Validation of an Innovation Mining Framework

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VALIDATION OF AN INNOVATION MINING FRAMEWORK

Karthikeyan Subramani

Thesis submitted to the faculty of the
Rochester Institute of Technology
In partial fulfilment of the requirements for the degree of
Master of Science in Industrial and Systems Engineering
Kate Gleason College of Engineering

Rochester, NY
July 31, 2018
M.S. DEGREE THESIS

The M.S. Degree Thesis of Karthikeyan Subramani has been examined and approved by the committee as satisfactory for the thesis requirement for the Master of Science Degree

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DEDICATION

I dedicate this respectful effort to My father (Dr. Subramani Jambulingam) and Mother (Bhuvaneswari Subramani), for their love and teachings over the years have made me the man I am today.

And

My Sister (Karthika Subramani), who made my Master’s journey possible.

And

My advisor (Dr. Marcos Esterman) and my friend (Srikanth Peyyeti), without whom this work would not have been possible.

And

My mentor (Dr. Korhan Sevenler), for his support and motivation.
ACKNOWLEDGEMENTS

I thank Dr. Marcos Esterman for presenting me the honor and opportunity to work on this thesis. I also thank him for his patience, guidance and most importantly for the time he invested in making this thesis possible. I owe a lot to him for the knowledge he imparted through his courses and research which helped leverage my understanding on concepts that constitute the basis for this work and source of inspiration for my career.

I thank Srikanth Peyyeti for giving me the opportunity to further develop his idea and research. I also thank him for relaying his knowledge on the subject and providing valuable inputs and guidance. I thank Dr. Brian Thorn for being part of the thesis committee and providing his valuable inputs and guidance for this thesis.

I take this opportunity to thank Dr. Korhan Sevenler, for his mentorship, support and most importantly for the learning experience gained working as his Teaching Assistant for the courses Engineering of Systems – I and Product Lifecycle Management.

I would like to thank Kim Eldridge, Jennifer Barretta and the other faculty and staff of Industrial and Systems Engineering department for their timely help and support.

A special thanks to my comrades Syed Imran Shajahan, Sanjairaj Gnanasundaram, Sree Gowrishankar Umamaheswaran, Sabari Girish and Ramprasad Tamilselvan for being a great moral support. I would like to extend my gratitude to fellow Industrial and Systems Engineering graduate students, my roommate Aravindh Kuppusamy and to all who helped me throughout my master’s journey.

Finally, I would like to thank my parents, sister, cousins, stalwarts, friends back in India who have been my inspiration and support throughout this journey.
ABSTRACT

The driving hypothesis of this thesis is that a quantitative approach linking business objectives of an organization with technological limitations of the physical product would enable industry to create more innovative products. The main goal of this research is to validate the applicability and reliability of the innovation mining framework developed by Peyyeti (2016) to identify innovation opportunities and components worth innovating in a product. In this work, the innovation mining framework is applied with minor modifications to a mechanical pencil, innovation scenarios were then compared to existing innovations in mechanical pencils. Based on the success of the feasibility trial, the innovation mining framework was applied to a Dirt-Devil vacuum and compared to innovations implemented in the Dyson-V6 vacuum to improve a set of chosen value-metrics. Based on this study, the following insights were developed: (1) The model sufficiently identified several innovation opportunities to improve each value-metric (2) Varying weighting schemes do not have significant effects on filtered data (3) The top-half of the dendrogram contains the most relevant clusters that present viable innovation opportunities (4) The relevant clusters must be viewed from a systems thinking perspective as a single chain that must be innovated for the most benefit (5) Implementing this model provokes systems thinking approach in the user. This gives a substantial advantage over intuitive and qualitative approaches by providing insights on hidden relationships and identifying innovation opportunities in a system that may otherwise be ignored or unexplored. Opportunities for future-work include developing a transfer-function system representing true relationships, performing SVD at every level of the coupling matrices to gain insights into the nature of transformation and cluster formation, comparing clusters obtained to failure-modes associated with the corresponding value-metric for systematic prioritization and comparing dendrogram clusters with function-structure map to get detailed insights on clusters and their interactions.
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1.0 Introduction

This first chapter provides the motivation for this research and summarizes the existing quantitative approaches to model innovation. It begins by providing background information regarding the Innovation Mining framework developed by Peyyeti (2016). This section also identifies the problems and challenges with the current Innovation Mining framework. The problem statement is then introduced along with a detailed research roadmap. Following the problem statement, the concrete research objectives are presented as are the research questions that will guide this thesis work. To conclude this chapter, an outline of the thesis is presented.

1.1 Motivation

The driving hypothesis of this work is that a quantitative approach that links the business objectives of an organization with the technological limitations of the physical product would enable industry to come up with more innovative products. The complex nature of innovation and the fact that the existing models on innovation (Abernathy and Utterback, 1978; Christensen, 2013) (despite providing useful insights in understanding the complex phenomenon of innovation) did not provide a concrete framework or a set of tools to guide designers in industry to make quick yet reliable decisions for innovation within products and services prompted the development of the Innovation Mining framework (Peyyeti, 2016). An understanding of the barriers and struggles faced by a product developer along with the challenges in the development of a quantitative Innovation model to address the above-mentioned needs and problems of the industry inspired this research.
1.2 Background on Innovation Mining

Given the unclear nature of innovation, Peyyeti (2016) aimed to answer the questions of “when to innovate?” and “what to innovate?”. The answers to these questions will help to reduce product development costs, product development time and the costs associated with missing opportunities in the market. This can be beneficial to the organization in that it can significantly reduce the time to market giving them a first mover advantage over its competitors.

Despite the fact that there is so much attention on the strategic value of innovation, very few organizations know how to make it a reliable and a repeatable practice. Business history says less than 4% of the innovation projects undertaken by businesses are proven successful and the remaining 96% fail (Kumar, 2013). Innovation of existing products is attracting the interests of many organizations from a wide range of industries that look to take advantage of the opportunities in the market (Christensen, 1992, 2013; Chandy and Tellis, 2000). Coming up with the next wave of innovative products before existing products fail in the market is crucial for a company to maintain its position and competence in the market. Failing to innovate will eventually be disastrous for the company as it will result in loss of market share and revenue.

The Innovation Mining framework was developed to identify components that are worth innovating given an existing system (Peyyeti, 2016). The framework developed by Peyyeti (2016) identifies and provides insights on clusters of subsystems rather than individual components but it shows great promise in aligning the business objectives with the challenges to innovation and provides guidance to innovate from both the customer perspective and the technological constraints that exist within a system.

The Innovation mining methodology from Peyyeti (2016) is shown in figure 1 and it consists of the following steps.
Step 1: Identifying the value metric as a benefit-to-cost ratio

The first step in Innovation Mining is value identification. Value or aspect of the product to be improved is identified as a benefit-to-cost ratio. Value is defined by the benefit-cost metric that is relevant to business objectives of the organization.

Step 2: Identifying Engineering Metrics (EMs) to focus on from the scenarios of innovation

The next step is to identify the engineering metrics to focus on based on the three scenarios that signal innovation, as postulated by Peyyeti (2016).

- **S-Curve slope decline**

  The first innovation scenario occurs when the rate of increase of value of the benefit-to-cost metric begins to diminish over time. The typical depiction of a benefit-to-cost as a function of time results in an S-curve (Clausing, 1994). This is shown in figure 2 and any decrease in the slope acts as the signal indicating the need for innovation. By focusing on the timeline when the product benefit-to-cost metric starts to flatten, the engineering metrics that directly affect this value metric can be identified.

---

1 Engineering Metric is a test or objective measure which can be used to determine how well the product meets the customer requirement. They are usually solution independent variables that can be quantified and measured but sometimes may be non-quantifiable metrics such as psychometrics, binary etc.
• **Technological trade-off**

The second innovation scenario occurs when there exist technological contradictions between the EMs or product parameters that can no longer be resolved. This scenario results because competing customer requirements continue to evolve until the conflict can no longer be resolved. These tradeoffs can manifest themselves at the system, subsystem, component or manufacturing requirement or parameter levels. An example of a tradeoff is wanting a longer pencil without an increase in weight, here a trade-off between length of the pencil and weight of the pencil exists.

• **New VOC inclusion**

The third innovation scenario simply consists of a new, never previously been satisfied customer requirement. Thus, the inclusion of a new need (VOC) from the customer is warranted. For example, the need for a camera in mobile phones.

**Step 3: Establishing links from VOCs to components**

The existing product architecture is then connected in a top-down approach from system level to component space using QFD matrices to capture the nature of relationships between EMs identified above and the solution elements as shown below in figure 3. In figure 1 only the
connections to subsystems were shown, but the full decomposition to components is shown in figure 3. The following is an explanation of all the acronyms,

- **VOC (Voice of the customer)** – Subjective descriptions of the customer needs, E.g. Drills holes
- **EM (Engineering Metric)** – A solution independent test or objective measure used to determine how well the product meets customer requirements, E.g. size of the hole to be drilled
- **DP (Design Parameters)** – A solution dependent variable that can be quantified and measured, E.g. diameter of the drill bit, rake angle etc.
- **SS (Subsystem)** – A self-contained system within a larger system, E.g. camera subsystem in a mobile phone
- **SSS (Sub-subsystem)** – A small self-contained system within a subsystem, E.g. zoom module in the camera subsystem, flash module in the camera subsystem etc.
- **Cs (Components)** – The major components that make up the sub-systems and subsystems in a larger system, E.g. lens in a zoom module
Step 4: Perform Singular Value Decomposition (SVD) to identify the patterns

SVD provides a convenient way for breaking a matrix, which perhaps contains some underlying structure that we are interested in, into simpler, meaningful pieces. It is a widely-used technique to decompose a matrix into several component matrices, exposing many of the useful and interesting properties of the original matrix. SVD is used to reveal the hidden patterns that lie within the matrices generated above. These patterns connect to a specific set of requirements and components which can be explored for innovation opportunities. SVD is explained in greater detail in section 2.2 Singular Value Decomposition.

Another method can be used to identify trade-offs existing in the matrix. Developing covariance matrix gives us a measure of how two engineering metrics change with respect to each other. It is positive when the two corresponding engineering metrics show similar behavior and negative otherwise. This can be used to identify and understand trade-offs in the system.

Step 5: Perform Hierarchical clustering

Hierarchical clustering is used to represent the patterns of relationships generated from SVD analysis. Hierarchical clustering is used to provide physical meaning to the links defined by SVD and define patterns hidden in relationship matrices. Clustering methods like Dendrograms along with Venn diagrams are used to help visually represent the results generated for better interpretation.

Step 6: Prioritize

The final step in the framework is to interpret meaning from the resulting clusters and prioritize the clusters to focus innovation efforts. The clusters will reveal all obvious and imperceptible relationships and interactions within the system that influence the value metric chosen. The product developer must make the decision to prioritize a specific cluster over others that present the most viable opportunities for innovation.
1.3 Opportunities

The stated primary goal of the Innovation Mining framework (Peyyeti, 2016) is to enable product developers to help realize the goals of the organization while addressing the challenges to innovate. However, when reviewing the literature and similar works in the industry, developing a reliable framework to help product developers systematically identify and prioritize areas within the design to focus their innovation efforts is an extremely difficult task. Although, the Innovation Mining framework addresses some aspects of these industry needs such as aligning the business objectives with the challenges to innovation and providing useful insights from the customer perspective and the technological trade-offs within the system, it needs to be intensively validated for reliability and consistency. Some of the other gaps that were identified in the innovation mining framework will be described below.

The Need for a Weighting System

Weighting system used in the matrix transformations will affect the results of the framework as it plays a major role in scaling the transfer function used and in determining the relative importance of the requirements. The current weighting system used is a 1, 3, 9 system similar to the transfer function described above but identifying a weighting system that better reflects the true contribution of the requirements will improve the quality of the results generated by the innovation mining framework. Hence, there is a need to identify an appropriate weighting scheme that gives actual data.

The Need for Detailed method to Identify Critical System Parameters

Detailed Method to identify critical system parameters is vital to achieve the goals of the framework as much of the innovation mining methodology depends on the identification of critical system parameters also known as engineering metrics that are related to the value metric chosen to be the focus of improvement. The framework depends on the scenarios of innovation to assist in identifying the critical system parameters based on the chosen value metric. These scenarios have shown promise in identifying critical system parameters but a more detailed method for the selection of engineering metrics which are used in filtering the matrix to reduce complexity will enhance the quality of the clusters of subsystems/components obtained.
The Need for Prioritized Clusters

Comparison and Prioritization of the subsystem clusters is another area to be focused upon as there is much value in the way these resulting clusters from hierarchical agglomerative clustering are interpreted and analyzed. In the existing framework methodology, there is no consideration to prioritize between the clusters of subsystems obtained after performing singular value decomposition and hierarchical clustering. Developing a means to distinguish between the resulting clusters as relevant and irrelevant to the benefit-to-cost metric and prioritize the relevant clusters in the order of the best alternative to be the focus of innovation efforts by the organization.

The Need for Identifying Specific Components

Identifying specific components that should be the focus of innovation is one of the primary goals of the innovation mining framework. The existing framework is successful in deducing clusters of subsystems but it needs human interpretation (preferably by an expert on the system being studied). But the framework does not explicitly indicate which out of the many components in a product should be the focus of innovation to create the most value. So, devising an advancement of the existing innovation mining framework that will identify specific components of interest in a product will prove to be beneficial in adding value to the product and the organization.

The Need for a Value Model

Development of a value model that aids in the analysis and selection of value metrics to guide the innovation process. A complex product can have many customer requirements each giving rise to a large number of system engineering metrics. However, to identify components or subsystem clusters that contribute to a specific aspect of product performance constituting the benefit-to-cost metric, there is a need to identify a set of engineering metrics that contribute to that value metric. This is achieved by the application of the innovation scenarios developed in the innovation mining framework. But the first scenario occurs when the rate of increase of the value metric begins to decline, which means a value metric must be identified as a benefit-to-cost ratio to begin with and so do the other scenarios. Hence, there is a need for a value model that helps in systematically identifying the right benefit-to-cost ratio to be focused upon. But, this opportunity is not addressed in this research as it has the potential to be a research on its own.
The Need for Actual Transfer Functions

Developing actual transfer functions that will help to carry true information about the relationships between row and column elements at each level of the matrix transformations is thought to be better than high-level approximations. The existing method uses a 1, 3, 9 rating which is the most widely used approximate transfer function in product design. The output of clusters produced by the framework utilizes the information from the transfer functions. Hence, there is thought to be a need for the development of actual transfer functions that captures true relationships at each level of the transformation matrices but developing an actual transfer function is a difficult task. This need will also not be addressed in this work but exploring the value for this need is described in future work.

1.4 Research Objectives

The main goal of this research is to validate the applicability and the reliability of the Innovation Mining framework in identifying Innovation opportunities and components worth innovating in a product. Furthermore, this thesis will apply the Innovation Mining framework to a set of products and provide a case study to evaluate the practical execution of the innovation mining framework, with the final objective of suggesting modifications to improve the Innovation Mining framework if deemed necessary.

The specific points to be fulfilled during this research along with the research questions that will guide the process for testing and improving the Innovation Mining framework can be defined as follows:

1. Apply the Innovation Mining framework to a concrete case study where innovation is known to have taken place to assess whether the areas that the framework identifies are the same as where the innovation happened.

2. Based on the insights developed from the case study, develop an appropriate weighting scheme to be deployed in the engineering matrices.
i. Can a weighting scheme be developed for different levels that will aid in the identification of components worth Innovating?

ii. How much does the weighting scheme affect the outputs?

3. Interpret meaning from the results of the case study analysis and prioritize the clusters that are identified
   i. Can the resulting pattern from the analysis be interpreted to identify relevant clusters and irrelevant clusters?
   ii. Do the patterns/clusters influence design decisions? What insights can be obtained?
   iii. How can the relevant clusters obtained be prioritized?
   iv. Does the identified component match with the changes that have taken place?

4. Propose modifications to improve the framework.
   i. What are the weak links in the Innovation Mining framework?
   ii. Why are they important? What is causing them?
   iii. How can they be solved or reduced?

5. Demonstrate the value created by the framework after modifications.

2.0 Literature Review

As discussed in the previous section identifying innovation opportunities within an existing product is a challenging task. The efforts made to overcome these challenges are presented in the literature review. The first section of the literature review concentrates on the approaches to innovation, the generic nature of Qualitative models, Quantitative models and the Innovation Mining framework. The second part describes SVD and the last part covers several views on the applications of SVD in the field of product development.
2.1 Approach of Innovation Mining

There are two major approaches to identify innovation opportunities in industry, the customer driven approach and the technology driven approach. While most approaches (von Hippel, 1986; Chesbrough, 2004; Brabham, 2008; Witell et al., 2011) consider customer opinions early in the product design phase, there are other approaches (Keathley et al., 2013) that have their roots in technological advancements. These are approaches in which innovation is a result of a technological advancement such as an invention or a new discovery.

von Hippel (1986) suggests that any product being developed should consider error-free judgment from its informed users about their needs. These informed users are called lead users and their input is critical to the regular product development process in identifying the real and implicit needs of the market. By this approach, customers with their well-informed judgment participate in shaping the needs of the product, however, their knowledge does not affect the technical aspects and the system level parameters that go into designing the actual solution which will satisfy the needs identified.

Chesbrough (2004) with his concept of open innovation describes the need to identify opportunities in uncertain markets where the lead users are indecisive. In such uncertain markets, companies should be receptive to ideas from both internal and external channels and have the capacity to use the knowledge accumulated by partners to their benefit. Although open innovation is widely adopted by many companies it does not provide a clear path to identify innovation opportunities. The reasons for this may be attributed to the noise added to the product data by the extensive sources that provide inputs. For example, the Boeing 787 ‘Dreamliner’ project involved working with 100+ partners and was nearly two years behind schedule spending lot more than the planned budget when structural problems were discovered where the wing was attached to the fuselage (Silverthorne, Sean. “Boeing: The Wrong Way to Manage Innovation” Money Watch, 23 Jul. 2009, https://www.cbsnews.com/news/boeing-the-wrong-way-to-manage-innovation/).

Another interesting customer-driven approach to innovation is customer co-creation that gathers inputs from both the customer’s preference and the firm’s technical experts (Prahalad.C, Ramaswamy.V, 2004). Prahalad and Ramaswamy (2004) mention that the
responsibility of creating value has shifted from just the firm to the interaction between the firm and its informed, networked, empowered and active customers. It is a shift from the traditional firm-centric models to unconventional methods of joint problem definition and problem solving thus creating a dialogue between the firm and its customers by evaluating their experiences to generate value for the product. O’hern and Rindfleisch (2010) describe this perspective of an unconventional approach as the transition of customers from being passive buyers to active co-creators where they play a big role from the identification of needs to the development of extensive solutions to satisfy those needs. Customers participate in changing or improving the new product’s underlying structure through processes like collaborating, tinkering, co-designing etc. to create variants of the products available in the market. It is mostly a time-consuming process and even though opportunities of innovation are identified they may not always prove to be productive. Despite creating valuable inputs to the product development process, it does not specify the conditions that prompt innovation and the right time for innovation.

Yet another increasingly popular method to tackle the problems associated with identifying innovation opportunities is crowdsourcing (Howe, 2006). In this method, the organization makes use of the contributions from individuals or groups. It is usually organized as an innovation competition where the people that participate present their ideas as inputs. According to Brabham (2008), crowdsourcing is an online, distributed problem solving approach. Crowdsourcing is a mix of the top-down and bottom-up models that opens the door to new ideas and to obtain knowledge that lies beyond the base knowledge of the employees in an organization.

In summary, the customer driven approaches (von Hippel, 1986; Chesbrough, 2004; Brabham, 2008; Witell et al., 2011) to innovation is an innovation pull where the need for better products with improved performance is influenced by the market through identification of the real needs of its customers. Whereas the technology driven approaches (Keathley et al., 2013) to innovation are innovation pushes from the organization into the markets where better products with improved performance are introduced because of the advancement in technology or the core competency of the organization. These methods are beneficial in improving costs, speed, flexibility, quality, scalability and diversity associated with product development but it lacks the following aspects which will help in reducing the complexity in identifying innovation opportunities.
1. Attempting to quantify the interactions between technologies at a detailed level to make the best out of the information that matters. A way to distinguish between relevant and irrelevant interactions and take advantage of the information in relevant interactions.

2. A method to prioritize the opportunities identified by these customer-driven and technology-driven approaches.

3. A method to systematically analyze if the range of possibilities for the solution is considered. Because a problem can have more than one solution and all alternatives must be considered and compared to arrive at the best solution.

Unfortunately, most of the innovation opportunities that are identified fail to make the transformation into actual products that satisfy the customer requirements. The reasons for this may be attributed to the technological constraints that are involved in identifying the appropriate time for innovation and the technological trade-offs in the product innovation process. There are many theories of innovation that aim to address the issue of identifying innovation opportunities. Most of these theories (Abernathy and Utterback, 1978; Teece, 1986; Utterback, 1996) are qualitative in nature while some others are quantitative in nature, but we are concerned more with the quantitative theories and models since the Innovation Mining framework falls within this category. While qualitative models are concerned with complete and detailed descriptions of events and provide valuable data about the complex nature of innovation including data about user needs, behavior patterns and use cases, quantitative models help in measuring and analyzing the data in detail and provides more objective findings. Since both qualitative and quantitative models play important roles in product development, the key aspects of the qualitative models were studied and included when the innovation mining framework was developed to benefit from the advantages of both the approaches.

The quantitative theories on innovation most commonly involve the tools used to assist in the process of innovation. These tools are employed in the product development processes for representing the product in the design space. Keathly (2013) describes some of the most important tools commonly used in the industry such as the affinity diagram, benchmarking, QFD, brainstorming, fish-bone diagram, mind-mapping, TRIZ, decision matrix, DFSS, FMEA, 5whys and 2H, flowcharts, kano model and forecasting methods to name a few. Among these TRIZ is more intriguing as it addresses innovation in a logical manner. TRIZ is a problem-solving analysis and forecasting method introduced by Genrich Altshuller (1969) that can be
used to define challenging problems and reduce the complexity to develop inventive solutions. This method systematically applies its strategies and tools to arrive at solutions that overcome the trade-offs between two elements of interest. There is great potential for innovation if the knowledge from a product history could be used to recognize patterns from the evolution of the product. Such information could prove to be instrumental in predicting the next generation of products.

The innovation mining framework combines the aspects of both qualitative and quantitative theories to provide a method that places emphasis on both customer-driven and technology-driven approaches to innovation in the following ways. The framework identifies three scenarios of innovation as follows,

1. S-curve slope decline
2. Trade-off scenario
3. New needs inclusion

The first scenario employs s-curve, it is a graphical representation to plot the effects of innovation with time on x-axis and the benefit to cost ratio on the y-axis. This plot is employed to identify a decrease in the slope of this curve which indicates a decreased rate of value delivery which needs to be addressed. The logic for this is that the market expects continued increase in benefit to cost over time. If the rate is decreasing, eventually value increase will be zero or negative resulting in a non-competitive product.

The trade-off scenario is when technological contradictions are identified in a product that can no longer be resolved to meet customer requirements. For instance, two contradicting requirements in a car can be that the door be easy to close and that the car interior be unaffected by the external environment. This leads to the technological contradiction that a small peak force is needed for requirement one and a large peak force is needed for requirement two. In this case, a passive seal might be used to resolve the trade-off to a certain extent but after a certain point of time the passive seal may not be able to meet the evolving requirement and a more active solution is required to resolve the trade-off. These scenarios are identified by employing correlation matrix of House I in Quality Function Deployment (QFD), through TRIZ analysis or from the experience of engineers and subject matter experts (SME’s). For a given engineering metric, trade-off between two parameters is defined as the required direction of improvement for critical parameters with both being in the opposite direction. The figure 4
represents a trade off in which the critical parameter CP\(_i\) is the required parameter to be improved and the CP\(_j\) is the critical parameter to be decreased.

\[
\begin{align*}
\frac{\partial CP}{\partial EM_i} < 0 \\
\frac{\partial CP}{\partial EM_j} > 0
\end{align*}
\]

*Figure 4 - Technological trade-off (adapted from Peyyeti, 2016)*

The third scenario in identifying innovation opportunities is rather simple and includes the identification and inclusion of a set of new customer needs from the market. Primary and secondary market analysis tools are used to detect this scenario and the new needs identified can be captured by employing tools like the House I of QFD. When a specific need arises within the circle of internal and external stakeholders or in a market with a target value higher than the current metrics, then that metric takes priority over the metric in use to be improved for the next wave of product.

Each of the scenarios mentioned above are associated with either a customer requirement or a technical requirement. So, it is important to establish the links from these requirements to the components to identify where the innovation efforts should be focused. There are many different approaches proposed by different authors to identify the links between physical components and the system space. Nam Suh (1998) suggested the axiomatic design approach, in which complex systems can be built using the top-down approach rather than the bottom-up approach. This systems design methodology uses matrix methods to systematically analyze the transformation of customer requirements (VOCs) into functional requirements (FR), design parameters (DP) and process variables (PV). The complex relationships for fixed systems is identified using a top-down approach by building from the functional requirement space to the component space. This theory is guided by two axioms called the independence axiom and the information axiom. The independence axiom states that the independence of the functional requirements must be maintained and the information axiom states that the information content of the design should be minimized as much as possible. The functional requirement space is a solution neutral space and is characterized by minimum number of independent requirements
(Suh, 1998). The innovation mining framework uses a matrix representation to connect the system level metrics to the product level metrics using a top-down approach like axiomatic design theory which preserves information across the different levels in the transformation of customer needs to a product. The following expressions represent mathematically the definition of the links and the design matrix used in the different levels of transformation from one space to another,

\[
\text{FRs} = [A] \ \text{DPs}
\]

\[
\text{DPs} = [B] \ \text{Cs}
\]

Matrix [A] represents design matrix used for transformation from functional requirement (FR) space to the design parameter (DP) space. Matrix [B] represents the design matrix used for transformation from design parameter (DP) space to the component (C) space.

### 2.2 Singular Value Decomposition

Singular value decomposition (SVD) (Strang, 2007) is a method to perform linear transformation and is one of the critical factorization techniques in linear algebra. Data can be represented in a matrix form where the information is represented by the different rows and columns of the matrix. SVD provides a convenient way for breaking a matrix, which perhaps contains some data we are interested in, into simpler, meaningful pieces. It is a widely-used technique to decompose a matrix into several component matrices, exposing many of the useful and interesting properties of the original matrix. SVD can be used as an approach to identify patterns in an existing matrix as follows.

Per the concept of SVD, any input data matrix \( A[mxnmn] \) can be taken and represented as a product of three different matrices \( U, \Sigma \) & \( V \) each with some constraints on them. Where ‘m’ indicates the number of rows and ‘n’ the number of columns in matrix A. The matrix \( U[mxr] \) stores left singular vectors where \( r \) is rank of matrix A and indicates the total number of concepts. The matrix \( \Sigma[rxr] \) is a diagonal matrix with elements only in its diagonal which indicate the strength of each concept. Every element in this matrix are zeroes except the diagonal elements and these non-zero elements are called singular values. It is assumed that these singular values are sorted in the decreasing order, the largest singular value comes first, then the second largest and so on. Finally, the matrix \( V[nxr]^{T} \) stores right singular vectors. This
serves as the conceptual basis for representing the given input data matrix into three different matrices with matrix $\Sigma$ having a special structure being the diagonal matrix.

The SVD theorem states that: It is always possible to decompose a real matrix $A$ into $A = U\Sigma V^T$, a matrix ‘$A$’ can get decomposed into only a unique set of matrices $U$, $\Sigma$, $V$, i.e. no other matrix can decompose into the same set of matrices $U$, $\Sigma$, $V$ as matrix ‘$A$’. where, the matrices $U$ and $V$ are column orthonormal which means that columns of $U$ and $V$ have Euclidean length = 1, so the sum of the squared values in each column of these two matrices equals one. Also, these columns are orthogonal which means that when we take two columns of $U$ or $V$ and multiply or dot product them with each other the result is zero. Another feature of the diagonal matrix $\Sigma$ is that its singular values are positive, they are sorted in decreasing order and they are all greater than zero,

$$\sigma_1 \geq \sigma_2 \geq \sigma_3 \geq \ldots \geq 0$$

An example provided by (Leskovec, Rajaraman and Ullman, 2014) uses SVD approach to identify hidden patterns in the matrices. In the example, rows are represented by various names of people like Joe, Jim, John, Jack, Jill, Jenny, Jane and the column vectors is represented by names of movies like Matrix, Alien, Star-wars, Casablanca and Titanic. The values in the matrix represent the scores that they provided based on the level of their fondness of the corresponding movies in the column vectors on a scale of 0 to 5. The rows have names of males and females and the columns indicate the movies of different genres, in this case, romantic and sci-fi genres only. This matrix does not explicitly provide information regarding the patterns that lie hidden in the matrix. After performing SVD on the movie ranking matrix, new and interesting patterns could be identified which were not clear with the original matrix.

The Goal here is to discover a set of concepts from the patterns hidden in the matrix. Now we can think of matrix

$U$ – as user to concepts similarity matrix

$V$ – as movie to concept similarity matrix

$\Sigma$ - diagonal values as strength of each concept
SVD gives the best low rank approximation of a matrix i.e. it helps represent matrix A into a matrix B of lower dimensionality by neglecting some columns, concepts and rows respectively from the matrices U, Σ and V. Where matrix B is the best approximation of Matrix A which means that the difference between matrices A and B is as small as possible. So, in a case, A and B are as close to each other as possible given that the data points should be represented with a small number of coordinate scale. To be precise, the theorem states that:

If \( A = UΣV^T \), where \( Σ: \sigma_1 \geq \sigma_2 \geq \sigma_3 \geq \ldots \geq 0 \) and \( \text{rank}(A) = r \) then \( B = USV^T \) is the best k-rank approximation to A where,

\[
S = \text{diagonal matrix nxn where } s_i = \sigma_i \text{ (} i = 1, 2, \ldots k \text{) else } s_i = 0
\]

The important thing to notice is that the matrix S is a diagonal matrix where the first k entries of S are the corresponding singular values from matrix Σ and the rest is zero. When matrix Σ is replaced by matrix S we obtain the new matrix B, the main idea is that, matrix B is the best reconstruction of matrix A. Because the singular values \( \sigma_i \) are ordered \( \sigma_1 \geq \sigma_2 \geq \sigma_3 \geq \ldots \geq 0 \), however, significant compression of the data is possible if the spectrum of singular values has only a very few strong entries. When attempting to reduce the dimensionality, zeroing out the lowest \( s \) values is the best thing to do because the vectors \( U_i \) and \( V_i \) are of unit length because they are column orthonormal and basically when the product of U and V is multiplied with \( s \), the value of \( s \) scales them. To have the least possible error, the vectors with small importance should be dropped i.e. the vectors that have small \( s \) must be dropped. Hence, zeroing out the lowest \( s \) values introduces the least possible error because large singular values point to important features in a matrix. It is best to reduce the dimensionality and at the same time preserve as much data as possible. Hence, a good thumb rule would be to preserve at least 80-90% of the energy. The total energy can be defined as the sum of the squares of the singular values \( (= Σ \sigma_i^2) \). To preserve 90% of the energy the following ratio must be maintained,

\[
\frac{\sum_k \sigma_i^2}{\sum_i \sigma_i^2} = 0.9
\]

Any real matrix A can be taken and be represented as the product of three special matrices U, Σ, V^T. This decomposition is unique. This transformation also reduces the dimensionality of the input data matrix. The following are achieved by dimensionality reduction using SVD:
1. 80-90% of the energy is preserved
2. SVD picks up linear correlations and identifies dimensions along which data is spread out the most
3. SVD discovers redundancy in a matrix and provides a format for eliminating it.

2.3 SVD in Product Development

SVD is used everywhere from physics to machine learning for dimensionality reduction; the algorithm commonly known as Principle Component Analysis (PCA), for instance, is just a simple application of the singular value decomposition. In computer vision, the first face recognition algorithms developed in the 1970’s and 1980’s used PCA and SVD to represent human faces as a linear combination of “eigenfaces”, perform dimensionality reduction, and then match faces with identities via simpler methods. Although modern methods are much more sophisticated, many still depend on similar techniques. With such strong presence in modern technology SVD has also penetrated the product development industry. The potential of SVD in product development can be seen in the works done by Höltä, Eun Suk and de Weck (2005) and Holtta-Otto and de Weck (2007).

Holtta and de Weck (2007) show that there is an inherent trade-off between modularity of product architecture and some technical constraints such as weight, size or other performance constraints. In contrast, when the design of the product is driven by business goals, the degree of modularity is higher. They point out that there appears to be a potential trade-off between the desire for modularity from a business standpoint and the desire for high performance and efficiency in the technical domain. Resolving this trade-off could open the door to new possibilities and provide new directions for identifying opportunities for innovation and maintain a balance between the business objectives and the technological constraints.

Holtta-Otto and de Weck (2007) have developed the SMI (Singular value Modularity Index) based on the decay pattern of the singular values of the binary DSM describing the interconnections between components. They used DSM to map the interconnections between elements of form. They perform SVD on the binary DSM matrix which reveals its singular values (the singular values are the square roots of the eigenvalues of DSM^TDSM) and
corresponding orthogonal eigenvectors. With the help of these singular values a modularity index is therefore postulated that reflects the degree to which the important information for describing system connectivity is concentrated in a few components that are highly connected across the system. A change to the single highly connected component has the potential for affecting all other components in the system. This suggests that deliberately architected products, especially those that are very integral or very modular do not emerge randomly but are either driven by technical or business considerations. The advantages of their approach are that (1) it does not depend on subjective definition of module boundaries and (2) always returns the same value regardless of the ordering of rows and columns of the DSM.

2.4 Hierarchical Clustering

Hierarchical clustering is method widely used in data mining and statistics. It is a method for cluster analysis that groups data by creating cluster tree or dendrogram over a variety of scales. The dendrogram is not a single set of clusters but rather a multilevel hierarchy. There are two strategies widely adopted in hierarchical clustering namely (Rokach and Maimon, 2005).

- Agglomerative: This is a bottom-up approach, each observation or data point starts in its own cluster and pairs of clusters are merged as one moves up the hierarchy.

- Divisive: This is a top-down approach, all observations or data points start in one cluster and splits are performed recursively as one moves down the hierarchy.

The hierarchical clustering analysis groups together clusters based on proximity/similarity of the observations and the clusters to each other. The proximity or similarity between clusters is determined by measuring a distance between them. There are many different distance metrics that can be used namely Euclidean distance, Squared Euclidean distance, Manhattan distance, Maximum distance, Mahalanobis distance etc. with Euclidean distance being the most commonly used distance metric ("The DISTANCE Procedure: Proximity Measures". SAS/STAT 9.2 Users Guide. SAS Institute. Retrieved 2009-04-260).
**Linkage Method:**
The linkage method used in the hierarchical clustering analysis determines how the distance measured between two clusters is defined. At each level two cluster closest to each other are joined. In the initial stage, each observation constitutes a cluster, the distance between clusters is the inter-observation distance. After the first level of joining the observations together, a linkage rule is necessary to compute inter-cluster distances when there are multiple observations in a cluster. There are several linkage methods that can be adopted based on the characteristics of the data (Szekely and Rizzo, 2005). The commonly used linkage methods are discussed below.

**Single Linkage**
It is based on the shortest distance and is also referred to as the nearest – neighbor approach as shown in figure (5). First it identifies two observations separated by the shortest distance and places them in the first cluster. Then the next shortest distance is found and either a third individual joins the first two to form a cluster or a new two – object cluster is formed. It produces long chains of clusters: a → b → c → .... → z

![Figure 5 - Single linkage](image)

**Complete Linkage**
It is based on the longest distance between the objects and is referred to as the farthest – neighbor approach as shown in figure (6). First, two objects at the longest distances are assigned to two separate clusters. Then the next longest distance is found and either a third individual joins the first two to form a cluster or a new two – object cluster is formed. Produces spherical clusters with consistent diameter.
Average Linkage
The clustering criterion used in this linkage method is the average distance from objects in one cluster to objects in another as shown in figure (7). It is based on all members of the clusters rather than on a single pair of extreme members. This method uses average of all pairwise distances and is least affected by outliers.

Centroid Linkage
This linkage method measures the distance between cluster centroids as shown in the figure (8). The process continues by combining the clusters according to the distance between their centroids, the clusters with the shortest distance being combined first and so on.
3.0 Research Methodology

In this chapter, the methodology utilized for conducting this research is detailed. As mentioned earlier the basic theories of innovation, principles of systems engineering and fundamental mathematical formulations employed in the development of the Innovation Mining framework and their limitations are of prime concern in the validation and improvement of the framework under study. Considering a thorough understanding and an extensive experimentation on the framework is required to propose modifications to improve the framework, an iterative process is envisioned to proceed with the validation of the framework. The work to be done can be organized into two phases shown below in figure 9.

![Figure 9 - Research Methodology](image)

The final phase of the research deals with the application of the demonstrated methodology to a product with medium level complexity. The main objective of the proposed methodology is to study the disparities that arise upon the application of the methodology, if any, to a more complex product. Based on the innovation opportunities identified from the Innovation Mining
Framework, a comparison will be made to existing innovative solutions to validate the ability of the framework in achieving its objective to identify opportunities for innovation. The comparison results are studied to identify areas for future research and recommending improvements to the framework. For instance, say the existing innovative solutions do not match with the results obtained after the application of the framework, it means that there are two possibilities. Firstly, it may be indicating that there are other component sets which upon innovating could have given the most benefits to the organization and the end users. Secondly, it could have been a result of the unreliability of the input data or the inadequacy of the framework itself, pointing out that the framework needs to be refined further to make it as reliable as possible. The following are the objectives for the proposed methodology,

- Application of the demonstrated framework methodology to complex products with more number of components.
- If the framework is successfully applied in a practical setting, the comparability of case study results and actual scenarios is a feasible objective.
- The following products have been chosen for the case study application
  1. Dirt Devil Ultra bagged hand-held vacuum
  2. Dyson V6 Hand-held vacuum cleaner

Several products are available to be used in the case study but the products are chosen considering the selection criteria, the rating for each criterion and the scope. The Product Selection Matrix displaying the criteria chosen and the rating metric used for selecting the products is shown in figure 10.

The following features of the products influenced their choice for the case study:

1. The products are simple electromechanical systems.
2. The products have a long history and line of predecessor products.
3. The design of the products is distinct from the dominant design in the industry (The dominant traditional design included a bag that acted as the pathway for both suction and dust collection).
4. The product system and subsystem complexities vary from low to medium but have enough components to be representative of a typical development project.
5. The unit cost of the products is low and they are easily available.
6. Since they are common products, product data can be created with measurements by
   the author and do not require knowledge of SMEs.
7. Disassembly of the products are simple and easy.
8. The market size of the products is significant enough to be considered high value
   products.

If the framework can be successfully applied to products in a practical setting, then validation
of the framework will be a feasible objective. This part of the methodology will help us
understand the strengths, weaknesses and gaps in the proposed methodology.
Phase – I: Implementing Innovation Mining framework

First part of the methodology is concerned with the application of the ‘Innovation Mining’ framework to a set of products with varying levels of complexity selected based on some research criteria. Assuming a value metric is identified as a benefit-to-cost ratio that is relevant to the business objectives of the organization, the following steps are involved in the application of the framework to the set of products selected for the case study.

a. Linking Innovation scenarios to the set of products

The links from the innovation scenarios to the components is established through engineering matrices like the QFD-I that link stakeholder requirements to system requirements and QFD-II that link system requirements, design parameters, subsystem requirements, subsystems and components as depicted in figure (3). The relationships are established based on the number of levels considered for the analysis. The number of levels is chosen depending on the complexity of the product and the degree of detail needed. This is done to establish the existing product architecture and understand the interactions happening at the different interfaces within the product. This will enable us to make changes to the existing VOCs or include new VOCs and perceive the significance of a set of EMs and their role in fulfilling a VOC.

b. Experimenting and Analyzing the effect of Weighting schemes

The weighting scheme at the different levels of the engineering matrices along with the transfer function links the VOCs to EMs, EMs to subsystems etc. The weights populated may indicate the importance of each requirement relative to the other requirements. This weight will then be used to scale the transfer function populated in the matrices carrying information regarding the degree of fulfilment of the attributes from the system level to the component space. The manipulation of the weighting scheme and the application of the framework is iterated with the different possibilities of combinations to obtain a set of relationships between the components for each weighting scheme used. The results are then examined to study the effects of changing the weighting schemes on the relationships generated. The experimentation methodology is explained in greater detail in chapter 4.0 Feasibility Case Study Results.
c. **SVD Analysis using Matlab**

Singular value decomposition is used on the relationships established above to identify the underlying pattern and arrive at a set of components from the existing design that should be the focus for innovation. This analysis does not delineate the underlying pattern directly rather it defines the links from the system level to the component level. SVD along with the concept of SVD is explained in greater detail in section 2.2 Singular Value Decomposition.

d. **Grouping Using Hierarchical agglomerative clustering**

Hierarchical clustering is used to provide physical meaning to the links defined by SVD and define patterns hidden in relationship matrices. Clustering methods like Dendrograms along with Venn diagrams are used to help visually represent the results generated for better interpretation.

**Phase – II: Comparison with Actual Scenario**

The set of results from the application of the Innovation Mining framework gives us a non-prioritized list of components where the innovation efforts must be focused for the most benefit. At this stage, we look for clever solutions existing in the market that solve these problems/failure modes. A question may arise as to why cannot these components be picked by inspection? but in this case, we are picking them based on actual available data by using a quantitative methodology whereas picking from inspection would be entirely based on human intuition. Our goal is to provide a quantitative method that is dependent on actual available product data. These components are then compared with the actual change/innovation that has occurred in a similar system, as these innovations could have been made to resolve a certain problem in the product. Ideally, the components highlighted by the framework to solve a specific problem should match with the components that have been innovated to solve the same problem in a similar improved system.

These results of comparison between the output and actual scenarios will be represented using an image displaying the components that make up the product. The image shows the results of the innovation mining framework by highlighting the components to be the focus of the innovation efforts. The image highlights those components of the product that has been innovated to solve a specific problem or to improve a chosen value metric of the product. The
use of this image to represent the comparison analysis makes interpretation easier for any person. After analysis, conclusions can be made and insights can be generated to help innovation efforts in an organization. Based on the ease of interpretation of the results generated to identify meaningful clusters of components that correspond with the actual scenarios, the ability of the framework in identifying innovation opportunities can be validated and further areas for improvement can be identified.

4.0 Feasibility Case Study Results

In this case example, a sample application of the innovation mining framework is done on a simple system with less than fifteen parts to demonstrate the feasibility of the effects of making changes to the framework in identifying components worth innovating. The case study is based on a mechanical/drafting pencil shown in figure 11 and the general characteristics of the system are listed below:

Figure 11 - Parts of a Mechanical pencil
Table 1 - General characteristics of a Mechanical Pencil

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of components</td>
<td>14</td>
</tr>
<tr>
<td>Product cost</td>
<td>&lt;$8</td>
</tr>
<tr>
<td>VOC</td>
<td>Easy to write, Last longer, Fine grip, Affordable, Good appearance, Easy to carry, Not damage paper, Easy to erase, Variable darkness, Variable line width</td>
</tr>
<tr>
<td>Engineering Metrics</td>
<td>Rigidity of the pencil, Hardness of the graphite, Length of the pencil, Weight of the pencil, Diameter of the pencil, Mean line width, Average line darkness, Time to remove a standard marked patch, Transport usability test</td>
</tr>
<tr>
<td>Parts</td>
<td>Lead, Lead sleeve, Lead retainer, Lead reservoir tube, Chuck, Chuck ring, Coil spring, Eraser, Eraser holder, Pocket clamp, Grip, End cap, Push button, Body barrel</td>
</tr>
</tbody>
</table>

This product for the feasibility study is represented with information that links VOCs to EMs and EMs to components. This information is represented in a matrix format by making use of the house of quality QFD matrices to establish the links from a system level to the component level as shown in figure 12. In this case example, we study the effects of varying the weighting schemes, effects of using filtered and non-filtered data sets and the effects of multiple weighting schemes. The results from the above scenarios are analyzed to check if their interpretation leads to successfully establishing a link between the resulting clusters and the innovations that have occurred in the mechanical pencil.
4.1 Effect of varying the VOC weighting schemes in QFD – I matrix

In this phase of the study, the innovation mining framework is applied to the mechanical pencil with the use of two different weighting schemes. The different weighting schemes used are 1-3-9 system and the 1-3-6-9 system with the corresponding values acting as the scaling factor for the transfer function depicting to what extent the VOCs are fulfilled by the EMs in the house of quality QFD – I matrix as shown in figure 12. The weights represent the importance of the voice of the customer relative to each other. The weights are categorized as follows,

**1-3-9 System**
- 1 – This value means that the VOC is the least important in the perception of the customer
- 3 – This value means that the VOC is important in the perception of the customer
- 9 – This value means that the VOC is the most important in the perception of the customer

**1-3-6-9 System**
- 1 – This value means that the VOC is the least important in the perception of the customer
- 3 – This value means that the VOC is moderately important in the perception of the customer
- 6 – This value means that the VOC is important in the perception of the customer
- 9 – This value means that the VOC is the most important in the perception of the customer

<table>
<thead>
<tr>
<th>Customer Requirements</th>
<th>Customer Weights</th>
<th>Engineering Metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Hardness of the pencil</td>
</tr>
<tr>
<td>Easy to write</td>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>Last longer</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>Fine grip</td>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>Affordable</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>Good appearance</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Easy to carry</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Not damage the paper</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Easy to erase</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Variable darkness</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Variable line width</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

**Figure 12 - Coupling matrix of VOCs and EMs**
By using the two weighting systems mentioned above the innovation mining framework is applied to the mechanical pencil where the weights scale the transfer function populated in the matrix that produces the relative importance of the engineering metrics of the system. This relative importance value of the engineering metrics is used as the weight in the house of quality QFD – II matrix as shown in figure 13, this matrix is the parent matrix used in the SVD analysis to identify the hidden patterns in the data. Then the columns of the resulting V matrix from SVD is multiplied with the strengths from the resulting S matrix after performing SVD.

<table>
<thead>
<tr>
<th>Engineering Metrics</th>
<th>Phase I Relative Weights</th>
<th>Mechanical Pencil</th>
<th>Part Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Raw score</td>
<td>Part score</td>
<td></td>
</tr>
<tr>
<td>Hardness of the pencil</td>
<td>21%</td>
<td>0 0 0 0 0 0 0 0 0 0 0 1 1 1 9</td>
<td></td>
</tr>
<tr>
<td>Hardness of the graphite</td>
<td>24%</td>
<td>0 0 0 0 0 0 0 0 0 0 0 0 0 0 0</td>
<td></td>
</tr>
<tr>
<td>Length of the pencil</td>
<td>9%</td>
<td>0 0 0 0 0 0 0 0 0 0 0 0 0 0 0</td>
<td></td>
</tr>
<tr>
<td>Weight of the pencil</td>
<td>17%</td>
<td>1 1 1 3 3 1 1 1 1 1 1 1 1 1 0</td>
<td></td>
</tr>
<tr>
<td>Diameter of the pencil</td>
<td>11%</td>
<td>0 0 0 0 0 0 0 0 0 0 0 0 0 0 0</td>
<td></td>
</tr>
<tr>
<td>Mean line width</td>
<td>2%</td>
<td>9 3 3 0 0 1 0 0 0 0 0 0 0 0 0</td>
<td></td>
</tr>
<tr>
<td>Average line darkness</td>
<td>7%</td>
<td>9 0 0 0 0 0 0 0 0 0 0 0 0 0 0</td>
<td></td>
</tr>
<tr>
<td>Time to remove a standard marked patch</td>
<td>5%</td>
<td>3 0 0 0 0 0 0 0 0 0 0 0 0 0 0</td>
<td></td>
</tr>
<tr>
<td>Transportability test</td>
<td>6%</td>
<td>0 0 0 0 0 0 0 0 0 0 0 0 0 0 0</td>
<td></td>
</tr>
<tr>
<td>Raw score</td>
<td>3.2</td>
<td>0.2</td>
<td>0.1</td>
</tr>
<tr>
<td>Relative Weight</td>
<td>24%</td>
<td>2%</td>
<td>6%</td>
</tr>
</tbody>
</table>

*Figure 13 - Coupling matrix for EMs and Components*

Then hierarchical clustering is performed to generate dendrograms for the resulting matrix to identify the hidden concepts that links the system level metrics with the components. The above procedure is followed in the case of both the weighting schemes and the resulting dendrograms are studied to note the effects of varying the weighting system. The dendrograms generated by employing the 1-3-9 system and the 1-3-6-9 system are shown in figure 14.
Figure 14 - Dendrograms for 139 & 1369 weighting schemes

From observing the dendrograms obtained for each of the weighting schemes it is seen that varying the weighting schemes produces different linkages between the system level metrics and the components. For instance, in the 1-3-9 system the cluster containing pushbutton and end cap is first linked with the grip whereas in the 1-3-6-9 system the cluster containing pushbutton and end cap is first linked with the cluster containing lead sleeve, lead retainer, chuck and eraser holder. It is evident from the above illustration that varying the weighting scheme used in the framework affects the nature of linkages between the system level metrics and the components leading to varied cluster formation. It was later observed from the experiments conducted to study the effects of multiple weighting schemes that the weighting scheme does not have significant impact on the cluster formation when a filtered operating matrix was used for the analysis.
4.2 Effect of filtered and unfiltered data sets

In this phase of the case study example, the innovation mining framework is applied to the mechanical pencil by using two different sets of data in the analysis, a filtered data set and an unfiltered data set. But in both the cases the same weighting scheme (1-3-6-9 system) is used to avoid the variability due to different weighting systems. The initial process is similar to the previous case; the VOCs are linked to the EMs by using phase – I QFD matrix and then the EMs are linked to the components (EMs to Subsystems is used in case of complex products with thousands of components) by using phase – II QFD matrix.

For the unfiltered analysis, SVD is performed on the phase – II QFD matrix by including all the rows and columns for the analysis. Then the columns of the resulting V matrix from SVD is multiplied with the strengths from the resulting S matrix after performing SVD. The resulting matrix is the operating matrix on which hierarchical clustering is performed to generate dendrograms to identify the hidden concepts that links the system level metrics with the components. The dendrogram generated for the unfiltered data set displays all the components of the mechanical pencil as shown in figure 16.

In the case of filtered analysis, a value metric is chosen and a set of engineering metrics that contribute to the value metric are selected from the list of all engineering metrics. This can be done by making use of the three scenarios of innovation developed in the innovation mining framework or by identifying the related engineering metrics from phase – I QFD matrix. Then the phase – II QFD matrix is filtered by taking only the rows of the selected engineering metrics, this resulting matrix is then used in the SVD analysis to get the unique set of matrices U, S and V. Then the columns of the V matrix are multiplied with the strength of the concepts.
from S matrix to generate the operating matrix on which hierarchical clustering is performed. This process gives us a dendrogram shown in figure 16 that displays only those components and their relationships that should be the focus in improving the value metric chosen in the beginning of the analysis.

![Dendrogram](image)

*Figure 16 - Dendrogram for filtered & unfiltered data set*

From the figure 16 it can be observed in the case of unfiltered analysis that the resulting dendrogram displays the relationships between all the components in the system. Although, it helps in understanding the nature of relationship between the different components it does not give out any information that will yield a specific set of components upon which focusing the improvement efforts will lead to innovation. However, the engineering judgement of a panel of experts on the relationships obtained can lead to insights that may help in the identification of any potential innovation opportunity not necessarily in correspondence to a specific value.
In the case of filtered analysis, the value metric chosen for improvement is ‘the consistency of the line width’. Based on the value metric chosen three engineering metrics were shortlisted from the total list of nine engineering metrics. The EMs selected for filtering were hardness of the graphite, mean line width and average line darkness. The phase – II QFD matrix used in the SVD analysis will contain only three rows and fourteen columns. SVD is performed on this 3x14 matrix and the columns of the resulting V matrix are multiplied by the strength of the concept values from the resulting S matrix. This will generate the operating matrix on which hierarchical clustering is performed and the dendrogram shown at the bottom in figure (16) displaying only the set of components that should be the focus in improving the consistency of the line width is generated. Hence, the filtered analysis yields better results in comparison with the unfiltered analysis as it produces results concentrated on a specific value of interest. Based on the interpretation of this clustering an expert panel can gain insights on the components to be the focus of innovation efforts to come up with design decisions that can improve the performance of a product aligned with a specific value of interest.

The above figure 17 is a comparison of the results of the analysis using weighted filtered data and the solution identified to be in use to solve the problems of inconsistent line width and lead breakage. The left part of the image shows in the red boxes the components highlighted by the innovation mining framework and the right part of the image shows in the red boxes components that were changed to solve the problems and come up with the next-in-line product.
The components highlighted in the right half are components that are directly impacted by the solution proposed to solve the issues of inconsistent line width and lead breakage in the identified solution. It can be observed that there is a striking correlation between the two which gives us good insights on the utility and strength of the framework.

The results of the case example were studied to identify solutions in use in the current market that solves the problems of inconsistent line width and lead breakage. A pencil named ‘Kuru Toga’ was identified which uses a three-gear mechanism named ‘Kuru-Toga engine’ that rotates the tip of the lead and solves the issue of inconsistent line width and lead breakage. The mechanism has three gears the upper gear, the middle gear and the lower gear mounted to the lead holding and dispensing mechanism. When writing, the lead makes contact on the paper and this causes the middle gear to move up mesh with the upper gear and rotates to the left and is held in this position as pressure is applied due to the contact. When the pencil is lifted from the paper and contact between lead and the paper is lost, the coil spring pushes the middle gear back down and it meshes with the lower gear and rotates to the left again. In short, whenever the pencil is pressed onto the paper and released, the internal gear moves up and down and rotates the lead a fraction at a time. This process continues until the writing continues and as the lead rotates a little to the left each time one writes it causes the lead to wear down evenly into a cone shape. Hence, helping in maintaining the consistency of the line width. Another solution this company has resorted to solve the issue of pencil breakage was to create a lead with a soft outer layer and a hard core thereby enabling easy and even wear of the lead as it is rotated and the conical shape prevents lead from getting stuck in the paper and breaking which is the most common reasons for lead breakage. As it is seen that the solutions discussed above are directly or indirectly involving the components identified by implementing the innovation mining framework to the mechanical drafting pencil. This proves that the innovation model applied with weighted filtered data holds promise in identifying innovations opportunities in an existing product. But a mechanical pencil is a rather simple product and an analysis of that cannot be considered representative of what the framework can accomplish. So, a further implementation and study of the model on more complicated products is envisioned to validate the framework and reflect on its capabilities.
4.3 Effect of multiple weighting schemes and failure modes

In this phase of the study, the innovation mining framework is applied to the mechanical pencil by using two weighting schemes in the QFD – II instead of one weighting scheme as shown in the figure 18. The results of using different VOC weighting schemes in QFD-I described in section 4.1 served as a motivation for experimenting with multiple weighting schemes. This phase consists of the following test combinations to be executed to determine the effects of using multiple weighting schemes and multiple value metrics for improvement. The test combinations are,

1. Single weighting scheme – Single failure mode
2. Multiple weighting scheme – Single failure mode
3. Single weighting scheme – Multiple failure mode
4. Multiple weighting scheme – Multiple failure mode

Executing the above-mentioned test cases and comparing them with their counterparts will enable in understanding the effects of using multiple weighting schemes and multiple value metrics in identifying components worth innovating in the product. The initial process is similar to the previous case; the VOCs are linked to the EMs by using phase – I QFD matrix and then the EMs are linked to the components (EMs to Subsystems is used in case of complex products with thousands of components) by using phase – II QFD matrix.

Figure 18 - Coupling matrices linking VOCs - EMs & EMs - Components
The intersection of the colored boxes in QFD – I shows us the coupling between the voice of the customer and the engineering metrics. It is observed that for the failure mode of inconsistent line width the related VOCs are ‘variable darkness’ and ‘variable line width’ whereas for the failure mode of pencil breakage the related VOC is ‘last longer’. Based on these VOCs the related engineering metrics are selected from the coupling matrix. The selected engineering metrics are highlighted using the red boxes in the QFD – II matrix for representation.

For the filtered analysis, two value metrics or failure modes are chosen for improvement namely consistency of the line width and rigidity of the pencil or inconsistent line width and breakage of the pencil respectively. The set of engineering metrics that contribute to the value metric are selected from the list of all engineering metrics. This can be done by making use of the three scenarios of innovation developed in the innovation mining framework or by identifying the related engineering metrics from phase – I QFD matrix as shown in figure 18. Then the phase – II QFD matrix is filtered by taking only the rows of the selected engineering metrics, this resulting matrix is then used in the SVD analysis to get the unique set of matrices U, S and V. Then the columns of the V matrix are multiplied with the strength of the concepts from S matrix to generate the operating matrix on which hierarchical clustering is performed. This process gives us a dendrogram for each test combination as shown in figure 19 and figure 20 that displays only those components and their relationships that should be the focus in improving the value metrics or solving the failure modes chosen in the beginning of the analysis.

The below displayed dendrograms in figure 19 are the results of the first two test combinations namely 1) Single weighting scheme – single failure mode and 2) Multiple weighting scheme – single failure mode. The analysis was carried out for the failure mode of pencil breakage and it can be observed from the highlighted clusters that the use of multiple scheme does not have significant effect on the nature of clusters formed. Adding multiple weighting schemes gave the same results as using a single weighting scheme. The only noticeable effect is that using multiple weighting schemes just increased the scale of the representation by several times. But the scale of the dendrogram does not alter the quality and the nature of the clusters formed as they are independent.
The above displayed dendrograms in figure 20 are the results of the third and fourth test combinations namely 3) Single weighting scheme – multiple failure modes and 4) Multiple weighting scheme – multiple failure modes. The analysis was carried out for the failure mode of pencil breakage and inconsistent line width. It can be observed from the highlighted clusters that although the position of one of the clusters varies between the two combinations, the use of multiple scheme does not have significant effect on the nature of clusters formed. Adding
multiple weighting schemes gave the same clusters as using a single weighting scheme. The only noticeable effect is that using multiple weighting schemes just increased the scale of the representation by several times. But the scale of the dendrogram does not alter the quality and the nature of the clusters formed as they are independent. Hence, it can be concluded from the analysis of the four test combinations that use of multiple weighting schemes does not have significant changes in the formation of clusters. It is also observed from the four test combinations that analysis using single failure mode yields better results in comparison with analysis using two failure modes simultaneously as it requires the opinion of experts to distinguish which cluster of components should be the focus for solving each of the failure modes. Whereas the use of single failure mode reduces the complexity and yields directly the cluster of components to be focused upon without the need for much interpretation by experts.

4.4 Covariance – Correlation – Direction matrix

Identification of engineering metrics from the scenarios of innovation is an important step in the methodology of Innovation Mining framework. The second scenario of innovation namely technological trade-off scenario occurs when the technological contradictions in the product can no longer be resolved. These scenarios are usually identified through QFD – I, TRIZ or engineer experience.

![Figure 21 - Covariance-correlation-direction of preferred improvement matrix](image)

The trade-off scenario proposes that for a given engineering metric the trade-off is defined as the required direction of improvement for the critical parameters with both being in the opposite direction. The most logical way to identify these trade-offs linked to the critical parameters is from the roof of House of Quality, through TRIZ contradiction analysis and
through engineering judgement. Another method can be used to identify trade-offs existing in the matrix. Developing covariance matrix gives us a measure of how two engineering metrics change with respect to each other. It is positive when the two corresponding engineering metrics show similar behavior and negative otherwise. This can be used to identify trade-offs.

The matrix shown in figure (21) is an account of the covariance values, correlation and the direction of preferred improvement of the column engineering metrics with the corresponding row engineering metric. In the correlation column, a ‘+’ means a positive correlation, ‘++’ means a high positive correlation, ‘-’ means a negative correlation, ‘- -’ means a high negative correlation and ‘0’ means no relation. Similarly, in the direction of preferred improvement column a ‘+’ indicates a need to increase and a ‘-’ indicates a need to decrease to resolve the trade-offs. The consolidated matrix gives a clear picture of the trade-offs existing in the system which can be analyzed to identify engineering metrics of interest to be used in the innovation mining framework.

The covariance-correlation-direction matrix can assist in identifying trade-offs that cannot be resolved to select EMs in the second scenario of innovation. This concept is not applied to the vacuum case study as we are only interested in validating the ability of the framework in identifying innovation opportunities given a value metric of interest. Also, in this work, we are validating a new method of selecting EMs for products that do not have enough history to use the three scenarios of innovation. Hence, importance is not given to creating the covariance-correlation-direction matrix for the vacuum case study.

5.0 Vacuum Case Study Results

Applying IM framework to Dirt Devil Ultra Handheld Vacuum

This section provides a detailed case study of the application of Innovation Mining framework as discussed in the preceding sections. The case study is on a Dirt Devil Ultra handheld bagged vacuum shown in figure (22), a more complex product than the mechanical drafting pencil analyzed in the research methodology section. The handheld vacuum is an integral system in the market of home cleaning appliances and the characteristics of the system chosen are as follows:
Table 2 - General characteristics of Dirt Devil Hand Vacuum

<table>
<thead>
<tr>
<th>No. of parts &amp; sub-assemblies</th>
<th>18</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product cost</td>
<td>$37</td>
</tr>
<tr>
<td>VOC</td>
<td>The vacuum picks up unwanted dust &amp; hair</td>
</tr>
<tr>
<td>VOC-2</td>
<td>The vacuum works on multiple surfaces</td>
</tr>
<tr>
<td>VOC-3</td>
<td>The vacuum is resistant to everyday impacts</td>
</tr>
<tr>
<td>VOC-4</td>
<td>The vacuum is safe to operate</td>
</tr>
<tr>
<td>VOC-5</td>
<td>The vacuum is comfortable to operate</td>
</tr>
<tr>
<td>VOC-6</td>
<td>The vacuum should contain the debris without releasing them into the air</td>
</tr>
<tr>
<td>VOC-7</td>
<td>The vacuum picks up pet hair</td>
</tr>
<tr>
<td>VOC-8</td>
<td>The vacuum cleans without damaging the surface</td>
</tr>
<tr>
<td>VOC-9</td>
<td>The user can easily dispose the debris without touching them</td>
</tr>
<tr>
<td>VOC-10</td>
<td>The vacuum is long lasting</td>
</tr>
<tr>
<td>VOC-11</td>
<td>The vacuum is easy to store</td>
</tr>
<tr>
<td>VOC-12</td>
<td>The vacuum is quiet while operating</td>
</tr>
<tr>
<td>VOC-13</td>
<td>The vacuum is easy to carry</td>
</tr>
<tr>
<td>VOC-14</td>
<td>The vacuum enables access to hard to reach areas</td>
</tr>
<tr>
<td>VOC-15</td>
<td>The vacuum has a long warranty</td>
</tr>
<tr>
<td>VOC-16</td>
<td>The vacuum is energy efficient</td>
</tr>
<tr>
<td>VOC-17</td>
<td>The vacuum is appealing to the customer</td>
</tr>
<tr>
<td>VOC-18</td>
<td>The vacuum is maintenance free</td>
</tr>
<tr>
<td>VOC-19</td>
<td>The vacuum is affordable</td>
</tr>
<tr>
<td>VOC-20</td>
<td>The vacuum does not require frequent consumable change</td>
</tr>
<tr>
<td>VOC-21</td>
<td>The vacuum has long run time</td>
</tr>
<tr>
<td>VOC-22</td>
<td>The vacuum does not leave behind large debris</td>
</tr>
<tr>
<td>VOC-23</td>
<td>The vacuum can sense dirt</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Engineering Metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td>EM-1</td>
</tr>
<tr>
<td>EM-2</td>
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<tr>
<td>EM-3</td>
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<td>EM-4</td>
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<td>EM-24</td>
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<td>EM-25</td>
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</tbody>
</table>
The product data of the Dirt Devil ultra handheld vacuum chosen for the case study can be represented in a data matrix that links the VOCs to the EMs and the EMs to the components and sub-systems (EMs to Subsystems is used in case of complex subsystems where a detailed decomposition is not needed. For instance, the motor in a vacuum because not all vacuum companies manufacture their own motors and they may decide to outsource it from a more competitive manufacturer). This information is represented in a matrix format by making use of the house of quality QFD matrices to establish the links from a system level to the component level as shown in figures 23 & 24. In this case study, we disregard the effects of varying the weighting schemes, effects of using un-filtered data sets and the effects of multiple weighting schemes as the feasibility study demonstrates that the effects of these scenarios are negligible and do not create significant changes in the results after analysis. We pay attention only to the effects of using filtered data as it gives the most pertinent cluster of components to improve the chosen value metric. The results from the above scenario is analyzed to check if their interpretation leads to successfully identifying the link between the resulting component clusters and the innovations that have occurred in the category of handheld vacuums.
<table>
<thead>
<tr>
<th>No.</th>
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**Figure 23 - VOC vs EM Relationship matrix for Dirt Devil Hand Vacuum**
From the results obtained in the feasibility study, the following was decided,

- **VOC weighting scheme** – Different VOC weighting schemes did not have significant effects on the output when a filtered matrix was used for analysis.
- **Filtered data set** – Data related to the value metric filtered from the parent operating matrix yielded better results for identifying innovation opportunities.
- **Single weighting scheme** – The results of the test combinations proved that multiple weighting schemes did not impact the cluster formation. So, a single weighting scheme is sufficient for the analysis.
- **Single value metric** – The framework was successful in identifying innovation opportunities simultaneously for two value metrics but performing the analysis for single value metric gives us more focused results related to that value metric.

The innovation mining framework is applied to the Dirt Devil handheld vacuum to identify potential innovation opportunities to improve a set of values or to solve a set of problems commonly seen in handheld vacuums. The set of values to be improved are listed below,

1) **Portability and reach**
Portability refers to the ease with which the vacuum can be carried and moved from one place to another. The reach refers to the ability of the vacuum to enable the user to clean hard to reach areas far from a power source.

2) **Reduced hair wrap**
Hair wrap refers to the mass of hair tangled around the brush roll of the vacuum that affects cleaning performance of the vacuum drastically.

3) **Cleaner exhaust**
Cleaner exhaust refers to the improved quality of exhaust air after cleaning. This value improvement requires the separation of fine dust particles from the air stream before being let out in the atmosphere as this can cause severe health problems to the users.

4) **Runtime experience**
Runtime experience refers to the ability of the vacuum to operate for long durations without significant loss in cleaning performance and user convenience.
5) Reduced cost of consumables
Reduced cost of consumables refers to the reduction in any cost of consumables to the user for operation, maintenance and disposal of the product.

6) Improved cleaning performance
Improved cleaning performance refers to the increase in the air flow and the amount of power produced by the vacuum to carry out its cleaning function.

By applying the innovation mining framework to the Dirt Devil hand held vacuum, we aim to arrive at clusters of components that upon innovation can solve for the above-mentioned value metrics.

The next step in the application of Innovation Mining framework is the development of relationships between VOCs – EMs and EMs – Components. The representation of the product architecture in terms of relationships between VOCs, EMs and components is achieved by using the QFD House of Quality matrix I & II as shown in figures 23 & 24. The transfer function used in the QFD – I relationship matrix is the 1-3-9 system and it is classified as follows,

1 – When the Engineering metric is completely fulfilled but satisfies the voice of the customer to the least extent relatively to the other Engineering Metrics.

3 – When the Engineering metric is completely fulfilled but satisfies the voice of the customer to a medium extent relatively to the other Engineering Metrics.

9 – When the Engineering metric is completely fulfilled but satisfies the voice of the customer to the highest extent relatively to the other Engineering Metrics.

The QFD – II matrix linking the EMs to the components is also filled similarly. The VOCs are assigned weights based on their importance from the point of view of the customer. This weighted rating of the VOCs is multiplied with the transfer function inputs in the QFD – I to get the relative importance of each Engineering Metric in comparison with one another and their contribution in satisfying the VOCs of the system. The relative importance rating from
QFD – I matrix is used in the QFD – II matrix as the weights associated with the EMs. The input parent matrix used in the Innovation Mining framework is obtained by multiplying these weights with the transfer functions populated in the QFD – II matrix linking the components to the EMs. The parent operating matrix for the Dirt Devil bagged handheld vacuum is shown in figure 25. The cells in the matrix that do not have any transfer function values are filled with zeros to denote no relationship between the associated component and EM.

The data sets pertaining to each of the value metric chosen is then filtered from the parent operating matrix shown in figure (25) by first identifying the VOCs related to the value metric from the QFD – I relationship matrix. The EMs associated with each of the VOCs are then identified and only the rows of data corresponding to these EMs are selected from the parent operating matrix for analysis using the Innovation Mining framework. The matrix obtained after filtering the data associated with each of the chosen value metric is called the Filtered Operation Matrix shown in tables (3.1, 4.1, 5.1, 6.1, 7.1 & 8.1). The summary of the related VOCs and EMs for each of the value metric chosen are shown in tables (3, 4, 5, 6, 7 & 8).
Singular value decomposition is performed on the filtered operating matrix and decomposed into its component matrices $U$, $\Sigma$ & $V$ to identify hidden relationships in the matrix. The ‘$V$’ matrix is then weighted with values from ‘$\Sigma$’ by multiplying the strength values to their corresponding columns in the ‘$V$’ matrix. This step is crucial to enhance the quality of the dendrograms obtained after hierarchical clustering of the components based on the data from the weighted ‘$V$’ matrix. The weighted ‘$V$’ matrix is better for analysis than the ‘$V$’ matrix because in addition to providing links to the concepts it also conveys data associated with the relative strength of each concept.

**Analysis for Improved Portability and Reach:**

The first value metric to be analyzed is Improved Portability and Reach. This value metric is a combination of two different metrics which can be analyzed independently for innovation opportunities. But however, analysis is done considering the two metrics jointly to validate the ability of the framework to identify clusters of components that present innovation opportunities to simultaneously improve the two metrics. The summary of VOCs and the related EMs associated to this value metric is listed in table 3.

<table>
<thead>
<tr>
<th>Portability and Reach</th>
<th>VOC</th>
<th>EM</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>The vacuum is easy to store</td>
<td>2</td>
</tr>
<tr>
<td>13</td>
<td>The vacuum is easy to carry</td>
<td>6</td>
</tr>
<tr>
<td>14</td>
<td>The vacuum enables access to hard to reach areas</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>11</td>
</tr>
<tr>
<td></td>
<td></td>
<td>16</td>
</tr>
</tbody>
</table>

The VOCs related to the value metric are then used to identify the EMs that contribute to these VOCs. The identified EMs are then used to select rows of data from the parent operating matrix and the filtered operating matrix associated with portability and reach is formed. This filtered operating matrix is shown in table 4.
Singular value decomposition is performed on the filtered operating matrix shown in table 4 and it is decomposed into its component matrices U, Σ & V. The ‘V’ matrix is then weighted with values from ‘Σ’ by multiplying the strength values to their corresponding columns in the ‘V’ matrix. The weighted ‘V’ matrix denoted by ‘VS’ is shown in table 5.

Table 4 - Portability & Reach Filtered Operating Matrix (Refer Table 2 & Figure 25)

<table>
<thead>
<tr>
<th></th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
<th>P7</th>
<th>P8</th>
<th>P9</th>
<th>P10</th>
<th>P11</th>
<th>P12</th>
<th>P13</th>
<th>P14</th>
<th>P15</th>
<th>P16</th>
<th>P17</th>
<th>P18</th>
</tr>
</thead>
<tbody>
<tr>
<td>EM2</td>
<td>0</td>
<td>0</td>
<td>0.09</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.09</td>
<td>0</td>
<td>0</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EM6</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0.06</td>
<td>0</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.18</td>
<td>0</td>
<td>0.18</td>
<td>0.54</td>
<td>0</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>EM11</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.09</td>
<td>0</td>
<td>0.09</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>EM16</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.27</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5 - Weighted 'V' matrix for Portability and Reach

\[ V^S = \]

\[
\begin{pmatrix}
-0.0347 & -0.3329 & -0.2631 & -0.0069 & -0.1891 \\
0.4323 & -0.2081 & -0.8381 & -0.2839 & -0.6126 \\
0.0100 & -0.1112 & 0.1544 & 0.1357 & 0.0735 \\
-0.5567 & -0.1364 & -0.0594 & -0.0040 & 0.0010 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
-0.0004 & -0.0004 & 0.0006 & 0.0794 & 0.0423 \\
-0.0729 & -0.0043 & 0.0034 & 0.1167 & -0.0286 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
-0.5567 & -0.1364 & -0.0594 & -0.0040 & 0.0010 \\
0 & 0 & 0 & 0 & 0 \\
-0.2778 & 0.1986 & -0.1707 & 0.0007 & -0.0000 \\
-0.7875 & 0.1232 & 0.1439 & -0.0055 & 0.0013 \\
0 & 0 & 0 & 0 & 0
\end{pmatrix}
\]
Hierarchical clustering is then performed on the weighted matrix ‘$V^S$’ to obtain a dendrogram which displays clusters of components grouped based on the known and hidden relationships in the data contained in the weighted matrix ‘$V^S$’. The dendrogram obtained after hierarchical clustering of the weighted matrix ‘$V^S$’ is shown in figure 26. The dendrogram shows components clusters that are closely related to each other with respect to impacting the chosen value metric namely portability and reach. We are most interested in the top half of the dendrogram which displays distinct clusters of components because the lower half is observed to be consisting of large clusters of components that impact the value metric the least and are unrelated to the value metric.

The dendrogram shown in figure 26 has nine clusters in total with six of them highlighted in different colors to distinguish between them. Only one out of these six highlighted clusters have two components/subassemblies in a single cluster.
It is important to understand that the clusters highlighted are deemed to be contributing to portability from the perspective of size, shape and weight of the device and those clusters contributing to reach are from the perspective of ability to access and clean hard to reach areas/places far from a power source. The value contribution of each of the highlighted cluster is listed in table 6.

### Table 6 - Value contribution for Portability & Reach

<table>
<thead>
<tr>
<th>Components highlighted by the framework</th>
<th>Value contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frame</td>
<td>Portability</td>
</tr>
<tr>
<td>Motor Assembly, Fan Assembly</td>
<td>Portability</td>
</tr>
<tr>
<td>Nozzle door</td>
<td>Portability</td>
</tr>
<tr>
<td>Hose Assembly</td>
<td>Portability, Reach</td>
</tr>
<tr>
<td>Swing door (Hose)</td>
<td>Reach</td>
</tr>
<tr>
<td>Power Cord</td>
<td>Reach</td>
</tr>
</tbody>
</table>

---

It is important to understand that the clusters highlighted are deemed to be contributing to portability from the perspective of size, shape and weight of the device and those clusters contributing to reach are from the perspective of ability to access and clean hard to reach areas/places far from a power source. The value contribution of each of the highlighted cluster is listed in table 6.
These component clusters are then analyzed and compared to the existing innovative solutions that address these issues or enhances the value metric considered. In this case, the components listed in table 6 are compared to the innovations in a Dyson V6 cordless vacuum. By comparing the two we can derive how each of these components can be innovated to improve the portability & reach and postulate how it could have led to the innovations seen in a Dyson V6 cordless vacuum. The highlighted components in figure 27 and their comparison to Dyson innovations are discussed below.

1. Frame
The frame is the outer casing of the vacuum that contains all other subassemblies and components. Its dimension is a significant factor in determining the space occupied by the vacuum and the ease of carrying the vacuum from one place to another. Because when the frame is huge, it limits mobility and portability. Hence, portability can be improved by choosing the optimal dimensions for the frame.

Dyson has a frame smaller than the Dirt Devil, compactly housing the motor and fan assembly without having to accommodate space/passage for the debris to be sucked into the dust bag like in the Dirt Devil hand vacuum and other traditional bagged vacuums. Thus, having a compact frame increases portability by reducing the nonessential spaces and thereby the overall dimension.

2. Motor & Fan Assembly
The motor and fan assembly function together to create the suction required to perform cleaning. The motor and the fan assemblies together make relatively one of the heaviest subsystems in the vacuum.

It is common knowledge that the more powerful a motor, the more is the suction created. If large motors are used to create powerful suction with an eye to boost cleaning performance then the trade-off between weight and portability is triggered. Using heavy motor and fan assembly creates an adverse effect on portability. However, in the Dyson design the motor and fan assembly are compactly packed which eliminates the need for accessories (Motor grommet etc.) that support the motor and fan assembly in Dirt Devil. In addition, an indirect trade-off is established that unfavorably affects portability. An increase in the size of motor and fan assembly sees an increase in the overall dimension of frame which is a critical factor to be
controlled in maintaining and improving portability. In this case, improved portability is achieved by weight & size reduction.

The Innovation Mining framework, in addition to identifying components to focus the innovation efforts is also helping us uncover and understand trade-off relationships, positive and negative correlations between the identified components and their impacts on the chosen value metric. Insights gained from comprehending these relationships will enable a product developer to make informed decisions and design changes to an existing product from a Systems Thinking perspective.

3. Nozzle door
The nozzle door is basically a lid that fits on an extension of the frame to constitute the nozzle assembly. This contains the brush roll assembly that makes contact on the surface to be cleaned and enables the user to close or open it to grant the brush roll access to the floor for cleaning. Closing this door will disengage brush roll contact with the floor and redirect the suction to the hose outlet provided the swing door - hose is open.

In the Dirt Devil hand vacuum, the nozzle is an extension of the frame and so having a large nozzle adds to the size of the frame and the vacuum. This increase in size and weight has an adverse impact on portability as discussed earlier. But a wide nozzle is required to maintain an effective cleaning width so a desirable solution will enable portability while still having a wide nozzle. Dyson designed the nozzle to be a detachable component like other cleaning tools such as the crevice tool etc. This nozzle is wide thereby maintaining effective cleaning width and can be detached when not in use. This leads to a reduction in carrying weight and size of the vacuum which favors portability.

4. Hose Assembly & Swing door
The hose assembly is a long flexible tube like structure attached to the frame-nozzle extension that can be extended to a limited length to clean places the nozzle cannot access. Crevice tool and other specialized cleaning tools can be attached to the hose outlet for effective cleaning. The swing door is a component that acts as a wall separating the hose and the nozzle to prevent loss of suction due to leakage when the nozzle is in use. This swing door can be closed or opened like the nozzle door in conjunction to redirect suction between nozzle outlet and the hose outlet.
In the Dirt Devil hand vacuum, the hose assembly and the swing door are attached directly to the frame and must be carried by the user even when he is using only the nozzle for cleaning. Being directly attached to the frame increases the overall size of the product and the space it occupies. Although the extended length of the hose can access areas where the nozzle cannot it is still inadequate to satisfy the cleaning requirements of the end users with its limited reach. The desirable outcome is to develop a solution that enables access to areas that are hard to reach even for the extended hose. Dyson eliminated the hose assembly by replacing it with a wand assembly to which the nozzle and other specialized cleaning tools can be attached. This wand assembly is detachable from the vacuum body and enables the user to clean the floor without having to bend or crouch and enables access to hard to reach areas. The reach of this wand assembly is twice as much of the hose assembly of the Dirt Devil vacuum. Replacing the hose assembly with a detachable wand assembly increases portability by reducing weight and dimension of the product. It also helps in increasing the reach of the vacuum by using a wand assembly with twice as much reach as the hose assembly.

5. Power Cord
The power cord is the electrical cable that connects the vacuum to a power supply for its operation. The reach of the vacuum is determined by the length of the power cord and it enables the user to clean a large area. But however, the length of the power cord is usually limited to access a single room from a fixed power outlet to reduce the complications caused by tangling of the cord. Other rooms can be cleaned by plugging the power cord to a different outlet in the room to be cleaned which requires the user to find a closer power outlet whenever he moves between rooms. There is also the problem of losing power supply when the user pulls the cord beyond reach causing it to unplug from the power outlet. The desired outcome is to develop a solution that will increase the reach of the vacuum beyond a single room and far from a power outlet with minimum or no user intervention.

Dyson eliminated the need for a power cord by including a chargeable battery pack that powers the vacuum. This improves reach by eliminating the need to find a power source at an operable distance from the vacuum every time the user wants to move between different rooms.
Analysis for Improved hair pick up/Reduced hair wrap:

The second value metric to be analyzed is Improved hair pick up or reduced hair wrap. This value metric is a key performance indicator of the ability of a vacuum to pick up hair and prevent hair wrap in the vacuum components. A vacuum that fails to address this problem causes great dissatisfaction to the end user in terms of cleaning performance and maintenance. Analysis is done considering the significance of this metric in user satisfaction to validate the ability of the framework to identify clusters of components that present innovation opportunities to improve the vacuum’s ability to pick up hair with minimum or no wrap in its components. The summary of VOCs and the related EMs associated to this value metric is listed in table 7.

Table 7 – Reduced hair wrap summary of VOCs and EMs

<table>
<thead>
<tr>
<th>Improved Hair Pick Up / Reduced Hair Wrap</th>
<th>VOC</th>
<th>EM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 The vacuum picks up unwanted dust &amp; hair</td>
<td>1 Suction power</td>
<td></td>
</tr>
<tr>
<td>7 The vacuum picks up pet hair</td>
<td>10 Max. size of debris that can be picked up</td>
<td></td>
</tr>
<tr>
<td>18 The vacuum is maintenance free</td>
<td>15 Particle collection capacity</td>
<td></td>
</tr>
<tr>
<td></td>
<td>16 Distance to edge of effective cleaning</td>
<td></td>
</tr>
<tr>
<td></td>
<td>19 Price</td>
<td></td>
</tr>
<tr>
<td></td>
<td>20 Consumables</td>
<td></td>
</tr>
<tr>
<td></td>
<td>21 Interface with surface</td>
<td></td>
</tr>
<tr>
<td></td>
<td>23 Time to clean the unit</td>
<td></td>
</tr>
</tbody>
</table>

The VOCs related to hair pick up are then used to identify the EMs that contribute to these VOCs. The identified EMs are then used to filter rows of data from the parent operating matrix and the filtered operating matrix associated with hair pick up / hair wrap is formed. This filtered operating matrix is shown in table 8.
Singular value decomposition is performed on the filtered operating matrix shown in table 8 and it is decomposed into its component matrices $U$, $\Sigma$ & $V$. The ‘$V$’ matrix is then weighted with values from ‘$\Sigma$’ by multiplying the strength values to their corresponding columns in the ‘$V$’ matrix. The weighted ‘$V$’ matrix denoted by ‘$V^S$’ is shown in table 9.

### Table 8 - Reduced Hair Wrap Filtered Operating Matrix (Refer Table 2 & Figure 25)

|   | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P11 | P12 | P13 | P14 | P15 | P16 | P17 | P18 |
|---|----|----|----|----|----|----|----|----|----|-----|-----|-----|-----|-----|-----|-----|-----|
| EM1 | 0.39 | 0 | 0 | 1.17 | 0 | 0 | 0.39 | 0 | 0.13 | 0 | 0 | 0.13 | 1.17 | 0 | 1.17 | 0 | 0 |
| EM10 | 0 | 0 | 0 | 0 | 0.02 | 0.18 | 0 | 0 | 0.06 | 0 | 0.18 | 0 | 0 | 0 | 0.18 | 0 | 0 |
| EM15 | 0 | 0 | 0 | 0 | 0.1 | 0.3 | 0 | 0 | 0.9 | 0 | 0.9 | 0 | 0.1 | 0 | 0.9 | 0 | 0 |
| EM16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.27 | 0 | 0 |
| EM19 | 0 | 0 | 0 | 0.27 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.27 | 0 | 0 |
| EM20 | 0 | 0 | 0 | 0 | 0.09 | 0 | 0.27 | 0 | 0 | 0 | 0 | 0.03 | 0 | 0 | 0 | 0 | 0 |
| EM21 | 0 | 0 | 0.9 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0.9 | 0 | 0 | 0 | 0.9 | 0 | 0 |
| EM23 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.09 | 0 | 0 | 0.09 | 0 | 0 | 0 | 0 | 0 | 0 |

### Table 9 - Weighted ‘$V$’ matrix for Reduced Hair Wrap

$V^S =$

<table>
<thead>
<tr>
<th></th>
<th>-0.2869</th>
<th>0.2545</th>
<th>0.0176</th>
<th>-0.0531</th>
<th>0.0131</th>
<th>-0.0440</th>
<th>0.0701</th>
<th>-0.0104</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.2105</td>
<td>-0.2332</td>
<td>-0.0252</td>
<td>0.0189</td>
<td>-0.0016</td>
<td>-0.0746</td>
<td>-0.0363</td>
<td>-0.0084</td>
</tr>
<tr>
<td></td>
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<td>-0.0746</td>
<td>0.0097</td>
<td>-0.0817</td>
</tr>
<tr>
<td></td>
<td>-0.8827</td>
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<td>0.0856</td>
<td>-0.0048</td>
<td>-0.0224</td>
<td>0.0615</td>
<td>-0.0088</td>
</tr>
<tr>
<td></td>
<td>0.0400</td>
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<td>0.0274</td>
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<td>-0.0211</td>
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<tr>
<td></td>
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<td>-0.0720</td>
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<td>0.0261</td>
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<td>-0.0921</td>
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<td>-0.1626</td>
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<td>-0.2253</td>
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<td>-0.0024</td>
<td>0.1935</td>
<td>0.1619</td>
<td>-0.0779</td>
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<td></td>
<td>-0.2933</td>
<td>0.2560</td>
<td>0.0170</td>
<td>-0.1255</td>
<td>-0.2550</td>
<td>0.0165</td>
<td>-0.0393</td>
<td>-0.0072</td>
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<td></td>
<td>-0.0445</td>
<td>-0.0544</td>
<td>0.0707</td>
<td>0.0055</td>
<td>-0.0016</td>
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<tr>
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<td>-0.0446</td>
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<td>-0.0094</td>
<td>0.0924</td>
<td>-0.0809</td>
<td>-0.0199</td>
<td>0.1021</td>
<td>0.0514</td>
</tr>
<tr>
<td></td>
<td>-0.0956</td>
<td>0.0848</td>
<td>0.0059</td>
<td>-0.0177</td>
<td>0.0044</td>
<td>-0.0147</td>
<td>0.0234</td>
<td>-0.0035</td>
</tr>
<tr>
<td></td>
<td>-0.9317</td>
<td>0.7576</td>
<td>-0.0131</td>
<td>0.0919</td>
<td>-0.0056</td>
<td>-0.0464</td>
<td>0.0458</td>
<td>-0.0106</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Hierarchical clustering is then performed on the weighted matrix \( V^S \) to obtain a dendrogram which displays clusters of components grouped based on the known and hidden relationships in the data contained in the weighted matrix \( V^S \). The dendrogram obtained after hierarchical clustering of the weighted matrix \( V^S \) is shown in figure 28. The dendrogram shows components clusters that are closely related to each other with respect to impacting the hair picked up by the vacuum and contributing to hair wrap. We are most interested in the top half of the dendrogram which displays distinct clusters of components because the lower half is observed to be consisting of large clusters of components that have the least impact on the value metric or are unrelated to the value metric.

![Hierarchical Clustering for Reduced Hair Wrap](image)

Figure 28 - Hierarchical Clustering for Reduced Hair Wrap

The dendrogram shown in figure 28 has seventeen clusters in total with four of those highlighted in different colors to distinguish between the clusters that impact the value metric from the clusters that have the least to no impact. Only the motor assembly and the fan assembly of the four highlighted clusters are closely related and can be seen connected with a short node having blue branches. The length of the branch from the node is a measure of the dissimilarity between the components with respect to the chosen value metric.
Table 10 - Value contribution for Reduced hair wrap

<table>
<thead>
<tr>
<th>Components highlighted by the framework</th>
<th>Value contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brush roll Assembly</td>
<td>Reduced hair wrap</td>
</tr>
<tr>
<td>Motor Assembly, Fan Assembly</td>
<td>Improved hair pick up</td>
</tr>
<tr>
<td>Nozzle door</td>
<td>Reduced hair wrap / improved hair pick up</td>
</tr>
</tbody>
</table>

It is important to understand that the components identified are partly contributing to reducing hair wrap by improving pick up. The metrics have an inverse relationship where a decrease in hair pick up leads to an increase in hair wrap due to the nature of the conventional brush roll. The highlighted clusters are deemed to be contributing the most to improving hair pick up and preventing hair wrap. The value contribution of the highlighted clusters is listed in table 10.

These component clusters are then analyzed and compared to the existing innovative solutions that address these issues or enhances the value metric considered. In this case, the components listed in table 10 are compared to the innovations in a Dyson V6 cordless vacuum. By comparing the two we can derive how each of these components can be innovated to improve hair pick up, reduce hair wrap and postulate how it could have led to the innovations seen in a Dyson V6 cordless vacuum. The highlighted components in figure 29 and their comparison to Dyson innovations are discussed below.
1. Brush roll Assembly

The Brush roll assembly consists of a cylindrical rod like structure with bristles for cleaning the carpet. The brush roll is run by the main motor through a belt drive that connects the main motor shaft and the brush roll.

The brush roll is the critical component affected by hair wrap and is considered the source of failures and diminishing cleaning performance due to hair wrap. There are many factors of the brush roll that influences hair wrap as follows,

- Brush roll drive mechanism
- Diameter of the brush roll
- Length of brush roll bristles
- Rotation speed of the brush roll

The Dirt Devil has a belt driven brush roll with a much smaller diameter which has a higher propensity to cause hair wrap leading to reduced performance. When the brush roll diameter is small the potential for the hair to wrap around it is twice as much and with longer hair the potential increases. Another factor is the length of the bristles on the brush roll which enable the hair to tangle and embed deeper making it almost impossible for the vacuum created by the motor to suck the tangled hair into the dust bag. A more powerful suction is required to cause the tangled hair to loosen up and be sucked into the dust bag. However, Dyson has a motor driven brush roll designed to prevent hair wrap. It has a separate motor to make the brush roll rotate at a high RPM to reduce the chances of hair wrap. Its brush roll also has a larger diameter which makes it difficult for hair no longer than 18 inches to wrap around and has shorter bristles to prevent embedding of hair. Due to a high rotation speed the contact of the hair with the brush roll is minimized which reduces the chances of a severe hair wrap. In this case, the improved hair pick up and reduced hair wrap is achieved by controlling the four brush roll factors mentioned above.

2. Motor & Fan Assembly

The motor and fan assembly function together to create the suction required to perform cleaning. The functions of the motor and the fan assemblies augment each other to bring about cleaning, the primary function of the vacuum.
It is common knowledge that the more powerful a motor, the more is the suction created. If powerful motors are used to create high suction then the cleaning performance of a vacuum can be rapidly improved. In the Dirt Devil vacuum, the suction created by the fan and motor assembly is affected by the quantity of debris contained in the dust bag. When the dust bag is filled or half-filled the suction at the nozzle is greatly reduced and the hair that is sucked in can cause a clog that reduces the suction created thereby increasing the chances of hair wrap at the brush roll. However, Dyson uses a motor with powerful suction to aid in the process of sucking in the hair wrapped around the brush roll. The hair sucked in gets collected in a clear bin and does not affect the suction created. In this case, improved hair pick up or reduced hair wrap is achieved by creating powerful suction and designing better exhaust for the air flow created by motor and fan assembly.

3. Nozzle door

The nozzle door is basically a lid that fits on an extension of the frame to constitute the nozzle assembly. This contains the brush roll assembly that makes contact on the surface to be cleaned and enables the user to close or open it to grant the brush roll access to the floor for cleaning. Closing this door will disengage brush roll contact with the floor and redirect the suction to the hose outlet, provided the swing door - hose is open.

In the Dirt Devil hand vacuum, the nozzle houses the brush roll and is one of the critical components that forms the interface with the floor. The design of the nozzle and its interface with the floor largely affects suction. A powerful suction will help prevent/reduce hair wrap in the brush roll by increasing the amount of hair picked up into the dust bag. Dyson designed the nozzle to be a detachable component like other cleaning tools such as the crevice tool etc. This detachable nozzle design has a very low floor clearance in comparison to other hand vacuums that maximizes suction at the interface between the vacuum and the floor. This causes the hair to experience a high suction at the interface that pulls it quickly into the dust cup thereby minimizing the hair wrap around the brush roll.
Analysis for Improved exhaust air quality:

The third value metric to be analyzed is Improved exhaust air quality or cleaner exhaust. This value metric is a significant factor in determining the safety of the user when using this vacuum. A vacuum that fails to address this problem causes great discomfort to the end user having allergies and may even cause breathing problems. Analysis is done considering the significance of this metric in user safety and comfort to validate the ability of the framework to identify clusters of components that present innovation opportunities to improve the vacuum’s ability in separating and containing allergens and fine dust particles from the exhaust air stream. The summary of VOCs and the related EMs associated to this value metric is listed in table 11.

<table>
<thead>
<tr>
<th>Cleaner Exhaust</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>VOC</td>
<td>EM</td>
</tr>
<tr>
<td>6 The vacuum should contain the debris without releasing them into the air</td>
<td>5 Max. size of debris escaping the vacuum</td>
</tr>
<tr>
<td></td>
<td>10 Max. size of debris that can be picked up</td>
</tr>
<tr>
<td></td>
<td>15 Particle collection capacity</td>
</tr>
</tbody>
</table>

The VOCs related to dust particles in the air are then used to identify the EMs that contribute to these VOCs. The identified EMs are then used to filter rows of data from the parent operating matrix and the filtered operating matrix associated with exhaust air quality is formed. This filtered operating matrix is shown in table 12.

| Table 12 - Cleaner Exhaust Filtered Operating Matrix (Refer Table 2 & Figure 25) |
|---------------------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
|                                | P1     | P2     | P3     | P4     | P5     | P6     | P7     | P8     | P9     | P10    | P11    | P12    | P13    | P14    | P15    | P16    | P17    | P18    |
| 6 The vacuum should contain the | 0      | 0      | 0      | 0.03   | 0      | 0      | 0      | 0.27   | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0.03   |
| debris without releasing them   | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0.27   | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      |
| into the air                    | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0.1    | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      |
| 10 Max. size of debris escaping | 0      | 0      | 0      | 0.03   | 0      | 0      | 0      | 0.27   | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      |
| the vacuum                      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0.27   | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      |
| 15 Particle collection capacity | 0      | 0      | 0      | 0.03   | 0      | 0      | 0      | 0.27   | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      |
Singular value decomposition is performed on the filtered operating matrix shown in table 12 and it is decomposed into its component matrices U, Σ & V. The ‘V’ matrix is then weighted with values from ‘Σ’ by multiplying the strength values to their corresponding columns in the ‘V’ matrix. The weighted ‘V’ matrix denoted by ‘VS’ is shown table 13.

Table 13 - Weighted ‘V’ matrix for Clean Exhaust

\[
VS =
\begin{bmatrix}
0 & 0 & 0 \\
-0.4230 & 0 & 0.0730 \\
0 & 0 & 0 \\
0 & 0.0300 & 0 \\
0 & 0 & 0 \\
-0.1019 & 0 & -0.0027 \\
-0.3263 & 0 & -0.1264 \\
0 & 0.2700 & 0 \\
0 & 0 & 0 \\
-0.8971 & 0 & 0.0940 \\
0 & 0.2700 & 0 \\
-0.9175 & 0 & -0.0243 \\
0 & 0 & 0 \\
-0.0985 & 0 & 0.0170 \\
0 & 0 & 0 \\
-0.9175 & 0 & -0.0243 \\
0 & 0.0300 & 0 \\
0 & 0 & 0
\end{bmatrix}
\]

Hierarchical clustering is then performed on the weighted matrix ‘VS’ to obtain a dendrogram which displays clusters of components grouped based on the known and hidden relationships in the data contained in the weighted matrix ‘VS’. The dendrogram obtained after hierarchical clustering of the weighted matrix ‘VS’ is shown in figure 30. The dendrogram shows components clusters that are closely related to each other impacting the quality of exhaust air from the vacuum. We are most interested in the top half of the dendrogram which displays distinct clusters of components because the lower half is observed to be consisting of large clusters of components that have the least impact on the value metric or are unrelated to the value metric.
The dendrogram shown in figure 30 has nine clusters in total with one of those highlighted in orange to distinguish between the clusters that impact the value metric from the clusters that have the least to no impact. The ‘Cloth bag’ and the ‘Type G bag’ in the highlighted clusters are closely related and can be seen connected with a short node having blue branches. The length of the branch from the node is a measure of the dissimilarity between the components with respect to the chosen value metric.

<table>
<thead>
<tr>
<th>Components highlighted by the framework</th>
<th>Value contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cloth Bag</td>
<td>Air Filtering</td>
</tr>
<tr>
<td>Type G bag</td>
<td>Air Filtering</td>
</tr>
</tbody>
</table>

It is important to understand that the components highlighted are directly contributing to removing fine dust particles from the incoming air stream before being released into the environment. The dendrogram also shows clusters containing components such as nozzle door,
brush roll assembly, hose assembly etc. preceding the cloth bag and the type g bag. This means that these components have a strong relationship with the value metric considered.

Although, on the surface these components may seem unrelated to the filtering function, when examined in detail from a systems thinking perspective reveals relationships between these components and the exhaust air. These components are the origin of the air stream that is filtered by the type g bag and the cloth bag and the amount of fine debris carried in the air stream is determined by their ability to suck in fine dust particles and rate of dust pick up. It is understood that they play an indirect role in defining the degree of filtration required from the dust bags (i.e.) the finer the particles a vacuum can pick up the higher is the degree of filtration required to comply with safety standards and regulations. The highlighted components are deemed to be contributing the most to filtering dust particles from the exhaust air. The value contribution of each of the highlighted component is listed in table 14.

These component clusters are then analyzed and compared to the existing innovative solutions that address this issue or enhances the value metric considered. In this case, the components listed in table 14 are compared to the innovations in a Dyson V6 cordless vacuum. By comparing the two we can derive how each of these components can be innovated to improve exhaust air quality, filtration and postulate how it could have led to the innovations seen in a Dyson V6 cordless vacuum. The highlighted components in figure 31 and their comparison to Dyson innovations are discussed below.
1. Type G Bag
In the Dirt Devil ultra-handheld vacuum, the type G bag is the component where all the dust collected is stored and is attached to the outlet of the motor and fan assembly. It also acts as the first level of air filter that retains the dust particles carried in the air stream from being released back into the atmosphere. This bag is made up of a material that has fine pores which allows air to pass through but retain dust particles that are larger than its pores. When fine dust particles smaller than these pores are picked up by the vacuum they get carried by the air stream released into the surroundings causing dust related allergies in end users. Some dust particles might clog the pores in the dust bag and lead to a loss of suction and cleaning performance. An ideal solution would be to have a filtration system that is efficient in separating and retaining fine dust particles with minimal or no loss in suction and cleaning performance. Dyson uses the cyclone technology to separate microscopic dust particles from the incoming air stream which acts as the first level of filter. It has a component called cyclone with radially arranged cones which uses centrifugal force acting on the dust particles to separate them from the air stream and guide them into the dust collector when the air stream carrying dust particles passes through it.

2. Cloth Bag
In the Dirt Devil ultra-handheld vacuum, the cloth bag is a protective layer seen covering the type G bag and acts as a second level of filter for the air passing through the type G bag before being released into the atmosphere. This is the final medium that the exhaust air should pass through before interacting with the environment and the end user. However, unlike the type G bag this bag is made up of fabric material with much larger pores in comparison. With larger pores, all the dust particles passing through the type G bag will escape the cloth bag and mix into the atmospheric air. This air can potentially cause breathing problems in the end user when exposed to it over a period of time. The main function of this bag is to protect the delicate type G bag from getting damaged and prevent the spilling of dust particles all over the floor when the type G bag ruptures thus acting as a secondary filter in case of type G bag failure. Although, it can protect and prevent the spilling of the dust collected in case of type G bag rupture it cannot contain the dust particles smaller than the pores of the fabric from escaping into the atmosphere. An ideal solution would be a system that can filter the microscopic dust particles carried in the air stream after passing through the primary filter or going through primary dust separation. The Dyson uses a HEPA (High Efficiency Particulate Air) filter to further remove
the microscopic dust particles that may be carried by the air stream coming out from the
cyclone after primary dust separation. This medium can filter 99.97% of particles of 0.3
microns and larger carried in the exhaust air stream.

Analysis for Improved runtime experience:

The fourth value metric to be analyzed is Improved runtime experience. This value metric is a
significant factor in demonstrating the comfort of the user when using this vacuum. A vacuum
that fails to satisfactorily address this value metric causes great discomfort to the end user and
will lose its competitive advantage in the market. The product data is analyzed to validate the
ability of the framework to identify clusters of components that present innovation
opportunities to improve the vacuum’s ability to provide a satisfactory runtime experience to
the end users. The summary of VOCs and the related EMs associated to this value metric is
listed in table 15.

Table 15 – Improved Runtime Experience summary of VOCs and EMs

<table>
<thead>
<tr>
<th>Improved Runtime Experience</th>
<th>VOC</th>
<th>EM</th>
</tr>
</thead>
<tbody>
<tr>
<td>21  The vacuum has a long runtime</td>
<td>1  Suction Power</td>
<td>3  Heat Dissipated</td>
</tr>
</tbody>
</table>

The VOCs related to runtime experience and comfort are then used to identify the EMs that
contribute to these VOCs. The identified EMs are then used to filter rows of data from the
parent operating matrix and the filtered operating matrix associated with exhaust air quality is
formed. This filtered operating matrix is shown in table 16.
Table 16 - Improved Runtime Experience Filtered Operating Matrix (Refer Table 2 & Figure 25)

<table>
<thead>
<tr>
<th></th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
<th>P7</th>
<th>P8</th>
<th>P9</th>
<th>P10</th>
<th>P11</th>
<th>P12</th>
<th>P13</th>
<th>P14</th>
<th>P15</th>
<th>P16</th>
<th>P17</th>
<th>P18</th>
</tr>
</thead>
<tbody>
<tr>
<td>EMI</td>
<td>0.39</td>
<td>0</td>
<td>0</td>
<td>1.17</td>
<td>0</td>
<td>0</td>
<td>0.39</td>
<td>0</td>
<td>0.13</td>
<td>0</td>
<td>0</td>
<td>0.13</td>
<td>1.17</td>
<td>0</td>
<td>1.17</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>EM3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.54</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.54</td>
<td>0.18</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Singular value decomposition is performed on the filtered operating matrix shown in table 16 and it is decomposed into its component matrices U, Σ & V. The ‘V’ matrix is then weighted with values from ‘Σ’ by multiplying the strength values to their corresponding columns in the ‘V’ matrix. The weighted ‘V’ matrix denoted by ‘V^S’ is shown in table 17.

Table 17 - Weighted ‘V’ matrix for Improved Runtime Experience

\[ V^S = \]

\[
\begin{bmatrix}
-0.3735 & -0.5068 \\
0 & 0 \\
0 & 0 \\
-1.2759 & 0.8168 \\
0 & 0 \\
0 & 0 \\
0 & 0 \\
-0.3735 & -0.5068 \\
0 & 0 \\
-0.1245 & -0.1689 \\
0 & 0 \\
0 & 0 \\
-0.1245 & -0.1689 \\
-1.2759 & 0.8168 \\
-0.0518 & 0.7791 \\
-1.1206 & -1.5205 \\
0 & 0 \\
0 & 0 \\
\end{bmatrix}
\]

Hierarchical clustering is then performed on the weighted matrix ‘V^S’ to obtain a dendrogram which displays clusters of components grouped based on the known and hidden relationships in the data contained in the weighted matrix ‘V^S’. The dendrogram obtained after hierarchical clustering of the weighted matrix ‘V^S’ is shown in figure 32.
The dendrogram shows components clusters that are closely related to each other impacting the runtime experience of the users when operating the vacuum. We are most interested in the top half of the dendrogram which displays distinct clusters of components because the lower half is observed to be consisting of large clusters of components that have the least impact on the value metric or are unrelated to the value metric. The dendrogram shown in figure 32 has six clusters in total with one of those highlighted in red to distinguish between the clusters that impact the value metric from the clusters that have the least to no impact. The ‘Motor assembly’ and the ‘Fan assembly’ in the highlighted clusters are closely related and can be seen connected with a short node having black branches. The length of the branch from the node is a measure of the dissimilarity between the components with respect to the chosen value metric.

It is important to understand that the components highlighted are from a perspective of causing discomfort to the user in terms of providing long runtime of operation. The dendrogram also shows the component nozzle door preceding the motor and fan assembly. This means that this component has a strong relationship with the value metric considered.
Although, on the surface these components may seem unrelated to runtime, when examined in detail from a system’s thinking perspective reveals the relationship of runtime experience with these components. These subassemblies form the core of the vacuum upon which its operation depend. They are the driving source of the functions performed by the vacuum and the most critical components influencing user satisfaction and experience. The highlighted components are deemed to be contributing the most to filtering dust particles from the exhaust air. The value contribution of each of the highlighted component is listed in table 18.

These component clusters are then analyzed and compared to the existing innovative solutions that address this issue or enhances the value metric considered. In this case, the components/subassemblies listed in table 18 are compared to the innovations in a Dyson V6 cordless vacuum. By comparing the two we can derive how each of these components can be innovated to improve exhaust air quality, filtration and postulate how it could have led to the innovations seen in a Dyson V6 cordless vacuum. The highlighted components in figure 33 and their comparison to Dyson innovations are discussed below.

Table 18 - Value contribution for improved runtime experience

<table>
<thead>
<tr>
<th>Components highlighted by the framework</th>
<th>Value contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motor assembly</td>
<td>Suction</td>
</tr>
<tr>
<td>Fan assembly</td>
<td>Suction</td>
</tr>
</tbody>
</table>

![Figure 33 - Innovation Opportunities for Improved Runtime Experience](image)
1. Motor and Fan assembly

The motor and fan assembly are the major assemblies functioning together to create the suction required to perform cleaning. The functions of the motor and the fan assemblies augment each other to bring about cleaning and other auxiliary functions of the vacuum.

The relationship between user runtime experience and the motor & fan assembly is a nonlinear relationship. These subassemblies are linked to the runtime experience in that they draw power from a source to operate and have significant moving parts. Hence, heat is generated and energy loss occurs. When this process continues, the heat generated reaches an undesirable level that affects the comfort and experience of the user in wanting to operate the vacuum over prolonged periods of time. This need for a prolonged usage may come from having an unlimited and undisrupted supply to power the vacuum seen in heavy duty upright and canister vacuums. This may lead users to think that hand vacuums are replacements for uprights and canister vacuums giving rise to high level expectations.

Ideally the Dirt Devil should be able to run so long as it is connected to a power source but in reality the moving components in the motor and fan subassemblies get heated up after a certain period of continuous usage. The unit may breakdown beyond this point if used continuously disregarding the heat. Hence the heat generated by the moving parts in motor and fan subassemblies limit the amount of continuous runtime. This makes the idea of a uninterrupted power supply look unnecessary and misleading.

A good solution to improving runtime experience is to have a system that can eliminate or reduce the heat generated over prolonged usage, provide a power supply to complete a cleaning task and demonstrate that a hand vacuum is not a heavy-duty vacuum to be used like an upright or canister vacuum. To achieve this, the system must be able to control the working of the moving parts in the motor and fan assembly as desired. Dyson has a trigger switch that powers the vacuum at will which is controlled by the user. This trigger switch enables the user to control the operation of the motor and fan assembly thereby limiting the amount of time the moving parts in these subassemblies are actively engaged and running. By limiting the runtime of these moving parts to only when needed, the amount of heat generated is drastically reduced and runtime experience is improved. It also uses a battery pack that can power up the vacuum for a limited amount of time, allowing enough runtime to complete a reasonable number of
cleaning tasks. The battery must be charged when it runs out and this gives time for the heated components to cool down before the next usage demonstrating the limits of a hand vacuum and the kind of workload it can fulfill. Run time experience can also be improved by simultaneously increasing battery capacity and using higher thermal capacity moving parts in the motor and fan assembly.

Analysis for Consumable cost reduction:

The fifth value metric to be analyzed is Consumable cost reduction. This value metric is an important factor in determining the cost of using a vacuum. A vacuum that involves significant operating cost brings up the questions of whether it offers value for the costs incurred. When the value gained fails to justify the price and operating cost of the vacuum it becomes less desirable for the user to buy the product. Analysis is done considering the significance of this metric in user desirability for buying the vacuum to validate the ability of the framework to identify clusters of components that present innovation opportunities to reduce the cost incurred in buying consumables and replacement parts. The summary of VOCs and the related EMs associated to this value metric is listed in table 19.

<table>
<thead>
<tr>
<th>Reduced Cost of Consumables</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>VOC</strong></td>
</tr>
<tr>
<td>20 The vacuum does not require frequent consumable change</td>
</tr>
<tr>
<td>10 Max. size of debris that can be picked up</td>
</tr>
<tr>
<td>20 Consumables</td>
</tr>
</tbody>
</table>

The VOCs related to cost of consumables are then used to identify the EMs that contribute to these VOCs. The identified EMs are then used to filter rows of data from the parent operating matrix and the filtered operating matrix associated with exhaust air quality is formed. This filtered operating matrix is shown in table 20.
Table 20 - Consumable cost reduction Filtered Operating Matrix (Refer Table 2 & Figure 25)

<table>
<thead>
<tr>
<th></th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
<th>P7</th>
<th>P8</th>
<th>P9</th>
<th>P10</th>
<th>P11</th>
<th>P12</th>
<th>P13</th>
<th>P14</th>
<th>P15</th>
<th>P16</th>
<th>P17</th>
<th>P18</th>
</tr>
</thead>
<tbody>
<tr>
<td>EM8</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.09</td>
<td>0</td>
<td>0.03</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EM10</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.02</td>
<td>0.18</td>
<td>0</td>
<td>0</td>
<td>0.18</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.18</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EM15</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.1</td>
<td>0.3</td>
<td>0</td>
<td>0</td>
<td>0.9</td>
<td>0</td>
<td>0.9</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EM20</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.09</td>
<td>0.27</td>
<td>0</td>
<td>0</td>
<td>0.03</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Singular value decomposition is performed on the filtered operating matrix shown in table 20 and it is decomposed into its component matrices U, Σ & V. The ‘V’ matrix is then weighted with values from ‘Σ’ by multiplying the strength values to their corresponding columns in the ‘V’ matrix. The weighted ‘V’ matrix denoted by ‘V^S’ is shown in table 21.

Table 21 - Weighted 'V' matrix for Consumable Cost Reduction

\[
V^S = \\
\begin{bmatrix}
0.0106 & -0.7007 & 0.0080 & -0.2133 \\
-0.4235 & 0.0340 & -0.0734 & 0.0116 \\
-0.0027 & 0.1750 & -0.0020 & 0.0533 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
-0.1032 & 0.0847 & 0.0017 & 0.0258 \\
-0.3262 & -0.0027 & 0.1263 & -0.0028 \\
-0.0039 & 0.2845 & -0.0043 & -0.0074 \\
0 & 0 & 0 & 0 \\
-0.8970 & -0.0139 & -0.0938 & -0.0026 \\
-0.0000 & 0.0087 & -0.0005 & -0.0287 \\
-0.9178 & 0.0163 & 0.0241 & 0.0047 \\
0 & 0 & 0 & 0 \\
-0.0985 & -0.0016 & -0.0170 & -0.0002 \\
0 & 0 & 0 & 0 \\
-0.9174 & -0.0124 & 0.0244 & -0.0040 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

Hierarchical clustering is then performed on the weighted matrix ‘V^S’ to obtain a dendrogram which displays clusters of components grouped based on the known and hidden relationships in the data contained in the weighted matrix ‘V^S’. The dendrogram obtained after hierarchical clustering of the weighted matrix ‘V^S’ is shown in figure 34. The dendrogram shows
components clusters that are closely related to each other impacting the cost of consumable in the vacuum. We are most interested in the top half of the dendrogram which displays distinct clusters of components because the lower half is observed to be consisting of large clusters of components that have the least impact on the value metric or are unrelated to the value metric.

The dendrogram shown in figure 34 has twelve clusters in total with two of those highlighted in grey to distinguish between the clusters that impact the value metric from the clusters that have the least to no impact. The ‘Style 1 Belt’ and the ‘Type G bag’ in the highlighted clusters are of interest in reducing the cost of consumables. The length of the branch from the node is a measure of the dissimilarity between the components with respect to the chosen value metric.

![Hierarchical Clustering for Reduced Cost of Consumable](image)

It is important to understand that the components highlighted are directly contributing to the cost involved in buying consumables. The dendrogram also shows clusters containing components such as nozzle door, brush roll assembly, hose assembly etc. preceding the Style 1 belt and the type g bag. This means that these components have a hidden relationship with the value metric considered.
Table 22 - Value contribution for reduced consumable cost

<table>
<thead>
<tr>
<th>Components highlighted by the framework</th>
<th>Value contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Style 1 Belt</td>
<td>Cost reduction</td>
</tr>
<tr>
<td>Type G bag</td>
<td>Cost reduction</td>
</tr>
</tbody>
</table>

Although, on the surface these components may seem unrelated to the cost of consumables or cost of operation, when examined in detail from a system’s thinking perspective reveals their hidden relationships with the value metric. These are the components that interact the most with the user and the environment. For instance, the switch, switch cover and swing door-hose interact the most with the user. The nozzle door, brush roll, crevice tool, hose assembly are the components that interact the most with the surface to be cleaned. It is understood that these components experience the most wear and tear because of the interactions and may have to be replaced in due time. This shows the analogy between the consumables and the parts experiencing wear and tear as they both have the need to be replaced which comes at a cost to the user. The highlighted components are deemed to be contributing the most to cost of consumables. The value contribution of each of the highlighted component is listed in table 22.

Figure 35 - Innovation Opportunities for Consumable Cost Reduction
These component clusters are then analyzed and compared to the existing innovative solutions that address this issue or enhances the value metric considered. In this case, the components listed in table 22 are compared to the innovations in a Dyson V6 cordless vacuum. By comparing the two we can derive how each of these components can be innovated to reduce cost of consumables and cost of operation and postulate how it could have led to the innovations seen in a Dyson V6 cordless vacuum. The highlighted components in figure 35 and their comparison to Dyson innovations are discussed below.

1. **Style 1 belt**

In Dirt devil hand vacuum, the style 1 belt is a small rubber belt which transmits power from the motor to the brush roll through the belt drive. One side of the belt is connected to a shaft extending from the motor while the other side is connected to the shaft of the brush roll.

The function of this belt is to transmit the rotation from the main motor shaft to the brush roll shaft that is perpendicular to it. As a result of this the belt makes a lot of contact with the shafts experiencing high degrees of wear and tear caused by friction. Upon continuous usage, the belt has a tendency to fail due to the wear and tear and has to be replaced to resume function or to maintain cleaning performance. An ideal solution would be a system that can bring about the rotation of the brush roll with minimal to no wear and tear over the lifetime of the vacuum.

Dyson uses a motorized brush roll that lasts longer instead of a belt drive and without deterioration in performance. Their brush roll design houses a dedicated motor in the shaft body that causes rotation. This motorized brush roll assembly experiences minimal wear and tear and can last as long as the vacuum itself. This eliminates the need to replace consumables more often.

2. **Type G Bag**

In the Dirt Devil ultra-handheld vacuum, the type G bag is the component where all the dust collected is stored and is attached to the outlet of the motor and fan assembly. It also acts as the first level of air filter that retains the dust particles carried in the air stream from being released back into the atmosphere. This bag is made up of a material that has fine pores which allows air to pass through but retain dust particles that are larger than its pores. When it gets filled the dust particles might clog the pores in the dust bag and lead to a loss of suction and
cleaning performance. The bag must be thrown out along with the debris and be replaced with a new one to continue collecting debris and regain cleaning performance.

An ideal solution would be to have a system that does not require frequent to no replacement of dust bag to continue to efficiently collect debris with minimal or no loss in suction and cleaning performance. Dyson uses the cyclone technology to separate microscopic dust particles from the incoming air stream which acts as the first level of filter. It has a component called cyclone with radially arranged cones which uses centrifugal force acting on the dust particles to separate them from the air stream and guide them into the dust collector when the air stream carrying dust particles passes through it. Dyson also uses a clear bin instead of a dust bag for containing the debris picked up. The clear bin is in close association with the cyclone which separated the dust particles from the incoming air stream. This clear bin enables the user to dispose the debris without the need to buy replacement dust bags thereby eliminating the cost of consumables.

The other components also must be replaced in due time but not as frequently as the type G dust bag and the style 1 belt. Hence, only these two clusters are considered as the most significant contributor to the chosen value metric. Also, cost is a metric that is associated with all the components in a system as cost is involved in the design, manufacturing and assembly of these components and subsystems. So, when cost is considered a value metric every component of the system becomes a potential candidate for innovation opportunities. This is seen as one of the reasons that the dendrogram shows many other components preceding the ‘type G bag’ and ‘style 1 belt’. But these two are highlighted as they provide the easiest and most viable opportunity for innovation.

**Analysis for Improved Cleaning Performance:**

The sixth value metric to be analyzed is Cleaning performance. This value metric is an important factor in determining the desirability of the vacuum. A vacuum that has a poor cleaning performance becomes least desirable for the user to purchase irrespective of its features. Because cleaning is the primary function of any vacuum and a satisfactory cleaning performance is a must have customer requirement. Analysis is done considering the
The significance of this metric in user desirability for buying the vacuum to validate the ability of the framework to identify clusters of components that present innovation opportunities to improve the cleaning performance. The summary of VOCs and the related EMs associated to this value metric is listed in table 23.

<table>
<thead>
<tr>
<th>Improved Cleaning Performance</th>
<th>VOC</th>
<th>EM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 The vacuum picks up unwanted dust &amp; hair</td>
<td>1</td>
<td>Suction power</td>
</tr>
<tr>
<td>2 The vacuum works on multiple surfaces</td>
<td>3</td>
<td>Heat dissipated</td>
</tr>
<tr>
<td>5 The vacuum is comfortable to operate</td>
<td>4</td>
<td>Types of surface</td>
</tr>
<tr>
<td>7 The vacuum picks up pet hair</td>
<td>10</td>
<td>Max. size of debris that can be picked up</td>
</tr>
<tr>
<td>8 The vacuum cleans without damaging the surface</td>
<td>11</td>
<td>Maximum reach</td>
</tr>
<tr>
<td>16 The vacuum is energy efficient</td>
<td>14</td>
<td>Required push force</td>
</tr>
<tr>
<td>21 The vacuum has long runtime</td>
<td>15</td>
<td>Particle collection capacity</td>
</tr>
<tr>
<td>22 The vacuum does not leave behind large debris</td>
<td>16</td>
<td>Distance to edge of effective cleaning</td>
</tr>
<tr>
<td></td>
<td>17</td>
<td>Maximum operating distance</td>
</tr>
<tr>
<td></td>
<td>19</td>
<td>Price</td>
</tr>
<tr>
<td></td>
<td>21</td>
<td>Interface with surface</td>
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<tr>
<td></td>
<td>22</td>
<td>User interface (UI) test</td>
</tr>
<tr>
<td></td>
<td>23</td>
<td>Time to clean the unit</td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>Time to dispose collected particles</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>Power consumption</td>
</tr>
</tbody>
</table>

The VOCs related to cleaning performance are then used to identify the EMs that contribute to these VOCs. The identified EMs are then used to filter rows of data from the parent operating matrix and the filtered operating matrix associated with exhaust air quality is formed. This filtered operating matrix is shown in table 24.
Singular value decomposition is performed on the filtered operating matrix shown in table 24 and it is decomposed into its component matrices U, Σ & V. The ‘V’ matrix is then weighted with values from ‘Σ’ by multiplying the strength values to their corresponding columns in the ‘V’ matrix. The weighted ‘V’ matrix denoted by ‘VS’ is shown in table 25.

**Table 25 - Weighted ‘V’ matrix for Improved Cleaning Performance**

\[ V^S = \]

<table>
<thead>
<tr>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
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<th>P13</th>
<th>P14</th>
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<td></td>
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</tr>
</tbody>
</table>
Hierarchical clustering is then performed on the weighted matrix ‘V^S’ to obtain a dendrogram which displays clusters of components grouped based on the known and hidden relationships in the data contained in the weighted matrix ‘V^S’. The dendrogram obtained after hierarchical clustering of the weighted matrix ‘V^S’ is shown in figure 36. The dendrogram shows components clusters that are closely related to each other impacting the cleaning performance of the vacuum. We are most interested in the top half of the dendrogram which displays distinct clusters of components because the lower half is observed to be consisting of large clusters of components that have the least impact on the value metric or are unrelated to the value metric.

The dendrogram shown in figure 36 has seventeen clusters in total with eight of those highlighted in colors to distinguish between the clusters that impact the value metric from the clusters that have the least to no impact. The nozzle door, brush roll assembly, motor & fan assembly, switch, hose assembly, crevice tool and type G bag of the highlighted clusters are of interest in improving the cleaning performance of the vacuum. The length of the branch from the node is a measure of the dissimilarity between the components with respect to the chosen value metric.

*Figure 36 - Hierarchical Clustering for Improved Cleaning Performance*
It is important to understand that the components highlighted are directly contributing to the cleaning performance or to creating suction that induces cleaning. Because the cleaning performance is driven by the suction created by the vacuum and without it the vacuum cannot pick up debris and other dust particles.

<table>
<thead>
<tr>
<th>Components highlighted by the framework</th>
<th>Value contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nozzle door</td>
<td>Suction &amp; Cleaning</td>
</tr>
<tr>
<td>Motor &amp; Fan assembly</td>
<td>Suction</td>
</tr>
<tr>
<td>Brush roll assembly</td>
<td>Cleaning</td>
</tr>
<tr>
<td>Switch</td>
<td>Suction</td>
</tr>
<tr>
<td>Hose assembly</td>
<td>Suction &amp; Cleaning</td>
</tr>
<tr>
<td>Crevice tool</td>
<td>Cleaning</td>
</tr>
<tr>
<td>Type G bag</td>
<td>Suction</td>
</tr>
</tbody>
</table>

Although, on the surface some of these components may seem unrelated to the cleaning performance, when examined in detail from a system’s thinking perspective reveals their hidden relationships with the value metric. These are the components that work together to create suction. There are so many factors that influence suction and indirectly these factors also influence cleaning performance. The relationship of these factors with the components identified and their influence on cleaning performance is discussed below. The highlighted components are deemed to be contributing the most to improving cleaning performance. The value contribution of each of the highlighted component is listed in table 26.

These component clusters are then analyzed and compared to the existing innovative solutions that address this issue or enhances the value metric considered. In this case, the components listed in table 26 are compared to the innovations in a Dyson V6 cordless vacuum. By comparing the two we can derive how each of these components can be innovated to improve
cleaning performance and postulate how it could have led to the innovations seen in a Dyson V6 cordless vacuum. The highlighted components in figure 37 and their comparison to Dyson innovations are discussed below.

Figure 37 - Innovation Opportunities for Improved Cleaning Performance

1. Nozzle door

The nozzle door is basically a lid that fits on an extension of the frame to constitute the nozzle assembly. This contains the brush roll assembly that makes contact on the surface to be cleaned and enables the user to close or open it to grant the brush roll access to the floor for cleaning. Closing this door will disengage brush roll contact with the floor and redirect the suction to the hose outlet, given the swing door - hose is open.

In the Dirt Devil hand vacuum, the nozzle houses the brush roll and is one of the critical components that forms the interface with the floor. The design of the nozzle and its interface with the floor largely affects suction. A powerful suction is required to pick up debris into the dust bag and the clearance of the nozzle from the floor determines the amount of suction acting on the floor surface. Hence, the clearance must be high enough to pick up the debris and low enough to not cause a high loss of suction.

An ideal solution would be a system that has an optimal interface between the nozzle and the floor surface that creates powerful suction and satisfactorily picks up debris. Dyson designed
the nozzle to be a detachable component like other cleaning tools such as the crevice tool etc. This detachable nozzle design has a very low floor clearance in comparison to other hand vacuums that maximizes suction at the interface between the nozzle and the floor. This causes the debris to experience a high suction at the interface that pulls it quickly into the dust cup thereby improving cleaning performance.

2. Motor and Fan assembly
The motor and fan assembly function together to create the suction required to perform cleaning. The functions of the motor and the fan assemblies augment each other to bring about cleaning, the primary function of the vacuum.

It is common knowledge that the more powerful a motor, the more is the suction created. If powerful motors are used to create high suction then the cleaning performance of a vacuum can be rapidly improved. In the Dirt Devil vacuum, the motor and fan assembly create a vacuum space which causes the air from the atmosphere to rush in through the nozzle to fill the vacuum created by the motor & fan assembly. This is experienced as suction at the nozzle. The vacuum space, because of this air flow suction is created. The amount of pressure in the vacuum space determines the intensity of the suction and depends upon the capacity of the motor used.

An ideal solution would be a system that can create powerful suction. A powerful motor with a high capacity can create stronger suction in comparison to a smaller capacity motor. With stronger suction comes better cleaning performance. Dyson uses a custom-built motor that creates powerful suction. In this case, improved cleaning performance is achieved by creating powerful suction and designing a better motor and fan assembly that can maximize air flow.

3. Brush roll assembly
The Brush roll assembly consists of a cylindrical rod like structure with bristles for cleaning the carpet. The brush roll is run by the main motor through a belt drive that connects the main motor shaft and the brush roll.

The brush roll is a critical component that contributes to improving cleaning performance. The brush roll also forms the interface between the floor surface and the device. This part interacts directly with the dust particles and its dimension influences the clearance of the nozzle from
the floor surface. There are many factors of the brush roll that influences cleaning performance as follows,

- Brush roll drive mechanism
- Dimension of the brush roll
- Density of the bristles
- Rotation speed of the brush roll

The Dirt Devil has a belt driven brush roll with sparsely arranged bristles. Because of this sparse arrangement, the area of contact between the brush roll and the floor is minimum leading to a mediocre cleaning performance. Since the brush roll is belt driven it cannot achieve a high RPM which also results in mediocre cleaning performance.

An ideal solution would be a system that can produce large area of contact between the brush roll and the floor surface and achieves a high brush roll RPM. Dyson has a motorized brush roll, it has a separate motor to cause the brush roll to rotate at a high RPM. Due to a high rotation speed the debris that is deeply embedded in the carpet floor gets muddled which makes it easier for the vacuum to suck them into the dust cup. Dyson also has two specially designed brush rolls with varying bristle density called the ‘motorhead’ and the ‘fluffy’ for cleaning hard floors and carpet floors respectively. In this case, the improved cleaning performance is achieved by controlling the four brush roll factors mentioned above.

4. Switch

The switch gives the user control over the vacuum. It is located on the handle and can be turned on or off to power the vacuum or shut it down.

The dirt devil has a switch that can toggle between a high and a low suction setting. Suction is controlled by having multiple suction settings for different floor types and cleaning requirements. Depending on the need of the user, he/she can choose between low and high suction modes for cleaning. High suction mode offers better cleaning results in comparison to low suction.
Dyson has a switch to toggle between three suction settings namely ‘min suction’, ‘extended run’ and ‘max suction’ and a trigger that activates the device for cleaning. The switch provides multiple suction settings to choose from depending upon cleaning requirements but it also has a trigger button that powers the vacuum only when needed. By providing multiple suction settings to meet different cleaning demands better cleaning is achieved.

5. Hose assembly

The hose assembly is a long flexible tube like structure attached to the frame-nozzle extension that can be extended to a limited length to clean places the nozzle cannot access. Crevice tool and other specialized cleaning tools can be attached to the hose outlet for effective cleaning.

In the Dirt Devil hand vacuum, the hose assembly is attached directly to the frame and interacts with the dust particles and floor surface using specially designed tools for specific cleaning duties. The suction is influenced by the dimensions of the hose assembly. For instance, having a large diameter for the hose will reduce the suction at the outlet. In addition, since the hose is flexible it tends to bend a lot causing the inner diameter of the hose to vary which disrupts the flow of incoming air. When the linearity of the air flow is disrupted, the cleaning performance is reduced. Dirt devil has both the nozzle and a hose that can be used for cleaning and the suction is shared between the two. This design does not allow for linearity of the air flow which affects cleaning performance of the vacuum.

An ideal solution is a system that can maintain the linearity of the air flow and the consistency of the hose dimensions. Dyson has a long hollow tube called ‘the wand’ that can fit different cleaning tools and a detachable nozzle. Dyson eliminated the hose assembly by replacing it with a wand assembly which helps maintain the linearity of the air flow. The wand assembly is rigid and hence there is no bending involved which helps maintain a constant dimension of the wand. Due to this, the flow of air is linear and the best possible suction is achieved leading to better cleaning performance.
6. Crevice tool
The crevice tool is a specialized cleaning accessory that is generally used for cleaning edges and places the nozzle cannot access. The design of the crevice tool significantly influences the amount of suction experienced at the tool-floor interface.

In Dirt Devil hand vacuum, the crevice tool is attached to the hose for cleaning. As discussed earlier the suction is affected by the flexibility of the hose. So, the suction gets affected further based on the dimensions of the crevice tool. However, the Dyson uses a wand assembly that prevents disruption of air flow and loss of suction. With the right dimensions for the crevice tool, better suction is experienced at the tool mouth leading to improved cleaning performance.

7. Type G bag
In the Dirt Devil ultra-handheld vacuum, the type G bag is the component where all the dust collected is stored and is attached to the outlet of the motor and fan assembly. It also acts as the first level of air filter that retains the dust particles carried in the air stream from being released back into the atmosphere. This bag is made up of a material that has fine pores which allows air to pass through but retain dust particles that are larger than its pores. When it gets filled the dust particles might clog the pores in the dust bag and lead to a loss of suction and cleaning performance. The bag must be thrown out along with the debris and be replaced with a new one to continue collecting debris and regain cleaning performance.

An ideal solution would be to have a system that does not require frequent to no replacement of dust bag to continue to efficiently collect debris with minimal or no loss in suction and cleaning performance. Dyson has a bag less design that uses a clear bin instead of a dust bag for containing the debris picked up by the vacuum. The clear bin is in close association with the cyclone which separated the dust particles from the incoming air stream. This clear bin enables the user to dispose the debris without the need to buy replacement dust bags thereby eliminating the loss of suction due to filling up of the dust bag. Since it can perform without loss in suction, consistent and better cleaning performance is achieved.
6.0 Conclusion and Future Work

Firstly, this chapter presents a synopsis of the enhancements and the validation of the innovation mining framework. Secondly, the synopsis is followed by a detailed assessment of the stated research objectives. Finally, the summary is concluded by identifying areas for future research and development of the innovation mining framework. These areas of future improvement are envisioned to refine the innovation mining framework into a reliable model to be used by product developers to identify innovation opportunities.

6.1 Inference and lessons learned

This section briefly discusses the experiments conducted as part of the feasibility study of mechanical pencil and the takeaways from each of them.

1) Effect of varying the VOC weighting schemes
   The implementation of the framework was experimented with varying VOC weighting schemes as part of the feasibility study. The results show that varying weighting schemes do not have a significant impact on the clusters obtained when a filtered operating matrix was used for the analysis. However, when an unfiltered matrix was used for the analysis, changes in cluster formations were observed.

2) Effect of filtered and unfiltered data set
   Analysis was carried out for the mechanical pencil using an unfiltered matrix and a matrix filtered based on the chosen value metric. It was observed that the results obtained from filtered matrix identified innovation opportunities specific to the value metric. Its interpretation was a lot easier in comparison to the results obtained from using an unfiltered matrix because it shows the relationships and interactions between all the components in a system with no regard to any specific metric. Filtering the input data matrix helps identify innovation opportunities by narrowing down the focus to a specific value metric.
3) Effect of multiple weighting schemes and failure modes

Four experimental combinations were tested to study the effects of using multiple weighting schemes and performing the analysis for two value metrics at the same time. The results of the experiments showed that for a filtered matrix multiple weighting schemes did not make a significant impact and performing analysis for a single value metric yields focused results and easier interpretation.

A case study on handheld vacuum was carried out by making use of the above-mentioned insights from pencil feasibility study. The framework was applied to identify innovation for six scenarios employing the 1-3-9 transfer function rating system and a filtered matrix for the analysis in all the cases. The following discusses the lessons learned from the analysis done on Dirt Devil handheld vacuum to improve the following six value metrics:

1. Portability and Reach
2. Reduced Hair Wrap
3. Cleaner Exhaust
4. Runtime Experience
5. Consumable cost reduction
6. Cleaning Performance

The results showed that the framework was successful in identifying innovation opportunities and providing valuable insights for the six scenarios. The analysis for cost reduction identified a few additional components that did not provide a ready innovation opportunity, since cost is a metric that is associated with all the components in a system as it is involved in the design, manufacturing and assembly of these components and subsystems. So, when cost is considered a value metric every component of the system becomes a potential candidate for innovation opportunities. The other scenarios involving failure modes yielded results consistent with innovative solutions in the market.

6.2 Synopsis

The innovation opportunities identified for each of the value metric may seem apparent, although they were not apparent from looking at the QFD – I & II matrices, and it could be contended that applying the ‘Innovation Mining’ framework is unnecessary: that a profound
product designer could, upon contemplation, infer the same or a better set of innovation opportunities without using the innovation mining framework. A second possible criticism of the methodology might be that it is potentially unreliable – that is, the reliability of the input data presented in a QFD matrix, may lead to significant distortion of the real relationships; or that the use of this framework may provide a disfavor for the product developer by acting as a substitute for thought, if he accepts the output uncritically.

These criticisms are valid for any kind of model development, and deserves an equally valid reply: the use of the ‘Innovation Mining’ framework requires the same knowledge for both model building and result interpretations that other models demand. The innovation mining methodology should be regarded as an assistance to the product developer who wants to understand the interactions and relationships in a complex system from a ‘Systems Thinking’ perspective. Construction of the input data, especially the need to linking VOCs, EMs, subsystems and components, requires diligent thinking, as does any form of quantitative model. In addition, the mechanics of the innovation mining model is free from assumptions as the clustering technique requires no prejudice about the size and number of clusters. When used for revealing hidden relationships and identifying innovation opportunities, this gives a substantial advantage over the intuitive and qualitative approaches, because it provides insights on underlying relationships that may otherwise be ignored or unexplored. The resulting innovation opportunities from the case study which are the output of the innovation mining model can serve to evoke the product developer. He is free to reflect upon them, reject them, or modify them in any way.

The innovation mining framework serves, therefore, as a fail-safe model for approaching innovation in a swift and efficient way, given the product developer examines the results diligently. The value of the model lies in its ease and speed for a first cut. The input variables can be listed in any order, the numerical data need not be exact, the clustering using Matlab is fast, the procedure makes use of quantitative data and does not lose any information. The mechanical algorithm using Matlab is more convenient and significantly faster for complex products with a large number of components and subassemblies.
6.3 Assessment

The research is assessed by looking back at the research goals and objectives previously stated.

1. Apply the Innovation Mining framework to a set of concrete case study where innovation is known to have taken place to assess whether the areas that the framework identifies are the same as where the innovation happened.

Assessment: The innovation mining framework was applied to two products namely a mechanical pencil as part of feasibility study and a handheld vacuum as part of case study to validate the ability of the model to identify innovation opportunities relevant to the chosen value metric. The results of both feasibility study and case study imply the success of the innovation mining framework in identifying areas to focus the innovation efforts for the most benefit. The innovation opportunities identified from the feasibility study on mechanical pencil and case study on vacuum for each of the value metric chosen were found to be consistent with the innovative solutions existing in the market.

2. Based on the insights developed from the case study, develop an appropriate weighting scheme to be deployed in the engineering matrices.

I. Can a weighting scheme be developed for different levels that will aid in the identification of components worth Innovating?

Assessment: The implementation of the framework was experimented with varying weighting schemes as part of the feasibility study. The results show that varying weighting schemes do not have a significant impact on the clusters obtained when a filtered operating matrix was used for the analysis. However, when an unfiltered matrix was used for the analysis, changes in cluster formations were observed. This observation is not pursued further, as later experiments showed that filtered input matrices yielded better results.

II. How much does the weighting scheme affect the outputs?

Assessment: The output for the different weighting schemes used did not vary significantly from each other. The clusters obtained for both the 1-3-9 and 1-3-6-9 weighting schemes were the same except that the position of one of the clusters had
shifted a little. The shift in position of the clusters are insignificant if they do not shift between extremes in the dendrogram.

3. Interpret meaning from the results of the case study analysis and prioritize the clusters that are identified

I. Can the resulting pattern from the analysis be interpreted to identify relevant clusters and irrelevant clusters?

Assessment: The results of the analysis for each of the value metric considered shows an underlying pattern in the clusters formed. It is observed that the most relevant clusters are present at the top half of the dendrogram and the least relevant to irrelevant clusters are present at the lower half of the dendrograms.

II. Do the patterns/clusters influence design decisions? What insights can be obtained?

Assessment: The patterns in the cluster formation helps distinguish between relevant and irrelevant clusters making it easier to narrow down focus of innovation efforts. With a narrow focus the product developer can make quick and efficient design decisions to improve the value metric. In addition, the framework reveals hidden relationships between components for each of the value metric which provokes the product developer to understand the product from a systems thinking perspective. Being exposed to systems thinking perspective will provide invaluable insights to the product developer which can be used in making design changes for innovation.

III. How can the relevant clusters obtained be prioritized?

Assessment: Rather than prioritizing, the relevant clusters must be looked as a chain of clusters that share direct and indirect relationships. Making changes to one link in the chain is going to affect the other links, which may result in unnecessary trade-offs or an increase of unintended value. Both are undesirable if they cannot be controlled. Hence, the relevant clusters have to be seen from a systems thinking perspective as a chain of clusters and the design changes have to be made accounting for all the links in the chain to gain the most benefit.

IV. Does the identified component match with the changes that have taken place?

Assessment: The results of the feasibility study on mechanical pencil and the case study on handheld vacuum are in accord with the respective innovations that have
occurred in their product categories. The identified clusters are in line with the components that are observed to be modified in the innovative solutions used for comparison.

4. Propose modifications to improve the framework.

I. What are the weak links in the Innovation Mining framework?

**Assessment:** The Innovation Mining framework initially defined three innovation scenarios that signal the need for innovation. The first scenario namely S-curve slope decline requires historical data of the product to identify a decline in the value metric plotted over time. This limits the possibility of identifying innovation opportunities in products with a relatively short history or no history at all.

II. Why are they important? What is causing them?

**Assessment:** It is important to be able to identify innovation opportunities or to gain insights that can help the product developers to innovate because the product companies face intense competitions in the market irrespective of whether they are start-ups or incumbents. Market leaders usually have a long line of products in each category with lot of historical data that can be made use of to identify innovation opportunities but however smaller companies and start-ups that do not have a long line of products and lack significant historical data, but they also have a need to identify innovation opportunities to stay in the competition or to ultimately disrupt the market with new innovations.

III. How can they be solved or reduced?

**Assessment:** This can be solved by making use of ‘Engineering Metric Filtering’ method used in this validation research. Given a value metric as a benefit-to-cost ratio, the VOCs related to the value metrics are selected from the QFD – I relationship matrix then all the EMs associated with them are identified. This set of EMs is used to filter out rows of data from the QFD-II matrix after the cells are multiplied with the weight of each EM. This set of filtered data from the parent operating matrix is used in the analysis. Applying SVD to this filtered operating matrix and performing hierarchical clustering on the weighted ‘Vs’ matrix gives the dendrogram with clusters of components that possess innovation opportunities.
5. Demonstrate the value created by the framework after modifications.

**Assessment:** The framework successfully identified innovation opportunities in the products chosen for the feasibility and case study. A product that is not modular is a complex system with many known and unknown relationships between its components, which makes innovating it more challenging. To approach innovation in such complex systems quickly and efficiently, a product developer must understand all the relationships and links between the components in that system. This framework assists in achieving a comprehensive understanding of the system by revealing hidden relationships between components and showing more than one way of enhancing a chosen value metric in a system. This model identifies clusters of components which can be each innovated to improve the value metric. This also means that the Innovation Mining framework identifies innovation opportunities by the systems thinking approach and not the linear thinking approach.

6.4 Future Work

This section presents a list of opportunities for future research to refine this model and make it more reliable and usable for the industry. The limitations of this work and enhancement opportunities are discussed below.

**Limitations:**

1) The transfer functions used in the research is QFD 1-3-9 system ratings. Developing actual transfer functions is a difficult task and can be a research on its own. Developing a system that reflects true relationships is thought to provide a better result as compared to the 1-3-9 common rating system. However, if the 1-3-9 system is found to yield satisfactory results then having this common transfer function system would simplify the implementation of the framework to any system.

2) As previously stated, the development of the value metrics, the analysis of the value metrics and the selection of the appropriate value metrics to guide the innovation activity is not addressed nearly as comprehensively as needed for the ultimate framework. A value metric must be identified as a benefit-to-cost ratio to begin with the implementation of the framework and so do the use of the scenarios of innovation. Hence, there is a need for a value model that helps in systematically identifying the right benefit-to-cost ratio to be focused upon. But, this opportunity is not addressed in this research as it has the potential to be a research on its own.
Opportunities:

The rating system used in the matrices to represent couplings is based on 1-3-9 system in the thesis but the true transfer functions for the row and column linkages should be studied. The effects of developing and using true transfer functions in the framework should be analyzed to check if they yield better results and insights to guide the product developers to come up with radical innovations. This is critical since the data within the clusters obtained at the end contains the information relayed by the transfer functions.

The definition of concepts should be explored. An analysis by performing SVD at every level of the coupling matrices between VOCs, EMs, DPs, SS, SSS and Cs might provide new insights into the nature of transformation and clusters. This information content can generate greater insights and a better understanding of the system.

An analysis and comparison of the clusters in the dendrogram to the different failure modes associated with the value metric to develop a concrete method for prioritization of clusters. There are many pathways to achieving innovation and one of the most promising ways is to developing solutions and solving for failure modes. So, making a comparison between the resulting clusters and the different failure modes associated with the value metric, along with knowledge of the root cause and the factors influencing those failure modes may enable the product developer to create radical innovative solutions.

Comparison of the dendrogram clusters with function-structure mapping to get more insights on the clusters and their interactions. The function-structure map shows the physical links between components, functional links in the system and ultimately the connections between the physical and functional space. Looking at these relationships along with the insights obtained from the dendrogram clustering, the product developer can gain the knowledge to make informed decisions early in the design phase. It will enable him to think thoroughly about the form-function relationship that the system should have at the end of the product development process.
7.0 References


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