



WITS BUSINESS SCHOOL
UNIVERSITY OF THE WITWATERSRAND

RESEARCH REPORT

**A diagnostic tool to identify new product introduction
model used by a manufacturing Organisation**

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DECLARATION

I declare that this research report is my own and unaided work. It is being submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Business Administration. It has not been submitted before for any degree or examination, nor has it been prepared with the assistance of any organisation, body or person outside the University of the Witwatersrand, Johannesburg.

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ABSTRACT

The research report aims to develop and illustrate the validation of a diagnostic tool that will enable a manufacturing organisation to identify what new product introduction model they are using when introducing products into their manufacturing process.

Using the logistic regression analysis theory, a logistic regression equation was developed to predict the NPI model. A questionnaire was generated using the key characteristics of the two NPI models and the empirical data from the responses is used as the independent variables to the developed NPI logistic regression equation.

For illustrating the validation of the diagnostic tool, the output dependent variable from the equation was compared to the response the respondents' view on the type of model been used by their manufacturing organisation. In addition, a NCSS logistic regression equation was also compared to the developed NPI logistic regression model.

The developed questionnaire together with its corresponding logistic regression equation provides a validated diagnostic tool that can be used to identify what type of NPI model a manufacturing organisation is using to introduce new products into their process.

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1. INTRODUCTION

1.1. Context of study

Timely and responsive new product development has become critical in the highly competitive global environment. The need to respond quickly to these dynamic global market forces requires companies to rapidly integrate the perspectives and needs of both product developers and potential customers (Barton and Krause 1985).

A recent focus of attention in the new product development literature has been the need to quicken the process of development in order to decrease “time-to-market”. The field of New Product Introduction (NPI) is widely researched in a variety of organizations such as universities, consulting firms and manufacturing companies and is located in a wide range of disciplines, including technology management, business policy, marketing and engineering. Much of that research has specifically focused on discovering what organizational, strategic and process-related factors characterize successful new product developments (Craig and Hart 1992; John and Snelson 1988; Lilien and Yoon 1989; Rothwell 1977).

A fact of modern industrial life is that companies vie with their competitors to be first with an innovative new product. It is becoming increasingly important to be able to bring new and improved products to the market quickly. Many world class manufacturing companies have set clear targets for improving the speed and quantity of new product introduction, often incorporating these objectives into the manufacturing strategy (Maskell 1991).

Delays in product rollout can pose significant problems for international companies seeking to introduce new products across many countries. In spite of the critical importance of new products in sustaining a company's competitiveness in both domestic and international markets, research into the antecedents of product rollout timeliness have, to date, been under-explored (Wong 2002).

Without doubt, time has become very important for companies that want to have a competitive superiority. Being the first to introduce a product into the market can certainly bring significant benefits, including greater market share and higher price premiums, which will consequently result in higher profitability. Conversely, delaying the introduction of new products into the market can lead to negative consequences such as lower market share, lower margins, and maybe most critical, the loss of customers' goodwill (Kumar and Motwani, 1995).

1.2. Problem statement

The research problem is to develop and illustrate the validation of a diagnostic tool that will enable a manufacturing organisation to identify what NPI model they are using to introduce new products into their manufacturing process.

1.3. Sub-problem

There are two sub-problems associated with this proposed research and these can be stated as the following questions:

- i. Can a diagnostic tool be developed to enable a manufacturing organisation to identify what NPI model they are using to introduce new products into their manufacturing process?

- ii. Can the illustration of the diagnostic tool be validated on a manufacturing organisation?

1.4. Significance of the Study

The inclusion of certain activities in the NPI process and their efficient execution has been identified as important factors for new product success. It is therefore important to be able to identify both what activities are present in a particular NPI model and what activities should be present (Fairlie-Clarke and Muller 2003).

Review of existing models for the NPI process illustrates the diversity of processes used in manufacturing industries, and provides a framework for understanding the product development process for a particular industry (May-Plumlee and Little 1998).

Sadd (1996) provided examples of how in-depth study of the product development process served to identify opportunities for increasing margins and sales volume, reducing development costs. A comprehensive study of a manufacturing company's NPI process has the potential for fostering competitive improvements in managing their process.

Effective NPI processes are an essential element in maintaining competitive advantage for a business. One way to improve the NPI process within companies is to assess existing NPI practices and use the assessment results as a foundation for improvement work (Gardiner and Gregory 1996).

The research report aims to develop and illustrate the validation of a diagnostic tool that will enable a manufacturing organisation to identify what NPI model they are using

when introducing products into their manufacturing process. By establishing what type of NPI model they are using, the manufacturing organisation will be able to highlight which areas and activities of their NPI process that can to be improved upon. A questionnaire based on the key characteristics of existing new product introduction models was used to gather the empirical data for the model.

1.5. Delimitation and Limitations

- The new product development process models reviewed in this research will focus primarily on new products which are modifications of existing products or existing products introduced to new markets.
- This study will be delimited to exploring the NPI process from the perspective of the manufacturer. No effort will be made to explore the process from a customer perspective.
- The development of the diagnostic tool will not be done on multiple manufacturing industries and their supply chain. It will be delimited to a NPI process of a particular autocatalyst manufacturer.
- The illustration and validation of the diagnostic tool will be delimited to the autocatalyst producer's R&D and manufacturing operations that fall within its European region.
- The sample for the study will be purposive. The elect respondents who been elected to participate have the required knowledge and exposure to NPI processes to answer the research questions.
- It is realised that the research is context specific and the designed questionnaire could have poor external validity.

1.6. Assumptions

The following assumptions underpin the research to be conducted:

- i. NPI models from literature can be generalised to reflect the processes involved in the manufacturing industry.
- ii. The respondents elected to answer the research questions have the required knowledge and exposure to NPI processes to answer the research questions.

2. LITERATURE REVIEW

2.1. Introduction

During the 1980's, companies eliminated many inefficiencies in their manufacturing process, but new product development is one of the few areas left with the greatest potential for improvement (Schmidt 1995).

Existing literature clearly documents the importance of new product development to the success of a manufacturing firm. Many examples of generic models of the processes can be found and the literature establishes that development of new products is a critical activity in a successful manufacturing company (Bruce and Biemans 1995; Craig and Hart 1992).

Many authors have developed normative models of the new product development process. Traditionally, the process was represented by models that are sequential in nature, while more recent ones tend to reflect concurrent product development processes that integrate multiple business units (May-Plumlee and Little 1998).

2.2. New Product Introduction defined

New product introduction is defined as the design and engineering of products which are, serviceable for the target consumer, marketable, manufacturable and profitable. Integrated efforts of multiple functional units within a business firm must be employed to develop such a product and achieve these outcomes (Kunz 1993).

The product development literature identifies several forms that new products may take. Simply stated, new products may be (May-Plumlee and Little 1998):

- “new to the world” inventions which create a new market;
- modifications of existing products; and
- existing products introduced to new markets

The new product development process models reviewed in this research will focus primarily on development of products which are modifications of existing products or existing products introduced to new markets.

2.3. Success and Failure in NPI

The vast literature on new product success and failure brings to light a host of factors that influence success. The literature has been reviewed extensively (Craig and Hart 1992; Snelson and Hart 1991) and three sets of issues are continually reinforced and validated:

- *The need for interdisciplinary inputs:* Discussions of the various NPI models shows that the tasks involved generally fall within the domain of different functions, themselves based on professional education, training and certification. The “success” literature consistently shows that where these various professions actively collaborate through the NPI process, its outcome is more successful (Cooper and Kleinschmidt 1986; Maidique and Zirger 1984). As the development of a new product may be the only purpose for which these people meet professionally, it is important that the NPI process adopted ensures that they work well and effectively together.

- *The need for quality inputs to the process:* Technical and marketing information, which are building blocks of NPI, have to be both accurate and timely, and must be constantly reworked in the light of changing circumstances during the course of the development. In addition, customer and supplier inputs need to be encouraged to ensure user-relevance and supplier support.
- *The need for speed in the process:* The NPI process has to be managed in such a way as to be quick enough to capitalize on the new product opportunity before competitors do so. The value of being first into the market with a new product is often significant and the window of opportunity for a new development may be fleetingly open. The speedy undertaking of the complex and intricate product development task will require careful consideration.

Although there are many other factors shown to be important to the success of NPI, these three have consistently appeared in new product success literature and therefore widely-accepted NPI models need to take full cognisance of these factors (Hart and Baker 1994).

2.4. NPI models

2.4.1. Stage Models

Figure 1 provides examples of stage models of the NPI process. As is clear from the diagrams, this type of model suggests that a product moves sequentially through a series of defined stages. The processes occurring at each stage, often conceived as taking place in a single department, must be complete before passing the developing product forward to the next stage (May-Plumlee and Little 1998).

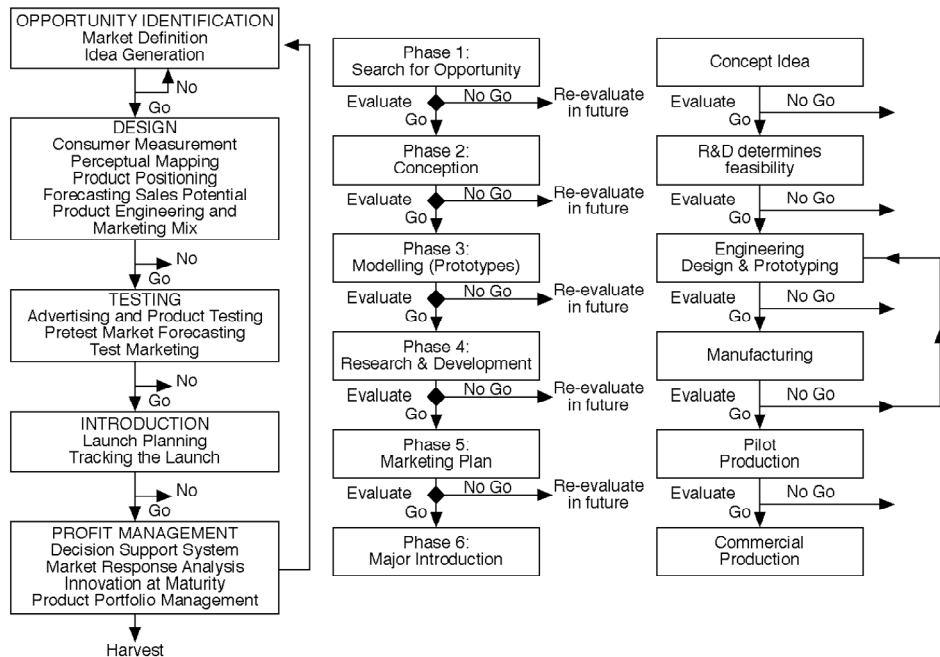


Figure 1: Sequential models by Urban and Hauser (1980), Gruenwald (1992) and Himmelfarb (1992)

i) Departmental-stage models

The “departmental stage” models view the new product development process in terms of the departments or functions that hold responsibility for various tasks carried out. For example, in an industrial context, the ideas are furnished by the R&D department, the detailed design is then carried out by the design department and engineering will then “make” the prototype after which production will become involved to work on the manufacturing problems. Finally, marketing will become involved to plan and carry out the launch. In addition to the criticism levelled by Saren (1984), such representations are now rather out-moded, failing, as they do, to take cognizance of the lessons to be learned from the research into success and failure in NPI.

ii) Activity-stage models

Activity-stage models improve on departmental-stage models in that they focus on actual activities carried out, including various iterations of market testing. However, they too have been criticized for continuing a pass-the-parcel approach to NPI since the activities are still seen to be the responsibility of separate departments or functions (Takeuchi and Nonaka, 1986). Cooper and Kleinschmidt (1986) used a model, shown in Figure 2, of 11 sequential activities

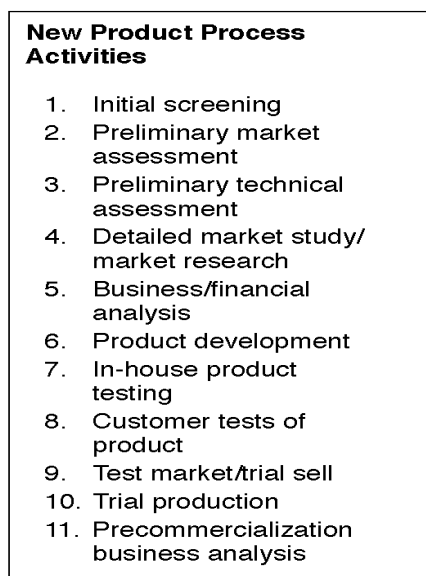


Figure 2: Cooper and Kleinschmidt's new product process activities (1986)

iii) Decision-stage models

Decision-stage models represent the NPI process as a series of evaluation points, where the decision to carry on or abandon the project is made (Cooper 1983; Ronkainen 1985). This approach underlines feedback loops, which, although not impossible within the framework of activity-stage models, are certainly not highlighted either. And yet, such feedback loops are critical, since the NPI process is one of continual refinement, until an ideal technical solution, which is easily manufactured and still relevant to customer needs, is produced.

How such a goal might be achieved without feedback from one task to another is difficult to see. Furthermore, if the necessity of feedback loops is accepted, the dimension of “information exchange” as a fundamental element of NPI flows naturally (Hart and Baker 1994).

2.4.2. Parallel Models

Many authors see industrial product development shifting toward a parallel or concurrent product development process model (Himmelfarb 1992; Nijssen et al. 1995; Zahra and Ellor 1993). This process is often represented as sequential steps, but with each step occurring simultaneously in a number of departments. Operating under a concurrent model, communication is enhanced and the expertise of all departments is employed throughout the process. A shorter product development cycle, better products and improved communication between departments are identified as advantages of this approach (May-Plumlee and Little 1998).

i) Integrated process model

Erhorn and Stark (1994) modelled an integrated approach, shown in Figure 3, where product development occurs simultaneously in multiple departments and product improvements are accomplished without hindering the process. According to the authors, use of this model facilitates product innovation, cost management, meeting quality requirements and a shortened product development cycle. Barclay, Holroyd and Poolton (1995) also emphasized the importance of an integrated approach in discussing their wedge shaped concurrent product development model. It incorporates multiple new product options which are narrowed into a single new product concept through a series of decision points.

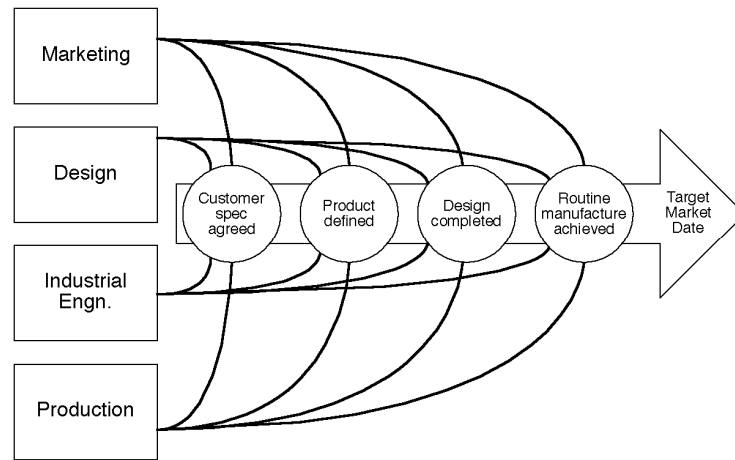


Figure 3: Erhorn and Stark's (1994) integrated process model

ii) Multi-convergent model

Hart and Baker (1994) attempted to limit the functional divisions suggested by “parallel” processes with a multiple convergent processing model (May-Plumlee and Little 1998). There are still functionally distinct tasks which must be carried out at specific points throughout the NPI process and that the tasks will be carried out simultaneously at some juncture and the results must converge. Due to iterations in the process, this convergence is likely to happen several times, culminating at the time of product launch. The process is a series of information gathering and evaluating activities, and as the new product develops from idea to concept to prototype and so on, the information gathered becomes more precise and reliable and decisions are made with greater certainty (Hart and Baker 1994). An example of the early stages of the multiple convergent process is shown in Figure 4.

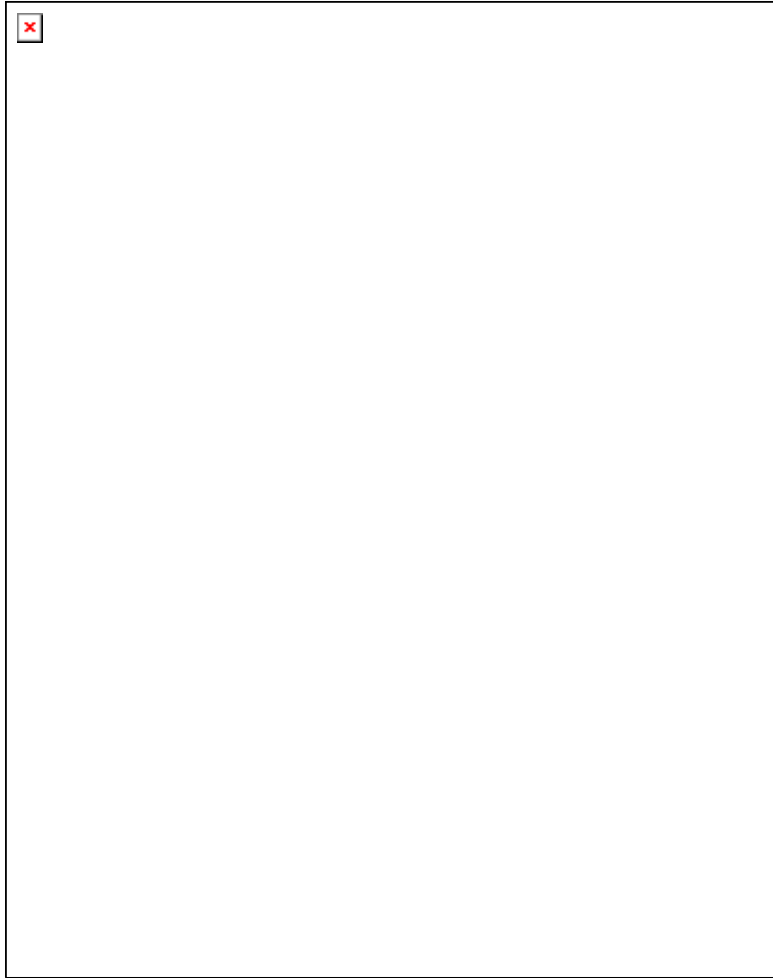


Figure 4: Hart and Baker (1994) multi-convergent model

The multiple convergent processing model addresses problems by focusing upon the multifarious and multi-participant tasks that compose the NPI process and by incorporating the opportunity for these tasks to be evaluated in an integrative fashion at several points throughout the iteration of the process (Hart and Baker 1994).

2.5. Literature Review Conclusion

It is now widely accepted that the “pass-the-parcel” approach to NPI from one department to the next is deficient in several respects. First, there is the likelihood that

the prototype differs from the accepted design, which was, in itself, merely one representation of the ideas from R&D, and that the prototype requires modification for manufacturing. Thus control of the process is lost as the idea is adapted, in an isolated way, from one set of functional exigencies to another. Second, it is unnecessarily time-consuming. Third, it does nothing to foster ownership of, or strategic responsibility for, new products (Kortge and Okonkwo 1989; Ramanjam and Mensch 1985) and, finally, there is nothing in the way of market feedback, since marketing is presented with the product to market (Cooper 1983; Nystrom 1985).

The stage models describe a segmented and consequently a slow approach to product development, minimising interaction between departments. Because critical departments have no input until later stages of development, important considerations may be omitted from the process resulting in missed market opportunities, an extended development cycle, and difficult to manufacture products that are too costly and require major revision late in the development process. By the time a developing product has been reviewed by all departments, and perhaps recycled several times, the market opportunity identified at the beginning of the process may no longer exist (May-Plumlee and Little 1998).

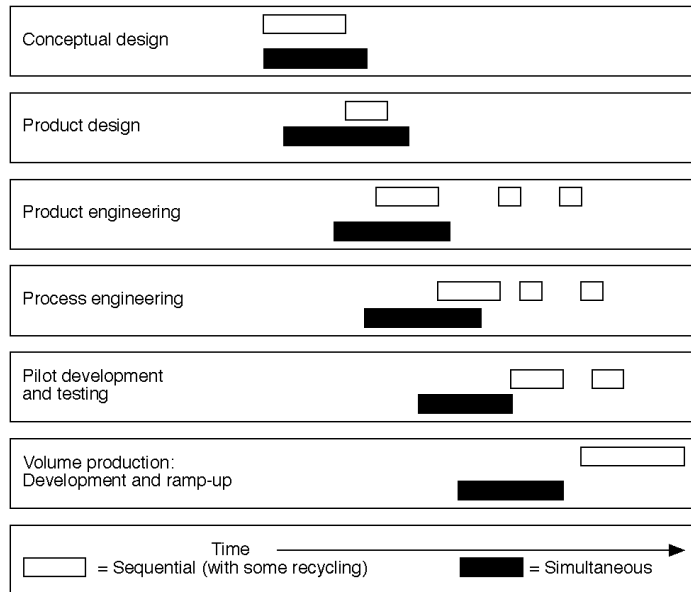


Figure 5: Sequential versus simultaneous process (Rosenthal, 1992)

Parallel or concurrent models offer advantages over sequential models of product development. First, the integrated approach supports a faster and more efficient product development cycle (May-Plumlee and Little 1998). Rosenthal (1992) illustrated this difference clearly in the diagram shown in Figure 5. This approach allows for continuous exchange of information and responsibility among many departments involved in development. Second, marketing and manufacturing play a larger role in the entire product development cycle helping to assure that a wide variety of external and internal design requirements are considered in the process (May-Plumlee and Little 1998).

The need for interdisciplinary inputs, quality inputs to the process and speed in the process are important factors that influence the success of a NPI process and NPI models need to take full cognisance of these.

2.6. Key Characteristic summary of NPI models

There are two broader models that are used in the NPI process and these are the Stage and Parallel models. The Stage models move in sequential steps, while the Parallel models have some or most of the key steps occurring concurrently. Table 1 below summarises the key characteristics of the NPI models.

Table 1: Key characteristics of the two broad NPI models

Stage models		
Key Characteristics		Outcome
The product moves sequentially through a series of defined stages. The processes occurring at each stage usually taking place in a single department, is completed before passing the developing product forward to the next stage	Departmental-stage models - departments or functional groups hold responsibility for various tasks carried out.	Likelihood that prototype differs from the accepted design. Likelihood prototype requires modification for manufacturing
	Activity-stage models - focus on actual activities carried out at each stage	Slow approach and minimal interaction between departments
	Decision-stage models - A series of evaluation points, where the decision to carry on or abandon the project is made	Critical departments have no input until later stages and important considerations may be omitted from the process
Parallel or Concurrent models		
Key Characteristics		Outcome
Models are also represented as sequential steps, but with most or some of the key steps occurring simultaneously or concurrently in a number of departments.	Integrated process model - The product development occurs simultaneously in multiple departments.	Integrated approach supports a faster and more efficient product development cycle and as the new product develops, the information gathered becomes more precise and reliable
	Multi-convergent model - Functionally distinct tasks which must be carried out at specific points will be carried out simultaneously at some juncture and the results must converge.	Allows for continuous exchange of information and responsibility among the many departments involved
		Manufacturing play a larger role in helping to assure that a wide variety of external and internal design requirements are considered

3. Propositions

Proposition 1

The first sub-problem of developing a diagnostic tool to enable a manufacturing organisation to identify what NPI model they are using to introduce new products into their manufacturing process will be addressed by developing a logistic regression equation that is based on the key characteristics of the two NPI models summarised in table 1. The key characteristics of the two NPI models will be in the form of a questionnaire and the responses to these questions will be the independent variables to the logistic regression equation. The questionnaire, together the logistic regression equation will provide the diagnostic tool that can be used to identify what type of NPI model a manufacturing organisation is using to introduce new products into their process.

Proposition 2

The second sub-problem of illustrating the validation of the diagnostic tool on a manufacturing organisation will be addressed by using the questionnaire developed in proposition 1 and getting it completed by employees of Johnson Matthey's autocatalyst manufacturing division. The responses to the questionnaire will then be used in the logistic regression equation developed in proposition 1 and the output probability of the NPI model will be used to validate the diagnostic tool. In addition, the Number Cruncher Statistical System (NCSS) software package will be used to compute a logistic regression equation and the responses to the questionnaire are to be used as the empirical data for the NCSS logistic regression equation. The regression model equation developed in proposition 1 will then be compared to the NCSS logistic regression model.

4. RESEARCH METHODOLOGY

4.1. Method

The research is synthetic in nature and a developed questionnaire together with a proposed logistic regression equation provides the diagnostic tool that can be used to identify what type of NPI model a manufacturing organisation is using to introduce new products into their process.

4.2. The Research Questionnaire

Advantages of written questionnaires (Kirakowski 1997)

- The responses are gathered in a standardised way, so questionnaires are more objective
- Generally it is relatively quick to collect information using a questionnaire
- Potentially information can be collected from a large portion of a group

Disadvantages written questionnaires (Kirakowski 1997)

- Questionnaires are standardised so it is not possible to explain any points in the questions that participants might misinterpret
- Open-ended questions can generate large amounts of data that can take a long time to process and analyse
- Respondents may answer superficially especially if the questionnaire takes a long time to complete
- Respondents may not be willing to answer the questions. They might not wish to reveal the information or they might think that they will not benefit from responding.

The two broader models that are used in the NPI process are the Stage and Parallel models. The questions asked in the questionnaire were synthesised based on the key characteristics of the two NPI models used in the NPI process. Table 1 shows the summary of the key characteristics of the two broad NPI models and the outcomes column was used as the baseline in defining the questions in the questionnaire.

The first seven questions of the questionnaire are based on the key characteristics of the two NPI model, viz. stage and parallel. Questions 1, 3 and 6 are based on the characteristics of the parallel model while questions 2, 4, 5 and 7 are based on the characteristics of the stage model. Question 8 asked the respondent to define what type of NPI model he/she believes their organisation is using in their NPI process, viz. stage or parallel model.

There was some attention given to the way the questions were worded in the questionnaire. The questions were intended to be uncomplicated and user friendly and were arranged randomly so that they do not lead the respondent towards a certain flow or pattern of thinking. The questions were phrased to prompt the respondents to respond based on their individual experience. The responses are mutually exclusive and only one tick is required for each question. Each question was scored on a scale of 1 to 10 with a score of 1 representing “NO” as an answer and 10 representing “YES” as an answer.

Figure 6 shows the questions (based on the characteristics of the two NPI models) that were used in the questionnaire that was used to collect the empirical data for illustrating and validating the diagnostic tool.

- 1 In your experience of your organisation's NPI process, does manufacturing/operations play a large role in helping to assure that external and internal design requirements are considered?

No									Yes
1	2	3	4	5	6	7	8	9	10

- 2 In your experience of your organisation's NPI process, do prototype samples sometimes differ from the original accepted design?

No									Yes
1	2	3	4	5	6	7	8	9	10

- 3 In your experience of your organisation's NPI process, does the information become more precise and reliable as the new product is developed and introduced?

No									Yes
1	2	3	4	5	6	7	8	9	10

- 4 In your experience of your organisation's NPI process, is there minimal interaction between the various departments/areas involved?

No									Yes
1	2	3	4	5	6	7	8	9	10

- 5 In your experience of your organisation's NPI process, do critical departments have minimal input until later stages and therefore important considerations are omitted?

No									Yes
1	2	3	4	5	6	7	8	9	10

- 6 In your experience of your organisation's NPI process, does the process allow for the continuous exchange of information and responsibility among the departments involved?

No									Yes
1	2	3	4	5	6	7	8	9	10

- 7 In your experience of your organisation's NPI process, do the prototype samples sometimes require modification for manufacturing?

No									Yes
1	2	3	4	5	6	7	8	9	10

- 8 In your experience of your organisation's NPI process, which model below best describes your NPI process?

(a). The product moves sequentially through a series of defined stages. The processes occurring at each stage takes place in a single department/area and is completed before passed forward to the next stage
(b). The NPI process is represented as sequential steps, But most or some of the key steps occur simultaneously or concurrently within departments.

Figure 6: Questionnaire used to collect the independent variable values for the diagnostic tool and the empirical data for the NCSS logistic regression model

4.3. Population and Sample

Johnson Matthey is a large multinational public limited company listed on the London Stock Exchange. The group's principal activities are the manufacture of autocatalysts, heavy duty diesel catalysts & pollution control systems, catalysts & components for fuel cells, catalysts & technologies for chemical processes, active pharmaceutical ingredients and the marketing, refining, and fabrication of precious metals.

The autocatalyst division has five R&D centres located in the United States, United Kingdom, Sweden, Japan and Brazil and ten autocatalyst manufacturing facilities located in United States, United Kingdom, Belgium, Mexico, Argentina, South Africa, Japan, Malaysia, India and China.

With the continuous tightening of emissions control legislation, car companies are constantly under pressure to design engine systems that meet allowable emissions. The autocatalyst market is therefore customer, technology and legislatively driven and Johnson Matthey invests large amounts of capital into the research and development of designing new and improved catalyst technologies.

The population will be drawn from Johnson Matthey's autocatalyst business' manufacturing and R&D facilities that fall under the European region. Two autocatalyst manufacturing sites (South Africa and United Kingdom) were targeted for this research report. The researcher is working within the European regional group, and therefore, access and cooperation was expected to be relatively unproblematic and unrestricted, thus facilitating the data collection method and a good response rate.

A purposive sampling method was used in order to attempt to gain a cross-section of key participants in Johnson Matthey's autocatalyst NPI process. The participants represent the four broad functional groups within the NPI process, viz. Product design; Sales & Marketing; Process scale-up & Engineering; Manufacturing & Operations.

As shown in table 2, the sample population that was requested to participate in the study comprised of 80 participants in total. The researcher is known to most of the sample population and has a good working and professional relationship with at least half of them. Therefore a minimum response rate of at least 60% was expected. The actual number of participants that responded to the questionnaire was 56 giving a response rate of 75%.

Table 2: Sample population and response rate

Functional NPI Group/Area	Requested Participants			Responded Participants	
	South Africa	United Kingdom		South Africa	United Kingdom
Product Design	0	10		0	4
Sales & Marketing	4	8		2	6
Process Scale up & engineering	12	10		8	7
Manufacturing & Operations	22	14		19	10
Total	80			56	

4.4. Validity and Reliability of the Questionnaire

A questionnaire that has been designed needs to be valid so that it measures what it claims to measure and reliable so that it yields consistent results from repeated samples over time. It is recognised that this research report is context specific and the designed questionnaire might have poor external validity. However, in order to internally validate the questionnaire and establish its reliability, clarity and understanding, the questionnaire was piloted on a sample group of 3 Johnson Matthey employees.

4.5. Data Collection

All 80 candidates were contacted via Johnson Matthey's internal e-mailing system. The communication message on the cover e-mail gave the participants a brief background and an explanation to the purpose of the study. The questionnaire was attached as an excel file and the participants were requested to complete it and send it back via Johnson Matthey's internal e-mailing system. 56 of the 80 candidates responded (75% response rate) and table 3 provides the summary of the values of the responses to the questions from the 56 individual participants.

4.6. Logistic Regression Analysis

Logistic regression competes with discriminant analysis as a method for analysing discrete response variables. The current feeling among many statisticians is that logistic regression is more versatile and better suited for most situations than a discriminant analysis because it does not assume that the independent variables are normally distributed, as discriminant analysis does (Hintze 2007).

Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. Logistic regression is used for analysing problems and data in which there are one or more independent variables that determine an outcome which is a dichotomous variable (Hintze 2007).

Logistic regression is used for predicting the probability of occurrence of an event by fitting the data to a logistic curve. Like many forms of regression analysis, it makes use of several explanatory variables that may be either numerical or categorical.

The logistic function is as follows:

$$f(z) = 1 / 1 + e^{-z}$$

The variable z , is defined as follows:

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots \beta_k x_k,$$

Where,

β_0 is the intercept and $\beta_1, \beta_2, \beta_3, \dots$ are the regression coefficients of $x_1, x_2, x_3, \dots$ respectively.

The variable z represents the exposure to a set of risk factors, while $f(z)$ represents the probability of a particular outcome, given the set of risk factors. The logistic function is useful because it can take an input value from negative infinity to positive infinity, whereas the output is confined to values between 0 to 1 (Hintze 2007).

5. RESULTS

5.1. Questionnaire Response (independent variables)

Table 3: Summary of responses to questionnaire

Candidate	Q8	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	Parallel	8	3	5	4	7	7	6
2	Parallel	6	4	9	8	3	4	7
3	Stage	4	6	6	4	5	5	9
4	Parallel	4	2	8	7	4	8	4
5	Parallel	2	5	9	4	6	7	8
6	Parallel	6	3	8	3	6	9	3
7	Parallel	4	6	5	2	2	7	7
8	Parallel	6	4	6	4	3	6	8
9	Parallel	7	2	8	3	6	4	4
10	Parallel	3	3	7	2	2	3	6
11	Parallel	8	5	3	2	5	3	3
12	Parallel	3	3	6	7	6	6	2
13	Parallel	4	3	5	3	2	8	3
14	Parallel	7	4	9	7	7	7	9
15	Parallel	6	1	10	6	3	8	6
16	Parallel	4	2	8	4	2	6	4
17	Parallel	8	3	9	6	4	5	8
18	Parallel	7	5	3	5	7	8	7
19	Parallel	4	2	7	4	3	7	7
20	Parallel	6	5	8	3	3	6	6
21	Stage	7	3	7	8	8	7	7
22	Parallel	7	4	4	5	2	7	7
23	Parallel	3	3	6	3	7	6	8
24	Parallel	3	4	7	4	3	5	9
25	Parallel	8	2	5	2	6	8	5
26	Stage	4	7	8	7	7	5	8
27	Parallel	3	2	7	3	2	7	4
28	Parallel	5	3	7	4	3	8	4
29	Parallel	4	1	8	2	4	7	4
30	Parallel	9	4	8	3	5	4	7
31	Parallel	3	2	5	6	7	4	9
32	Parallel	7	3	8	1	4	8	4
33	Stage	4	3	5	6	8	7	6
34	Parallel	9	7	9	2	1	7	3
35	Parallel	3	3	8	4	2	3	8
36	Parallel	8	4	9	3	3	6	6
37	Stage	3	4	4	3	4	2	4
38	Parallel	4	2	8	5	7	7	7
39	Parallel	8	6	6	1	1	6	6
40	Parallel	7	3	7	4	3	4	7
41	Parallel	3	2	6	5	8	8	6
42	Parallel	4	4	9	3	7	4	4
43	Stage	4	3	7	7	3	7	5
44	Parallel	8	3	6	2	6	5	8
45	Parallel	7	1	8	2	3	6	9
46	Stage	2	7	4	4	3	4	7
47	Parallel	8	4	9	2	1	9	6
48	Parallel	7	2	5	3	4	9	3
49	Parallel	8	4	9	6	6	6	4
50	Parallel	4	3	8	7	2	6	3
51	Parallel	7	2	7	3	6	5	8
52	Parallel	6	1	8	2	4	7	9
53	Parallel	3	7	5	4	5	5	4
54	Parallel	8	3	9	2	1	4	6
55	Stage	6	6	6	7	8	3	8
56	Parallel	6	3	8	3	5	8	6

The questions in the questionnaire as shown in figure 6 summarises the key characteristic of the two broader NPI models, viz. stage and parallel. The individual responses of the 56 respondents to this questionnaire are summarised in table 3.

5.2. Defining the NPI Logistic Regression Equation

The goal of NPI logistic regression equation is to find a model that describes the relationship between the dichotomous dependent variable and the set of independent variables. The dependent variable (z) in this research is the type of NPI model (either parallel or stage which is asked in question 8 of the questionnaire) and the independent variables ($x_1, x_2, x_3 \dots x_7$) are the response values to the questions that are based on the key characteristic of the two models (questions 1 to 7 in the questionnaire).

Therefore, the logistic regression equation for the diagnostic tool used in this research will be as follows:

$$f(z) = 1 / 1 + e^{-z}$$

where, $f(z)$ is the probability of the type NPI model being a stage NPI model and,

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7,$$

The variable z , is determined by the above equation and $x_1, x_2, x_3 \dots x_7$ are the response values to the first 7 questions in the questionnaire. These independent variables will have a response value from 1 to 10. The intercept β_0 , and $\beta_1, \beta_2, \beta_3, \dots$, which are the regression coefficients of $x_1, x_2, x_3, \dots$ respectively, will be estimated in section 5.2.2.

The ideal response to the questions that are based on the key characteristics of the two NPI models is shown in table 4, where a response of 1 represents “NO” as an answer and 10 represents “YES” as an answer.

Table 4: The ideal response to the questionnaire for a stage and parallel model

		QUESTION						
		1	2	3	4	5	6	7
MODEL	Parallel	10	1	10	1	1	10	1
	Stage	1	10	1	10	10	1	10

5.2.1. Determining the value of the variable z

For the logistic function $f(z) = 1 / 1 + e^{-z}$ to be 1 (or 100%) for either of the two NPI models, the value of z must be greater than or equal to 12.3. This value of z was determined by substituting various values for z in $f(z) = 1 / 1 + e^{-z}$. Table 5 shows the values of f(z) for varying points of z and highlights the point at which a value of z equal to 12.3 gives a probability of 1 (or 100%).

Table 5: Values of f(z) for varying z

z	f(z)
0.0	50.000
1.0	73.106
2.0	88.080
3.0	95.257
4.0	98.201
5.0	99.331
6.0	99.753
7.0	99.909
8.0	99.966
9.0	99.988
10.0	99.995
11.0	99.998
12.0	99.999
13.0	100.000
14.0	100.000
15.0	100.000

z	f(z)
12.0	99.999
12.1	99.999
12.2	99.999
12.3	100.000
12.4	100.000
12.5	100.000
12.6	100.000
12.7	100.000
12.8	100.000
12.9	100.000
13.0	100.000

5.2.2. Estimation of Regression Coefficients (β)

The first seven questions of the questionnaire are based on the key characteristics of the two NPI model, viz, stage and parallel. Questions 1, 3 and 6 are based on the characteristics of the parallel model and questions 2, 4, 5 and 7 are based on the characteristics of the stage model.

If the probability function $f(z)$ is defined to determine the probability of the NPI model being the stage NPI model, then $\beta_2, \beta_4, \beta_5$ and β_7 will need to be positive and β_1, β_3 and β_6 will need to be negative. The inverse is true for when the probability function $f(z)$ is defined to determine the probability of the NPI model being the parallel NPI model. The intercept, β_0 will be made equal to zero for the NPI logistic regression model, as $z = 0$ gives a 50% probability for either NPI model, thus making the intercept non-biased to the stage or parallel NPI model.

The sum of the regression coefficients that determine the probability of the stage model (β_{stage}) will be made equal but negative to the sum of the regression coefficients that determine the probability of the parallel model (β_{parallel}). This constraint has been made to ensure that the proposed logistic regression equation that is developed is not biased towards any particular NPI model given a set of independent variable.

Therefore,

$$\beta_{\text{stage}} = - \beta_{\text{parallel}}$$

or,

$$(\beta_2 + \beta_4 + \beta_5 + \beta_7) = - (\beta_1 + \beta_3 + \beta_6)$$

Using the ideal response to the questionnaire for a stage and parallel model shown in table 4, the spreadsheet in figure 7, was created to establish a value for β_{stage} and β_{parallel} that computes a variable z value of greater than or equal to 12.3. The weighting of the regression coefficients for each of the β_{models} (β_2 , β_4 , β_5 and β_7) and (β_1 , β_3 and β_6) were kept equal for this exercise.

Therefore,

$$\beta_2 = \beta_4 = \beta_5 = \beta_7$$

and,

$$\beta_1 = \beta_3 = \beta_6$$

The spreadsheet shows that a β_{stage} of 1.4 and a β_{parallel} of -1.4 gave a variable z value of 12.6 with a corresponding $f(z)$ of 100% when using the ideal stage model responses as input for the independent variables, and a variable z value of -12.6 with a corresponding $f(z)$ of 0% when using the ideal parallel model responses as input for the independent variables.

Therefore,

$$(\beta_2 + \beta_4 + \beta_5 + \beta_7) = 1.4$$

and,

$$(\beta_1, \beta_3 \text{ and } \beta_6) = -1.4$$

Question		1	2	3	4	5	6	7				
Parallel		10	1	10	1	1	10	1				
Stage		1	10	1	10	10	1	10				

Question	Sum of β	1.0	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0
	Weight equal	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	β_2	0.2500	0.2750	0.3000	0.3250	0.3500	0.3750	0.4000	0.4250	0.4500	0.4750	0.5000
	β_4	0.2500	0.2750	0.3000	0.3250	0.3500	0.3750	0.4000	0.4250	0.4500	0.4750	0.5000
	β_5	0.2500	0.2750	0.3000	0.3250	0.3500	0.3750	0.4000	0.4250	0.4500	0.4750	0.5000
	β_7	0.2500	0.2750	0.3000	0.3250	0.3500	0.3750	0.4000	0.4250	0.4500	0.4750	0.5000
Check		1.0000	1.1000	1.2000	1.3000	1.4000	1.5000	1.6000	1.7000	1.8000	1.9000	2.0000

Question	Sum of β	-1.0	-1.1	-1.2	-1.3	-1.4	-1.5	-1.6	-1.7	-1.8	-1.9	-2.0
	Weight equal	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	β_1	-0.3333	-0.3667	-0.4000	-0.4333	-0.4667	-0.5000	-0.5333	-0.5667	-0.6000	-0.6333	-0.6667
	β_6	-0.3333	-0.3667	-0.4000	-0.4333	-0.4667	-0.5000	-0.5333	-0.5667	-0.6000	-0.6333	-0.6667
	β_3	-0.3333	-0.3667	-0.4000	-0.4333	-0.4667	-0.5000	-0.5333	-0.5667	-0.6000	-0.6333	-0.6667
	Check	-1.0000	-1.1000	-1.2000	-1.3000	-1.4000	-1.5000	-1.6000	-1.7000	-1.8000	-1.9000	-2.0000

Ideal STAGE resoponse	Z	9	9.9	10.8	11.7	12.6	13.5	14.4	15.3	16.2	17.1	18
	f(z)	99.988	99.995	99.998	99.999	100.000	100.000	100.000	100.000	100.000	100.000	100.000

Ideal PARALLEL resoponse	Z	-9	-9.9	-10.8	-11.7	-12.6	-13.5	-14.4	-15.3	-16.2	-17.1	-18
	f(z)	0.012	0.005	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Figure 7: Determining β_{stage} and $-\beta_{parallel}$ values (equal weighing) to give z variable greater than 12.3.

However, it is unlikely that the regression coefficients for each of the β_{models} have an equal weighting as the key characteristic outputs defined in table 1 have varying influence and impact on the NPI process. Therefore some regression coefficients will have more influence and impact on the probability of a particular model than other regression coefficients.

Based on the literature review, the summary of the key characteristics, and the researcher's personal experience of the NPI process, the following assumptions and constraints have been made on the ranking of regression coefficients for each of the β_{models} .

For β_{stage} , $\beta_7 > \beta_5 > \beta_4 > \beta_2$

and,

For $\beta_{parallel}$, $\beta_3 > \beta_6 > \beta_1$

Even with this assumption and hence constraint on the regression coefficients, there are still numerous possible values and combination of values for the regression coefficients. For this research, it has been assumed that the difference between the regression coefficients is a fixed value and a 10% weighting difference based on the sum of regression coefficients is used for this difference. i.e. If the sum of the regression coefficients is 1.4, then a 10% difference value equal to 0.14 is applied between the regression coefficients.

Therefore,

$$\beta_{\text{stage}} = \beta_2 + \beta_4 + \beta_5 + \beta_7$$

and the difference between regression coefficients = $0.1 \beta_{\text{stage}}$

$$\beta_7 - \beta_5 = \beta_5 - \beta_4 = \beta_4 - \beta_2 = 0.1 \times \beta_{\text{stage}}$$

and,

$$\beta_{\text{parallel}} = \beta_1 + \beta_3 + \beta_6$$

and the difference between regression coefficients = $0.1 \beta_{\text{parallel}}$

$$\beta_3 - \beta_6 = \beta_6 - \beta_1 = 0.1 \times \beta_{\text{parallel}}$$

Using the ideal response to the questionnaire for a stage and parallel model shown in table 4, the spreadsheet in figure 8, was created to establish a value for β_{stage} and β_{parallel} that computes a variable z value of greater than or equal to 12.3 (with 10% difference between regression coefficients).

Question		1	2	3	4	5	6	7				
Parallel		10	1	10	1	1	10	1				
Stage		1	10	1	10	10	1	10				

Question	Sum of β	1.0	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0
	Weight (2.5%)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
	β_2	0.1000	0.1100	0.1200	0.1300	0.1400	0.1500	0.1600	0.1700	0.1800	0.1900	0.2000
	β_4	0.2000	0.2200	0.2400	0.2600	0.2800	0.3000	0.3200	0.3400	0.3600	0.3800	0.4000
	β_5	0.3000	0.3300	0.3600	0.3900	0.4200	0.4500	0.4800	0.5100	0.5400	0.5700	0.6000
	β_7	0.4000	0.4400	0.4800	0.5200	0.5600	0.6000	0.6400	0.6800	0.7200	0.7600	0.8000
Check		1.0000	1.1000	1.2000	1.3000	1.4000	1.5000	1.6000	1.7000	1.8000	1.9000	2.0000

Question	Sum of β	-1.0	-1.1	-1.2	-1.3	-1.4	-1.5	-1.6	-1.7	-1.8	-1.9	-2.0
	Weight (2.5%)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
	β_1	-0.2333	-0.2567	-0.2800	-0.3033	-0.3267	-0.3500	-0.3733	-0.3967	-0.4200	-0.4433	-0.4667
	β_6	-0.3333	-0.3667	-0.4000	-0.4333	-0.4667	-0.5000	-0.5333	-0.5667	-0.6000	-0.6333	-0.6667
	β_3	-0.4333	-0.4767	-0.5200	-0.5633	-0.6067	-0.6500	-0.6933	-0.7367	-0.7800	-0.8233	-0.8667
	Check	-1.0000	-1.1000	-1.2000	-1.3000	-1.4000	-1.5000	-1.6000	-1.7000	-1.8000	-1.9000	-2.0000

Ideal STAGE response	Z	9	9.9	10.8	11.7	12.6	13.5	14.4	15.3	16.2	17.1	18
	f(z)	99.988	99.995	99.998	99.999	100.000	100.000	100.000	100.000	100.000	100.000	100.000

Ideal PARALLEL response	Z	-9	-9.9	-10.8	-11.7	-12.6	-13.5	-14.4	-15.3	-16.2	-17.1	-18
	f(z)	0.012	0.005	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Figure 8: Determining β_{stage} and $-\beta_{parallel}$ values (10% weighting for difference between regression coefficients) to give z variable greater than 12.3.

As expected, the spreadsheet shows that a β_{stage} of 1.4 and a $\beta_{parallel}$ of -1.4 gave a variable z value of 12.6 with a corresponding f(z) of 100% when using the ideal stage model responses as input for the independent variables, and a variable z value of -12.6 with a corresponding f(z) of 0% when using the ideal parallel model responses as input for the independent variables.

However, as shown in figure 8, the regression coefficients are not kept equal but have been assumed to have a fixed difference between them based on 10% of the sum of the regression coefficients. Based on the above constraint and assumption, table 6 shows the regression coefficients that will be used in the proposed NPI logistic regression equation.

Table 6: Regression coefficient values for logistic regression equation

β_1	-0.3267
β_2	0.1400
β_3	-0.6067
β_4	0.2800
β_5	0.4200
β_6	-0.4667
β_7	0.5600

5.2.3. Proposed NPI Logistic Regression Equation

The following logistic regression equation is proposed to be used to predict the probability of what type of NPI model a manufacturing organisation is using to introduce new products into their process.

$$z = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7,$$

where,

$$\beta_1 = -0.3267$$

$$\beta_2 = 0.1400$$

$$\beta_3 = -0.6067$$

$$\beta_4 = 0.2800$$

$$\beta_5 = 0.4200$$

$$\beta_6 = -0.4667$$

$$\beta_7 = 0.5600$$

and,

$x_1, x_2, x_3 \dots x_7$ are the response values to the first 7 questions in the questionnaire defined in 4.2.

5.3. The Diagnostic Tool

The questionnaire (figure 6), together with the proposed NPI logistic regression equation (5.2.3) provides the diagnostic tool that can be used to identify what type of NPI model a manufacturing organisation is using to introduce new products into their process.

For illustrating the validation of the defined diagnostic tool, the output dependent variable from the equation, which estimates the probability of the type of model (either parallel or stage), was then compared to the response to question 8, which requests the respondents' view on the type of model been used by Johnson Matthey. The 56 responses to the questionnaire were used as the independent variables into the logistic regression equation (questions 1 to 7 in the questionnaire).

5.4. NCSS Logistic Regression Equation

A logistic regression analysis was carried out on the responses to the questionnaire (summarised in table 3) using the Number Cruncher Statistical System (NCSS) software package. The full NCSS logistic regression output report is shown in appendix 2. The NCSS logistic regression report gave regression coefficients as shown in table 7:

Table 7: Regression coefficient values for NCSS logistic regression equation

β_1	-0.4542
β_2	0.4262
β_3	-0.8155
β_4	1.0527
β_5	0.0737
β_6	-0.4827
β_7	0.1515

The NCSS software package used to compute a logistic regression equation produced the following regression equation.

$$z = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + B_7 x_7,$$

where,

$$\beta_1 = -0.4542$$

$$\beta_2 = 0.4262$$

$$\beta_3 = -0.8155$$

$$\beta_4 = 1.0527$$

$$\beta_5 = 0.0737$$

$$\beta_6 = -0.4827$$

$$B_7 = 0.1515$$

and,

$x_1, x_2, x_3 \dots x_7$ are the response values to the first 7 questions in the questionnaire defined in 4.2.

Using the ideal response to the questionnaire for a stage and parallel model shown in table 4 and the above NCSS logistic regression equation, the spreadsheet in figure 9 was created to calculate the value of variable z and the probability $f(z)$ for the type NPI model being used.

The NCSS logistic regression equation gives a $f(z)$ probability of 100% for the stage NPI model (corresponding z value = 15.28) when using the ideal stage model independent variable values. The sum of β_{stage} is equal to 1.7042. The NCSS regression model also gives a $f(z)$ probability of 0% for the stage NPI model (corresponding z value = 15.819)

when using the ideal parallel model independent variable values. The sum of β_{parallel} is equal to 1.7523

Question	1	2	3	4	5	6	7
Parallel	10	1	10	1	1	10	1
Stage	1	10	1	10	10	1	10

β_2	0.4262
β_4	1.0527
β_5	0.0737
β_7	0.1515
Sum of β stage	1.7042

β_1	-0.4542
β_6	-0.4827
β_3	-0.8155
Sum of β_{parallel}	-1.7523

Ideal STAGE response	z	15.2894
	f(z)	100.000

Ideal PARALLEL response	z	-15.819
	f(z)	0.000

Figure 9: Determining z and f(z) when ideal responses used in the NCSS logistic regression equation

5.5. Validation of the Diagnostic Tool

5.5.1. Illustration of Diagnostic tool

For illustrating the validation of the diagnostic tool defined in 5.2., the output dependent variable from the equation which estimates the probability of the type of model (either parallel or stage), was compared to the response to question 8, which requests the respondents' view on the type of model been used by Johnson Matthey. The summary of the questionnaire response values of the 56 respondents and the

variable z together with a corresponding output probability $f(z)$ is shown in table 11 of appendix 1.

Table 8: Diagnostic Tool output compared to actual response for NPI model

Diagnostic Tool output				
Response	No of candidates	Prob > 50%	Prob < 50%	Response vs Model output
Stage	8	7	1	87.5%
Parallel	48	42	6	87.5%

Table 8 shows that from the 56 respondents that completed the questionnaire, only 8 respondents stated that Johnson Matthey utilises a stage model approach in their NPI process while the remaining 48 stated that Johnson Matthey utilises a parallel model approach in their NPI process. When the responses to the questions for the 8 stage model respondents (independent variables, $x_1, x_2, x_3 \dots x_7$) were substituted into the proposed logistic regression equation, the output probability $f(z)$ for 7 out of the 8 responses (87.5%) were calculated to be >50% for a stage NPI model.

From the 56 respondents that completed the questionnaire, 48 respondents felt that Johnson Matthey utilises a parallel model approach in their NPI process. When the responses to the questions for the 48 parallel model respondents (independent variables, $x_1, x_2, x_3 \dots x_7$) were substituted into the proposed logistic regression equation, the output probability $f(z)$ for 42 out of the 48 responses (87.5%) were calculated to be >50% for a parallel NPI model.

Table 9 summarises the average NPI model probability for each set of respondents. For the 8 respondents that felt that Johnson Matthey utilises a stage model approach

in their NPI process, the proposed NPI logistic regression equation calculates an average NPI model probability of 71.6% for a stage model. For the 48 respondents that felt that Johnson Matthey utilises a parallel model approach in their NPI process, the logistic regression equation calculates an average NPI model probability of 81.0% for a parallel model.

Table 9: Average NPI model probability for each set of respondents

Average output f(z) probability for each model			
Response	No of candidates	Stage model probability	Parallel model probability
Stage	8	71.6%	28.4%
Parallel	48	19.0%	81.0%

5.5.2. Comparison to NCSS Logistic Regression Equation

The regression coefficients for the proposed NPI logistic regression equation and the NCSS logistic regression equation are tabulated in table 10.

Table 10: Regression coefficients for the two logistic regression equations

Coefficients	Research Logistic Regression	NCSS Logistic Regression
β_1	-0.3267	-0.4542
β_2	0.1400	0.4262
β_3	-0.6067	-0.8155
β_4	0.2800	1.0527
β_5	0.4200	0.0737
β_6	-0.4667	-0.4827
β_7	0.5600	0.1515
β_{stage}	1.4000	1.7042
β_{parallel}	-1.4000	-1.7523

Comparison of the regression coefficients shows that for both of the logistic regression equations, $\beta_1, \beta_3, \beta_6$ (β_{parallel}) are all negative and $\beta_2, \beta_4, \beta_5, \beta_7$ (β_{stage}) are all positive. This confirms that the questions in the questionnaire are based on the key characteristics of the stage and parallel NPI models as summarised in table 1.

In the proposed NPI logistic regression equation the following assumption was made for the ranking of the regression coefficients:

For β_{stage} , $\beta_7 > \beta_5 > \beta_4 > \beta_2$

and,

For β_{parallel} , $\beta_3 > \beta_6 > \beta_1$

The NCSS logistic regression equation output report gave the following ranking for the regression coefficients

For β_{stage} , $\beta_4 > \beta_2 > \beta_7 > \beta_5$

and,

For β_{parallel} , $\beta_3 > \beta_6 > \beta_1$

For the parallel model independent variables (questions 1, 3 and 6), there is a good match between the assumed ranking of the NPI regression coefficients and the NCSS logistic regression coefficients. However, for the stage model independent variables (questions 2, 4, 5 and 7), there is a mismatch between the assumed ranking of the NPI regression coefficients and the NCSS logistic regression coefficients. Based on the regression analysis of the empirical data using NCSS, the key characteristics of questions 4 and 2 have greater influence and impact on the NPI process than questions 7 and 5, whereas for the proposed NPI logistic regression equation, it is assumed that question 7 and 5 have greater influence and impact on the NPI process than questions 4 and 2.

For the NCSS logistic regression equation output, β_{stage} (1.7042) $\neq$ $-\beta_{\text{parallel}}$ (-1.7523) and $-\beta_{\text{parallel}} > \beta_{\text{stage}}$, where as for the developed logistic regression equation the following assumption and constraint that $\beta_{\text{stage}} = -\beta_{\text{parallel}}$ was made to ensure that the developed logistic regression equation is not biased towards any particular NPI model given a set of independent variable. This therefore implies that the NCSS logistic regression equation is biased towards the parallel NPI model. This bias could be as a result of the fact that 48 out of the 56 (86%) respondents felt that Johnson Matthey utilises a parallel model approach in their NPI process.

6. SUMMARY AND CONCLUSION

It is important for organisations to be able to identify both what activities are present in a particular NPI model and what activities should be present (Fairlie-Clarke and Muller 2003). By establishing what type of NPI model they are using, a manufacturing organisation will be able to highlight which areas and activities of their NPI process that can to be improved upon.

There are two broader types of models that are used in the NPI process and these are the Stage and Parallel models. The Stage models move in sequential steps, while the Parallel models have some or most of the key steps occurring concurrently.

The key characteristics of the stage model are as follows:

- Likelihood that prototype differs from the original accepted design.
- Likelihood prototype requires modification for manufacturing
- Slow approach and minimal interaction between departments
- Critical departments have no input until later stages

The key characteristics of the Parallel model are as follows:

- The information gathered becomes more precise and reliable
- Allows for continuous exchange of information and responsibility
- Manufacturing play a large role

Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. Logistic regression analysis

is used for predicting the probability of occurrence of an event by fitting the data to a logistic curve. A questionnaire was generated using the key characteristics of the two NPI models and the empirical data from the responses is used as the independent variables to the logistic regression equation. Using the logistic regression analysis theory, the following logistic regression equation was developed to predict the NPI model.

$$z = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + B_7 x_7,$$

where,

$$\beta_1 = -0.4542$$

$$\beta_2 = 0.4262$$

$$\beta_3 = -0.8155$$

$$\beta_4 = 1.0527$$

$$\beta_5 = 0.0737$$

$$\beta_6 = -0.4827$$

$$B_7 = 0.1515$$

and,

$x_1, x_2, x_3 \dots x_7$ are the response values to the first 7 questions in the questionnaire defined in 4.2.

The questionnaire, together the logistic regression equation will provide the diagnostic tool that can be used to identify what type of NPI model a manufacturing organisation is using to introduce new products into their process.

For illustrating the validation of the diagnostic tool, the output dependent variable from the equation which estimates the probability of the type of model (either parallel or stage), was compared to the response to question 8, which requests the respondents' view on the type of NPI model been used in their manufacturing organisation. There is an 87.5% agreement between the NPI model output of the proposed diagnostic tool and the respondents view on the type of NPI model being used by the manufacturing organisation.

The proposed NPI logistic regression equation calculates an average probability of 71.6% (for stage model) when using the responses of the 8 respondents that felt that Johnson Matthey utilises a stage model approach and in their NPI process, and an average probability of 81.0% (for parallel model) when using the responses of the 48 respondents that felt that Johnson Matthey utilises a parallel model approach and in their NPI process,.

The Number Cruncher Statistical System (NCSS) software package was used to compute a logistic regression equation. The responses to the questionnaire were used as the empirical data for the NCSS logistic regression equation and the regression model equation developed was then compared to the NCSS logistic regression model. The regression coefficients for NCSS logistic regression equation, β_1 , β_3 , β_6 (β_{parallel}) are all negative and β_2 , β_4 , β_5 , β_7 (β_{stage}) are all positive as defined in the NPI logistic regression equation. This confirms that if the probability function $f(z)$ is defined to determine the probability of the NPI model being the stage NPI model, then β_2 , β_4 , β_5 and β_7 will need to be positive and β_1 , β_3 and β_6 will need to be negative.

When comparing the ranking of the regression coefficients between the developed NPI regression equation and NCSS regression equation, there is a good match for the parallel independent variables (questions 1, 3 and 6) as $\beta_3 > \beta_6 > \beta_1$. However, for the stage independent variable (questions 2, 4, 5, 7), the assumed ranking in the developed NPI regression equation do not match with that of the coefficients from NCSS regression equation. This implies that the assumption made that the key characteristics of questions 7 and 5 have a greater influence than questions 4 and 2, will need to be reviewed and compared with additional empirical data analysis.

In conclusion, the developed research questionnaire together with its corresponding logistic regression equation provides a validated diagnostic tool that can be used to identify what type of NPI model a manufacturing organisation is using to introduce new products into their process.

7. FUTURE WORK AND RECOMENDATIONS

The diagnostic tool that has been developed in this research report can be further validated externally. The diagnostic tool can used to verify or confirm the NPI models of numerous other manufacturing organisations, both in the motor industry as well other manufacturing industries.

The 10% weighting on the differences between the regression coefficients, and the order of ranking of the regression coefficients are assumption that need further validation and optimisation. The additional empirical data that is gathered by sending out the questionnaire to other manufacturing firms will enable the researcher to validate or optimise the assumptions that have been made for the regression coefficients.

There is an option of increasing the scope of the diagnostic tool by including some demographics into the questionnaire and logistic regression equation. Some examples of the possible demographics include the functional groups of the population (viz. Product design & Development; Sales & Marketing; Process scale-up & Engineering; Manufacturing & Operations), the organisational hierarchy within each of the functional groups (viz. Senior/Executive management, Middle/Supervisory management, and Non-managerial) and the number of years of experience the respondent have with the organisation. These demographic variables can indicate a persons understanding of their business and NPI process and hence influence their response to the questions in the diagnostic tool.

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Appendix 1 – Output probability summary

Table 11: Summary of output probabilities $f(z)$ using the developed logistic regression equation

Candidate	Q8	Q1	Q2	Q3	Q4	Q5	Q6	Q7	z	f(z)
1	Parallel	8	3	5	4	7	7	6	-1.07	25.477
2	Parallel	6	4	9	8	3	4	7	-1.31	21.305
3	Stage	4	6	6	4	5	5	9	1.82	86.057
4	Parallel	4	2	8	7	4	8	4	-3.73	2.335
5	Parallel	2	5	9	4	6	7	8	-0.56	36.355
6	Parallel	6	3	8	3	6	9	3	-5.55	0.386
7	Parallel	4	6	5	2	2	7	7	-1.45	19.052
8	Parallel	6	4	6	4	3	6	8	-0.98	27.289
9	Parallel	7	2	8	3	6	4	4	-3.13	4.202
10	Parallel	3	3	7	2	2	3	6	-1.45	19.052
11	Parallel	8	5	3	2	5	3	3	-0.79	31.145
12	Parallel	3	3	6	7	6	6	2	-1.40	19.782
13	Parallel	4	3	5	3	2	8	3	-4.29	1.348
14	Parallel	7	4	9	7	7	7	9	-0.51	37.441
15	Parallel	6	1	10	6	3	8	6	-5.32	0.487
16	Parallel	4	2	8	4	2	6	4	-4.48	1.121
17	Parallel	8	3	9	6	4	5	8	-2.15	10.464
18	Parallel	7	5	3	5	7	8	7	1.12	75.399
19	Parallel	4	2	7	4	3	7	7	-2.24	9.622
20	Parallel	6	5	8	3	3	6	6	-3.45	3.067
21	Stage	7	3	7	8	8	7	7	0.14	53.494
22	Parallel	7	4	4	5	2	7	7	-1.26	22.097
23	Parallel	3	3	6	3	7	6	8	1.26	77.903
24	Parallel	3	4	7	4	3	5	9	0.42	60.348
25	Parallel	8	2	5	2	6	8	5	-3.22	3.842
26	Stage	4	7	8	7	7	5	8	1.87	86.607
27	Parallel	3	2	7	3	2	7	4	-4.29	1.348
28	Parallel	5	3	7	4	3	8	4	-4.57	1.022
29	Parallel	4	1	8	2	4	7	4	-4.81	0.811
30	Parallel	9	4	8	3	5	4	7	-2.24	9.622
31	Parallel	3	2	5	6	7	4	9	4.06	98.304
32	Parallel	7	3	8	1	4	8	4	-6.25	0.192
33	Stage	4	3	5	6	8	7	6	1.21	77.089
34	Parallel	9	7	9	2	1	7	3	-8.03	0.033
35	Parallel	3	3	8	4	2	3	8	-0.37	40.774
36	Parallel	8	4	9	3	3	6	6	-4.85	0.774
37	Stage	3	4	4	3	4	2	4	0.98	72.711
38	Parallel	4	2	8	5	7	7	7	-0.89	29.180
39	Parallel	8	6	6	1	1	6	6	-4.15	1.547
40	Parallel	7	3	7	4	3	4	7	-1.68	15.710
41	Parallel	3	2	6	5	8	8	6	0.05	51.166
42	Parallel	4	4	9	3	7	4	4	-2.05	11.372
43	Stage	4	3	7	7	3	7	5	-2.38	8.471
44	Parallel	8	3	6	2	6	5	8	-0.61	35.282
45	Parallel	7	1	8	2	3	6	9	-2.94	5.021
46	Stage	2	7	4	4	3	4	7	2.33	91.160
47	Parallel	8	4	9	2	1	9	6	-7.37	0.063
48	Parallel	7	2	5	3	4	9	3	-5.04	0.643
49	Parallel	8	4	9	6	6	6	4	-3.87	2.037
50	Parallel	4	3	8	7	2	6	3	-4.06	1.696
51	Parallel	7	2	7	3	6	5	8	-0.75	32.155
52	Parallel	6	1	8	2	4	7	9	-2.66	6.538
53	Parallel	3	7	5	4	5	5	4	0.09	52.332
54	Parallel	8	3	9	2	1	4	6	-5.18	0.560
55	Stage	6	6	6	7	8	3	8	3.64	97.442
56	Parallel	6	3	8	3	5	8	6	-3.83	2.132

Appendix 2 – Logistic Regression Report

Logistic Regression Report

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 Response Model

Run Summary Section

Parameter	Value	Parameter	Value
Dependent Variable	Model	Rows Processed	56
Reference Group	PARALLEL	Rows Used	56
Number of Groups	2	Rows for Validation	0
Frequency Variable	None	Rows X's Missing	0
Numeric Ind. Variables	7	Rows Freq Miss. or 0	0
Categorical Ind. Variables	0	Rows Prediction Only	0
Final Log Likelihood	-11.12500	Unique Row Patterns	56
Model R-Squared	0.51560	Sum of Frequencies	56
Actual Convergence	7.344146E-08	Likelihood Iterations	8
Target Convergence	0.000001	Maximum Iterations	20
Model D.F.	7	Max Like Message	Normal Completion

Question_1|Question_2|Question_3|Question_4|Question_5|Question_6|Question_7

Response Analysis Section

Model Categories	Count	Unique Rows	Prior	Act vs Pred R-Squared	% Correctly Classified
PARALLEL	48	48	0.85714	0.44668	93.750
STAGE	8	8	0.14286	0.44668	50.000
Total	56	56			87.500

Parameter Significance Tests Section (Reference Group: Model = PARALLEL)

Parameter	Regression Coefficient (B or Beta)	Standard Error	Wald Z-Value (Beta=0)	Wald Prob Level	Odds Ratio Exp(B)
B1: Question_1	-0.45415	0.35621	-1.275	0.20233	0.63499
B2: Question_2	0.42624	0.31451	1.355	0.17534	1.53149
B3: Question_3	-0.81545	0.41259	-1.976	0.04811	0.44244
B4: Question_4	1.05270	0.49258	2.137	0.03259	2.86538
B5: Question_5	0.07374	0.30214	0.244	0.80718	1.07653
B6: Question_6	-0.48273	0.34213	-1.411	0.15826	0.61710
B7: Question_7	0.15149	0.28901	0.524	0.60017	1.16356

Parameter Confidence Limits Section (Reference Group: Model = PARALLEL)

Parameter	Regression Coefficient (B or Beta)	Standard Error	Lower 95% Confidence Limit	Upper 95% Confidence Limit	Odds Ratio Exp(B)
B1: Question_1	-0.45415	0.35621	-1.15231	0.24401	0.63499
B2: Question_2	0.42624	0.31451	-0.19019	1.04267	1.53149
B3: Question_3	-0.81545	0.41259	-1.62412	-0.00678	0.44244
B4: Question_4	1.05270	0.49258	0.08726	2.01814	2.86538
B5: Question_5	0.07374	0.30214	-0.51844	0.66592	1.07653
B6: Question_6	-0.48273	0.34213	-1.15330	0.18784	0.61710
B7: Question_7	0.15149	0.28901	-0.41497	0.71794	1.16356

Logistic Regression Report

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 Response Model

Odds Ratios Section (Reference Group: Model = PARALLEL)

Parameter	Regression Coefficient (B or Beta)	Odds Ratio Exp(B)	Lower 95% Confidence Limit	Upper 95% Confidence Limit
B1: Question_1	-0.45415	0.63499	0.31591	1.27635
B2: Question_2	0.42624	1.53149	0.82680	2.83678
B3: Question_3	-0.81545	0.44244	0.19709	0.99325
B4: Question_4	1.05270	2.86538	1.09118	7.52431
B5: Question_5	0.07374	1.07653	0.59545	1.94629
B6: Question_6	-0.48273	0.61710	0.31559	1.20664
B7: Question_7	0.15149	1.16356	0.66036	2.05020

Estimated Logistic Regression Model(s)

Model For Model = STAGE

$-.454149824563577 * \text{Question_1} + .426240864193378 * \text{Question_2} - .815448667515254 * \text{Question_3} + 1.05269931740176 * \text{Question_4} + 7.37423607463672E-02 * \text{Question_5} - .482730742542898 * \text{Question_6} + .15148608528417 * \text{Question_7}$

Note that each model estimates B for a specific group, where $\text{Logit}(Y) = XB$.
 To calculate a probability, transform the logit using $\text{Prob}(Y \neq \text{group}) = 1/(1 + \exp(-XB))$
 or $\text{Prob}(Y = \text{group}) = \exp(-XB)/(1 + \exp(-XB))$.

Transformation Note:

Regular transformations must be less the 255 characters. If this expression is longer the 255 characters, copy this expression and paste it into a text file, then use the transformation FILE(filename.txt) to access the text file.

Analysis of Deviance Section

Term	DF	Deviance	Increase From Model Deviance (Chi Square)	Prob Level
Omitted				
Question_1	1	24.46544	2.21544	0.13664
Question_2	1	24.26272	2.01271	0.15599
Question_3	1	28.01627	5.76627	0.01634
Question_4	1	29.79583	7.54582	0.00601
Question_5	1	22.30991	0.05991	0.80664
Question_6	1	24.63695	2.38695	0.12235
Question_7	1	22.53775	0.28775	0.59167
None(Model)	7	22.25000		

The Prob Level is for testing the significance of that term after considering all other terms.

Logistic Regression Report

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 Response Model

Log Likelihood & R-Squared Section

Term(s) Omitted	DF	Log Likelihood	R-Squared of Remaining Term(s)	Reduction From Model R-Squared	Reduction From Saturated R-Squared
Question_1	1	-12.23272	0.46737	0.04823	0.53263
Question_2	1	-12.13136	0.47178	0.04382	0.52822
Question_3	1	-14.00814	0.39006	0.12554	0.60994
Question_4	1	-14.89791	0.35132	0.16428	0.64868
Question_5	1	-11.15496	0.51429	0.00130	0.48571
Question_6	1	-12.31848	0.46363	0.05197	0.53637
Question_7	1	-11.26888	0.50933	0.00626	0.49067
None(Model)	6	-11.12500	0.51560	0.00000	0.48440
None(Saturated)	56	0.00000	1.00000		0.00000

R-Squared is not defined when the intercept is not included in the model.

Classification Table

Actual	Estimated PARALLEL	STAGE	Total
PARALLEL	45	3	48
STAGE	4	4	8
Total	49	7	56

Percent Correctly classified = 87.5%

Logistic Regression Report

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 Response Model

ROC Section for Value PARALLEL

Prob Cutoff	N(1 1) A	N(1 0) B	N(0 1) C	N(0 0) D	Sensitivity A/(A+C)	Specificity D/(B+D)	Sensitivity +Specificity	Proportion Correct
0.02500	48	8	0	0	1.00000	0.00000	1.00000	0.85714
0.05000	48	8	0	0	1.00000	0.00000	1.00000	0.85714
0.07500	48	7	0	1	1.00000	0.12500	1.12500	0.87500
0.10000	48	6	0	2	1.00000	0.25000	1.25000	0.89286
0.12500	48	6	0	2	1.00000	0.25000	1.25000	0.89286
0.15000	48	6	0	2	1.00000	0.25000	1.25000	0.89286
0.17500	47	6	1	2	0.97917	0.25000	1.22917	0.87500
0.20000	47	6	1	2	0.97917	0.25000	1.22917	0.87500
0.22500	47	5	1	3	0.97917	0.37500	1.35417	0.89286
0.25000	47	5	1	3	0.97917	0.37500	1.35417	0.89286
0.27500	47	5	1	3	0.97917	0.37500	1.35417	0.89286
0.30000	47	5	1	3	0.97917	0.37500	1.35417	0.89286
0.32500	47	5	1	3	0.97917	0.37500	1.35417	0.89286
0.35000	47	5	1	3	0.97917	0.37500	1.35417	0.89286
0.37500	47	5	1	3	0.97917	0.37500	1.35417	0.89286
0.40000	47	5	1	3	0.97917	0.37500	1.35417	0.89286
0.42500	46	5	2	3	0.95833	0.37500	1.33333	0.87500
0.45000	45	5	3	3	0.93750	0.37500	1.31250	0.85714
0.47500	45	4	3	4	0.93750	0.50000	1.43750	0.87500
0.50000	45	4	3	4	0.93750	0.50000	1.43750	0.87500
0.52500	45	4	3	4	0.93750	0.50000	1.43750	0.87500
0.55000	45	3	3	5	0.93750	0.62500	1.56250	0.89286
0.57500	45	3	3	5	0.93750	0.62500	1.56250	0.89286
0.60000	45	3	3	5	0.93750	0.62500	1.56250	0.89286
0.62500	45	3	3	5	0.93750	0.62500	1.56250	0.89286
0.65000	43	3	5	5	0.89583	0.62500	1.52083	0.85714
0.67500	43	2	5	6	0.89583	0.75000	1.64583	0.87500
0.70000	43	2	5	6	0.89583	0.75000	1.64583	0.87500
0.72500	43	1	5	7	0.89583	0.87500	1.77083	0.89286
0.75000	43	1	5	7	0.89583	0.87500	1.77083	0.89286
0.77500	43	1	5	7	0.89583	0.87500	1.77083	0.89286
0.80000	43	0	5	8	0.89583	1.00000	1.89583	0.91071
0.82500	43	0	5	8	0.89583	1.00000	1.89583	0.91071
0.85000	42	0	6	8	0.87500	1.00000	1.87500	0.89286
0.87500	42	0	6	8	0.87500	1.00000	1.87500	0.89286
0.90000	40	0	8	8	0.83333	1.00000	1.83333	0.85714
0.92500	37	0	11	8	0.77083	1.00000	1.77083	0.80357
0.95000	36	0	12	8	0.75000	1.00000	1.75000	0.78571
0.97500	31	0	17	8	0.64583	1.00000	1.64583	0.69643

Area Under ROC Curve = 0.94271

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ROC Section for Value STAGE

Prob Cutoff	N(1 1) A	N(1 0) B	N(0 1) C	N(0 0) D	Sensitivity A/(A+C)	Specificity D/(B+D)	Sensitivity +Specificity	Proportion Correct
0.02500	8	17	0	31	1.00000	0.64583	1.64583	0.69643
0.05000	8	12	0	36	1.00000	0.75000	1.75000	0.78571
0.07500	8	11	0	37	1.00000	0.77083	1.77083	0.80357
0.10000	8	8	0	40	1.00000	0.83333	1.83333	0.85714
0.12500	8	6	0	42	1.00000	0.87500	1.87500	0.89286
0.15000	8	6	0	42	1.00000	0.87500	1.87500	0.89286
0.17500	8	5	0	43	1.00000	0.89583	1.89583	0.91071
0.20000	8	5	0	43	1.00000	0.89583	1.89583	0.91071
0.22500	7	5	1	43	0.87500	0.89583	1.77083	0.89286
0.25000	7	5	1	43	0.87500	0.89583	1.77083	0.89286
0.27500	7	5	1	43	0.87500	0.89583	1.77083	0.89286
0.30000	6	5	2	43	0.75000	0.89583	1.64583	0.87500
0.32500	6	5	2	43	0.75000	0.89583	1.64583	0.87500
0.35000	5	5	3	43	0.62500	0.89583	1.52083	0.85714
0.37500	5	3	3	45	0.62500	0.93750	1.56250	0.89286
0.40000	5	3	3	45	0.62500	0.93750	1.56250	0.89286
0.42500	5	3	3	45	0.62500	0.93750	1.56250	0.89286
0.45000	5	3	3	45	0.62500	0.93750	1.56250	0.89286
0.47500	4	3	4	45	0.50000	0.93750	1.43750	0.87500
0.50000	4	3	4	45	0.50000	0.93750	1.43750	0.87500
0.52500	4	3	4	45	0.50000	0.93750	1.43750	0.87500
0.55000	3	3	5	45	0.37500	0.93750	1.31250	0.85714
0.57500	3	2	5	46	0.37500	0.95833	1.33333	0.87500
0.60000	3	1	5	47	0.37500	0.97917	1.35417	0.89286
0.62500	3	1	5	47	0.37500	0.97917	1.35417	0.89286
0.65000	3	1	5	47	0.37500	0.97917	1.35417	0.89286
0.67500	3	1	5	47	0.37500	0.97917	1.35417	0.89286
0.70000	3	1	5	47	0.37500	0.97917	1.35417	0.89286
0.72500	3	1	5	47	0.37500	0.97917	1.35417	0.89286
0.75000	3	1	5	47	0.37500	0.97917	1.35417	0.89286
0.77500	3	1	5	47	0.37500	0.97917	1.35417	0.89286
0.80000	2	1	6	47	0.25000	0.97917	1.22917	0.87500
0.82500	2	1	6	47	0.25000	0.97917	1.22917	0.87500
0.85000	2	0	6	48	0.25000	1.00000	1.25000	0.89286
0.87500	2	0	6	48	0.25000	1.00000	1.25000	0.89286
0.90000	2	0	6	48	0.25000	1.00000	1.25000	0.89286
0.92500	1	0	7	48	0.12500	1.00000	1.12500	0.87500
0.95000	0	0	8	48	0.00000	1.00000	1.00000	0.85714
0.97500	0	0	8	48	0.00000	1.00000	1.00000	0.85714

Area Under ROC Curve = 0.94271

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Residual Report

Row	Actual Model	Pearson Residual	Deviance Residual	Maximum Hat Diagonal
1	PARALLEL	-0.12400 	-0.17470 	0.05101
2	PARALLEL	-0.74577 	-0.94046 	0.50758
3*	STAGE	1.36521 	1.45062 	0.27214
4	PARALLEL	-0.21441 	-0.29982 	0.09366
5	PARALLEL	-0.16283 	-0.22877 	0.10860
6	PARALLEL	-0.01609 	-0.02275 	0.00261
7	PARALLEL	-0.18248 	-0.25596 	0.10728
8	PARALLEL	-0.20545 	-0.28755 	0.05963
9	PARALLEL	-0.03735 	-0.05281 	0.01315
10	PARALLEL	-0.13014 	-0.18328 	0.04752
11	PARALLEL	-0.29113 	-0.40338 	0.40462
12*	PARALLEL	-1.12835 	-1.28155 	0.42992
13	PARALLEL	-0.09457 	-0.13344 	0.03204
14	PARALLEL	-0.22949 	-0.32040 	0.06980
15	PARALLEL	-0.03225 	-0.04559 	0.00545
16	PARALLEL	-0.06654 	-0.09400 	0.01519
17	PARALLEL	-0.11741 	-0.16548 	0.04570
18	PARALLEL	-0.77262 	-0.96756 	0.50253
19	PARALLEL	-0.10234 	-0.14435 	0.02668
20	PARALLEL	-0.05711 	-0.08071 	0.01407
21*	STAGE	1.58063 	1.58259 	0.29125
22	PARALLEL	-0.43964 	-0.59449 	0.40597
23	PARALLEL	-0.22463 	-0.31377 	0.13563
24	PARALLEL	-0.37086 	-0.50767 	0.19584
25	PARALLEL	-0.02454 	-0.03471 	0.00467
26	STAGE	0.51509 	0.68604 	0.24663
27	PARALLEL	-0.05826 	-0.08232 	0.01404
28	PARALLEL	-0.06316 	-0.08924 	0.01440
29	PARALLEL	-0.01587 	-0.02244 	0.00228
30	PARALLEL	-0.04394 	-0.06212 	0.01600
31*	PARALLEL	-2.31363 	-1.92297 	0.40125
32	PARALLEL	-0.00571 	-0.00807 	0.00046
33*	STAGE	1.09373 	1.25439 	0.29083
34	PARALLEL	-0.01011 	-0.01430 	0.00154
35	PARALLEL	-0.28861 	-0.40002 	0.15965
36	PARALLEL	-0.01949 	-0.02756 	0.00308
37	STAGE	0.91655 	1.10436 	0.17618
38	PARALLEL	-0.13354 	-0.18802 	0.05311
39	PARALLEL	-0.03289 	-0.04649 	0.00822
40	PARALLEL	-0.13219 	-0.18614 	0.04837
41	PARALLEL	-0.28620 	-0.39680 	0.19190
42	PARALLEL	-0.07803 	-0.11018 	0.05191
43*	STAGE	1.89419 	1.74553 	0.25949
44	PARALLEL	-0.05231 	-0.07393 	0.01797
45	PARALLEL	-0.01439 	-0.02035 	0.00185
46	STAGE	0.30497 	0.42174 	0.23683
47	PARALLEL	-0.00519 	-0.00733 	0.00034
48	PARALLEL	-0.03270 	-0.04623 	0.00652
49	PARALLEL	-0.09076 	-0.12809 	0.04269

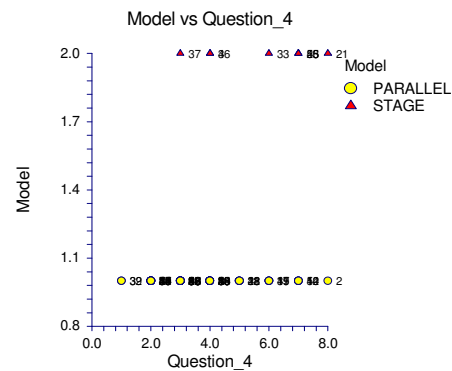
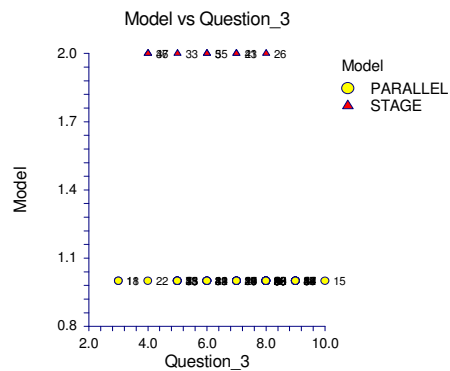
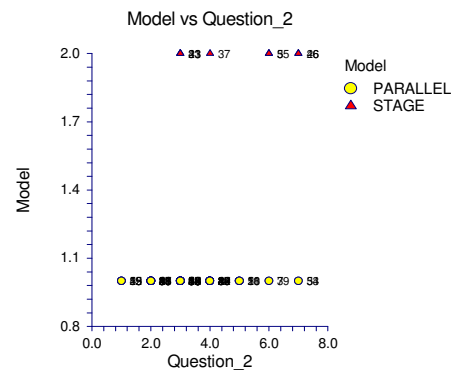
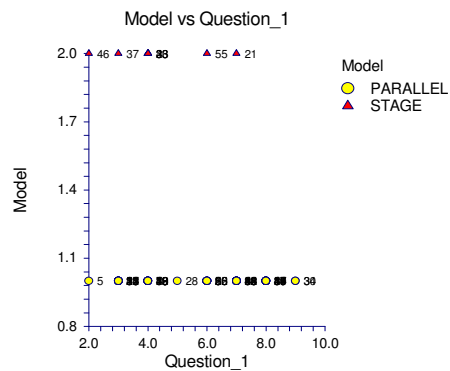
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Residual Report

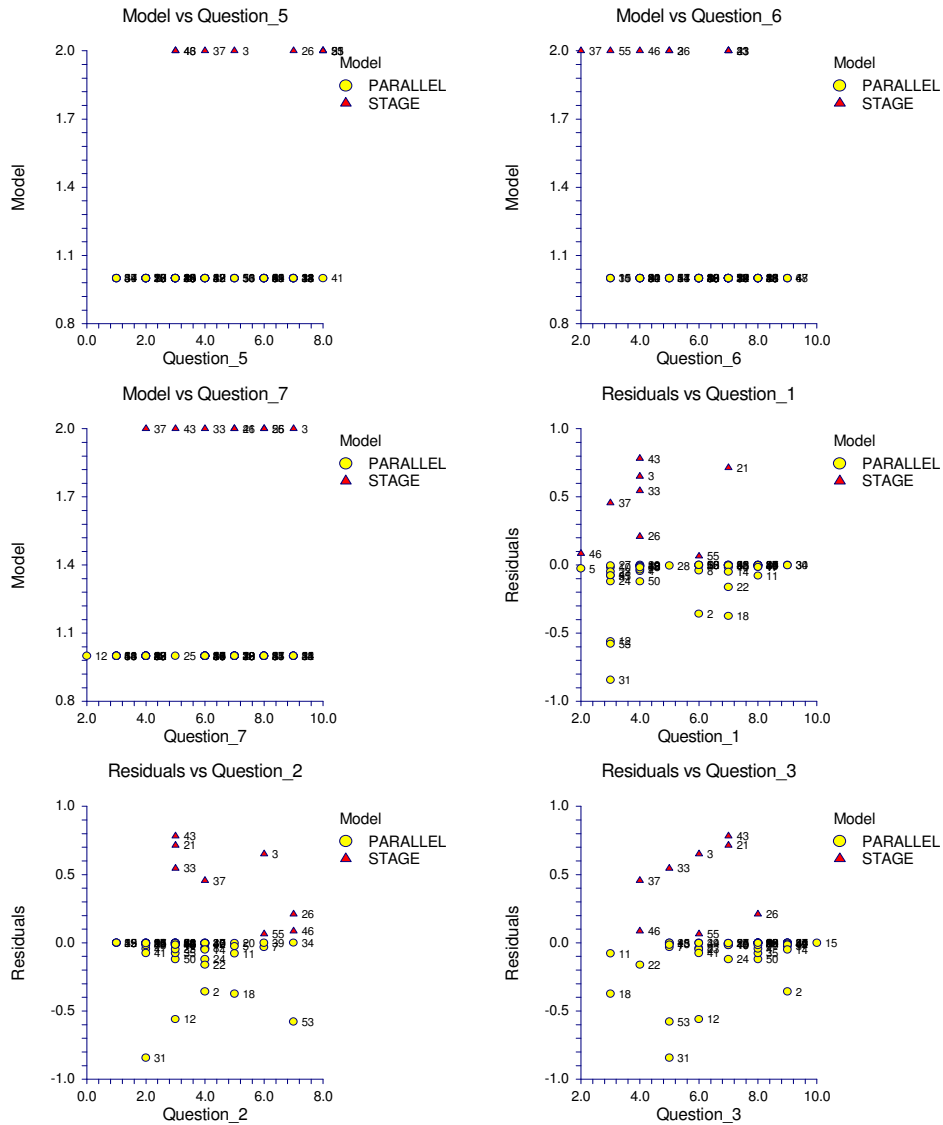
Row	Actual Model	Pearson Residual	Deviance Residual	Maximum Hat Diagonal
50	PARALLEL	-0.37028 	-0.50692 	0.22288
51	PARALLEL	-0.05973 	-0.08439 	0.01982
52	PARALLEL	-0.01472 	-0.02081 	0.00192
53*	PARALLEL	-1.17104 	-1.31412 	0.46545
54	PARALLEL	-0.01401 	-0.01981 	0.00205
55	STAGE	0.26416 	0.36730 	0.19583
56	PARALLEL	-0.02477 	-0.03503 	0.00396

Diagnostic Plots



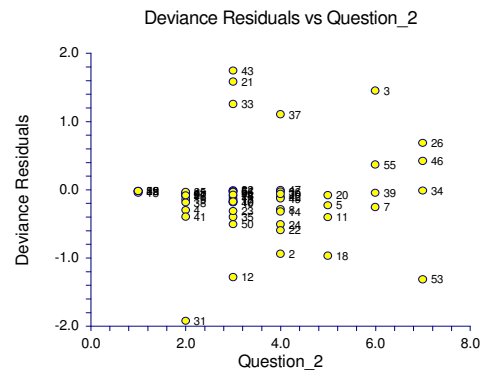
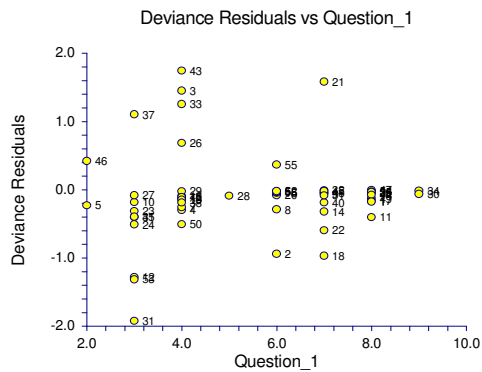
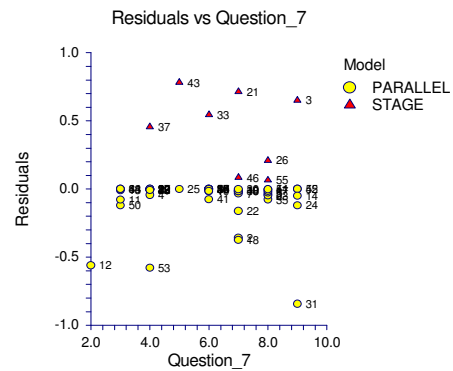
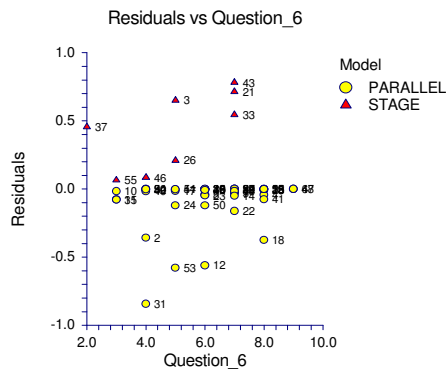
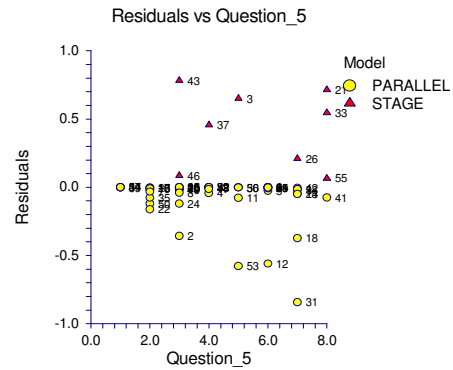
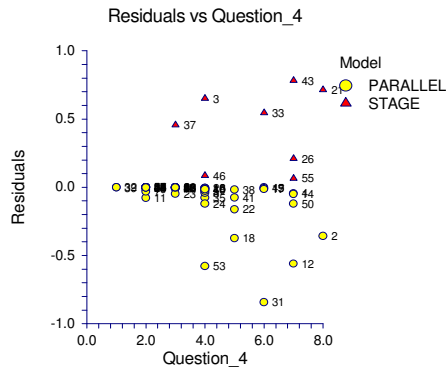
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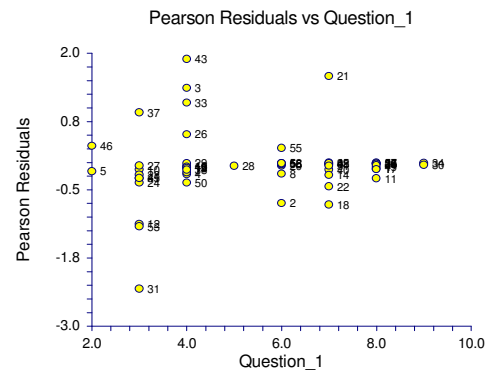
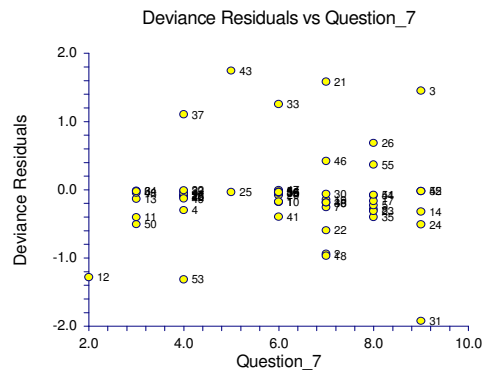
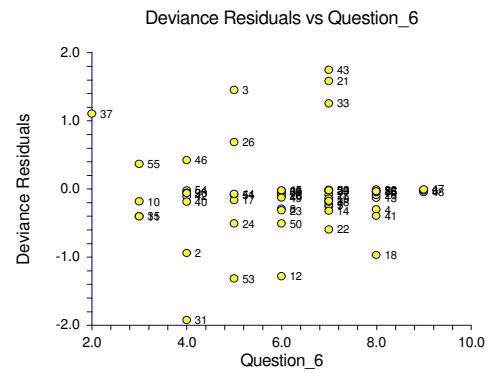
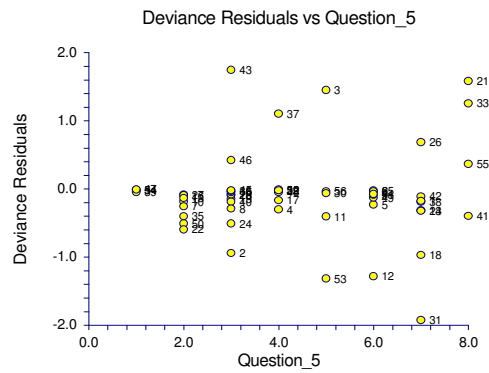
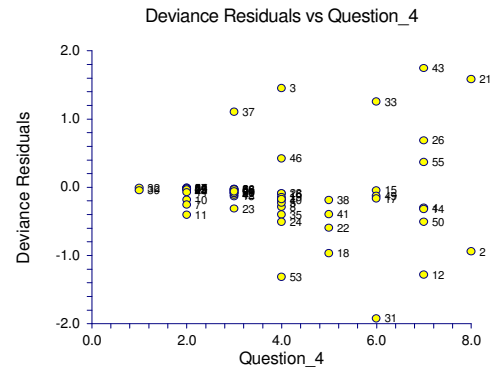
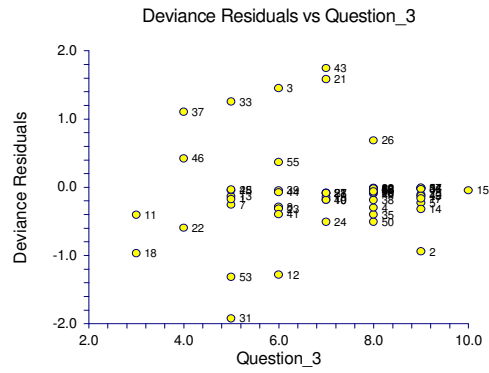
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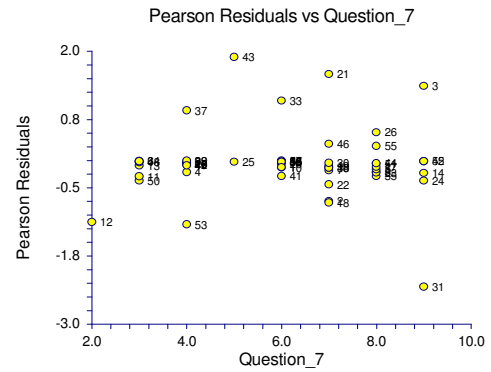
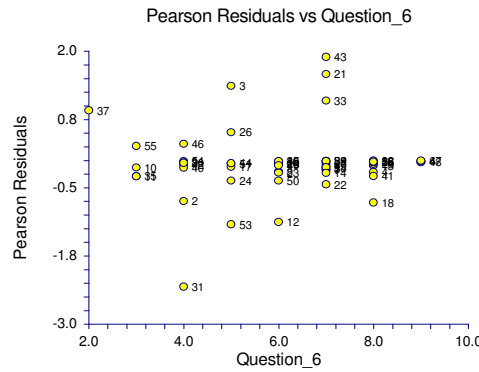
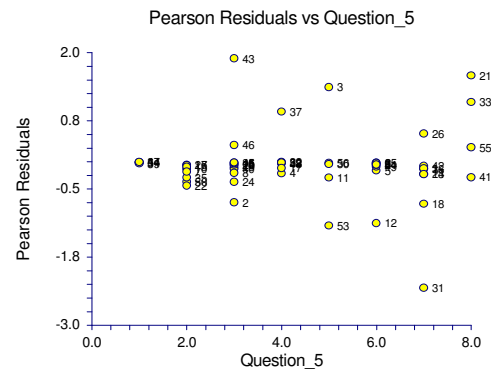
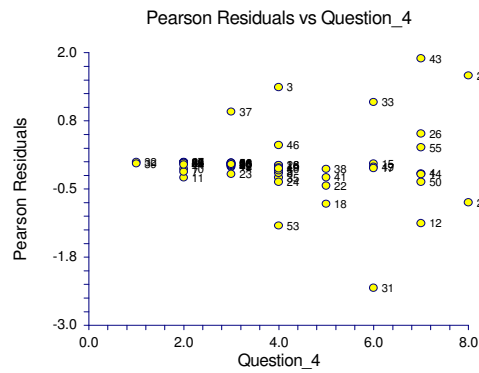
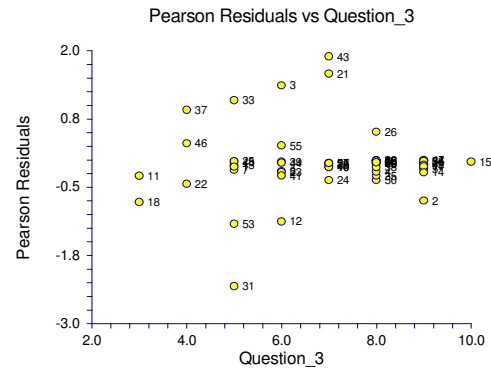
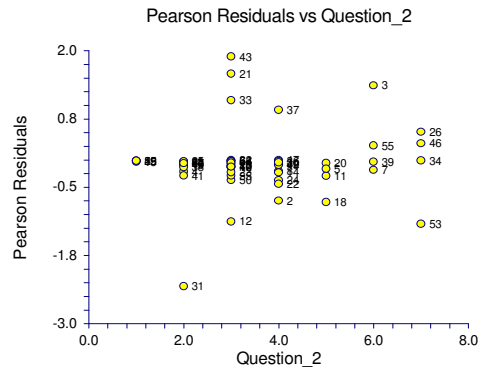
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