using the independent variables: operation engagement, NPI transition team establishment, use of digital methods, and a supportive organizational environment. The Adjusted R-squared value is 0.277, meaning that changes in the independent variables account for 27.7% of changes in the dependent variable. The multiple regression model equation, derived as follows, is based on the previously displayed coefficients and uses the unstandardized coefficient values for the independent variables and the constants to determine the value of the dependent variable. The TPD and training values are 1.506 + 0.166 (operations engagement value) + 0.135 (NPI transition team establishment value) + 0.223 (use of digital methods) + 0.147 (supporting environment value).

Table 14. Model summary for multi-linear regression

Model	R	R^2	Adjusted R^2	Std. Error of Estimate	R^2 Change	F Change	df1	df2	Sig. F Change
1	0.529	0.280	0.277	0.345	0.280	10.578	4	100	0.000

5. Conclusions

The study presents the challenges of new product development and the factors affecting technical product documentation. An extensive literature review identified the important factors, and hypotheses were developed. To test the proposed hypothesis, a survey research method was adopted. The data were collected using a self-administered questionnaire from employees working at two reputable firms in Singapore. The collected data were processed, and preliminary requirements for conducting a t-test and ANOVA were met. In addition, standard data screening procedures, including checks for missing values, normality, and reliability, were performed to ensure robustness of the results. Firstly, the results of the one-way ANOVA test reveal that perceptions of digital method use do not differ significantly across levels of experience within equipment firms, indicating that digital adoption perceptions are uniform irrespective of tenure. The Cronbach alpha indicates that the items have good internal consistency for further analysis. Using correlation analysis, this study examined the relationships among the stated variables. This analytical approach ensured that both the strength and direction of associations among constructs were systematically evaluated.

All independent variables are positively and significantly associated with efficient TPD and training. Among them, digital methods usage emerged as the strongest predictor, followed by operations engagement and supporting environment, though their contributions were statistically non-significant in the regression model. This suggests that while employees perceive these factors as important, their relative impact may vary depending on implementation maturity and contextual firm dynamics. Further, individual correlation analyses confirmed strong, significant relationships between efficient TPD and training and critical NPI success factors, including reduced time-to-market, improved manufacturing quality, decreased rework and waste, and faster volume ramp-up. The strongest correlation was observed with the ability to ramp up volume quickly, underlining the strategic importance of robust TPD and training mechanisms. This highlights that well-structured training and documentation practices play a pivotal role in accelerating production readiness and operational scaling. Lastly, the study reinforces the necessity of cross-functional collaboration, the adoption of digital tools, early operational involvement, and supportive organizational structures to drive successful TPD and training outcomes. Collectively, these findings emphasize that organizations seeking to enhance NPI performance must integrate process discipline with digital enablement and strong interdepartmental alignment. These elements collectively enhance NPI performance, reduce time and cost inefficiencies, and foster long-term competitiveness in product development processes.

Successful NPI in manufacturing hinges on three key factors: quality, speed, and cost-efficiency. To maintain a competitive advantage, firms must focus on innovation supported by clear technical documentation and early operations involvement. The lack of proper documentation and training can delay production, reduce quality, and lead to costly non-conformities. Engaging operations personnel during the design phase helps ensure a smoother transition to volume production, as their insights support design-for-manufacturing decisions and reduce late-stage changes. This reinforces the first research objective: that strong TPD and early training directly contribute to NPI success. Survey findings from 105 respondents confirmed that technical documentation and training significantly enhance time-to-market, quality, and ramp-up efficiency. Independent variables such as operational engagement, use of digital methods, NPI team establishment, and supportive organizational environments showed strong correlations with NPI outcomes. Recommendations include early and active involvement of experienced technicians, digital transformation of documentation and training, and the adoption of structured feedback and change management systems. A shift toward concurrent engineering and virtual tools, along with basic training and lessons-learned sharing, can further align theory with practice and improve long-term NPI effectiveness.

The initial research plan was to gather data within an organization from technicians to understand their perceptions related to the company's performance. Although taking into consideration the research focus, possible outcomes for managing company staff through appropriate administrative procedures, the significance of NPD, and the implementation of concepts rather than performance. It was decided to include current and former employees from two manufacturing firms, with the supervisor's consultation. A larger sample could have been targeted for feedback to ensure the survey was distributed evenly across groups and to highlight respondents' different viewpoints on specific variables. Since this study used convenience sampling, bias may affect its findings. Future studies could focus on random sampling methods to generalize the study's findings across different industries and regions. Additionally, expanding the sample size and including multiple firms would further strengthen the robustness of the conclusions.

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Declaration of Competing Interest
The author declares no conflicts of interest.

CRediT Authorship Contribution Statement
M. Deivanayakani: Study conception and design, data collection, analysis, and interpretation of results.

Availability of Data and Materials
The data supporting this study's findings are available on request from the corresponding author.

Ethics Declarations
This study did not involve human participants or animals. Ethical approval was therefore not required.

Generative Artificial Intelligence Declarations
The authors claim that artificially intelligent-assisted technologies, such as generative AI, were not used to generate content, ideas, or theories. We have just utilized AI to enhance readability and refine the language. This was used with extreme human control and oversight. The authors take full responsibility for reviewing and approving the content.

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