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Concept for enhanced intuition in development management through exploratory data analysis using an extended factor analysis of mixed data

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Abstract

With the shift from mechanical value delivery to mechatronic value delivery, development environments are becoming more complex. Intuitive decision-making in development management is becoming increasingly challenging. Meanwhile, the use project management software is spreading, bringing about a new level of project data for development projects, holding to potential to enhance human decision making. To this end, the paper presents an extension to factor analysis of mixed data, which can facilitate usage of exploratory data analysis to improve decision-making in development project planning.

Keywords: factor analysis of mixed data (FAMD), decision making, development management, exploratory data analysis, project management

1. Introduction

Engineering is facing challenges of increasingly complex products (Schuh and Dölle, 2021, p. 11) being developed with a higher degree of individualisation (Oluyisola et al., 2022, p. 312; Bender and Gericke, 2021, p. 182) in shorter lifecycles (Sabadka et al., 2019, p. 1298). The transfer of value delivery from primarily mechanical product features to mechatronics results in more dynamic system behaviour and raises the level of interdisciplinarity in product development (Krzywinski and Wölfel, 2021, p. 684; Schuh et al., 2019, p. 367). Shorter lifecycles challenge the robustness of development processes and decision-making, as the increasing number of influencing factors from various disciplines are to be taken into account (Riesener et al., 2021b, p. 443; Riesener et al., 2021a, p. 258). Cowan (2001, p. 90) shows human cognition to be limited to addressing four to six information objects in parallel. This is far lower than the number of factors influencing the outcome of decisions in development management. The need for a comprehensive decision support rises with the complexity of decision situations.

While software has added to complexity, mechatronic systems and sensors as well as software tools in engineering have resulted in an unprecedented amount of data available to engineering companies (Lauth and Scholz, 2023, p. 12). Knowledge discovery in databased has been around for many years, laying the foundation for decision makers to better comprehend the complexity of decision scenarios and come to valid results. However, as of now companies do not fully access the available potential. The reason for this appears to be the applicability of existing methodologies: It is difficult for decision makers unfamiliar with data science and its methods to ask the right questions and interpret the answers they may receive. Decision makers are not to be replaced by artificial intelligence (AI). Instead, their natural intuition should be enhanced through data analysis, which allows for a more appropriate representation of real world decision complexity.

To this end, research is being done on databased heuristics for development management. Working with project metadata and variables, decision guidelines for development managers are to be identified. Variables can for example be the degree, to which time and cost goals have been met and what team size, team experience or supplier network size were like for a given project. A key aspect to this challenge is the reduction of data set dimensionality in a way that allows for results to be interpreted by decision makers. This is the objective of the paper. We suggest an extension of the factor analysis of mixed data (FAMD), which allows for a better interpretation of results, enabling enhanced intuition based on data analysis in development management.
Section 2 will elaborate the current state of research, both for development management and factor analysis. Section 3 will elaborate the extended FAMD methodology, the application of which is outlined in Section 4. The methodology is currently at a conceptual level, hence validation with industrial datasets is pending.

2. State of research

In the following section, the state of research in relevant research areas is presented. Section 2.1 covers research on development management. Section 2.2 covers factor analysis as means to dimensionality reduction. Section 2.3 details the concept of intuition after which Section 2.4 summarizes the research deficit.

2.1. Development management

In considering development management, both the general scope of the field and approaches to quantitative development management will be discussed.

2.1.1. General understanding of development management

According to Holzbaur (2007, p. 159 ff.), development management is the task of coordinating, which development efforts a company undertakes, coordinating the people and the organizational structure tasked with development efforts and coordinating the development efforts themselves. The management is considered responsible for assigning goals as well as for creating an environment in which these goals can be achieved. From this perspective, it is clear that development management covers various decision levels within a company.
The complexity of decisions in development management increases with the complexity of the development subjects. This is especially the case when systems become connected to each other: influences to one system become influences to many systems of the company. In this context, Fricke and Lohse (1997, p. 52) underline the role of development management in defining visions for product development as well as in breaking theses visions down into goals and strategies. Development management can be considered bridging the gap between company strategy and operative development efforts of a company.
Similar to Holzbaur, Hahn et al. (2013, p. 21) propose an explicit differentiation of the levels at which development management takes place, specifically naming the strategic, tactical and operative level. Their view differs however with regard to the tasks of development management. Hahn et al. (2013, p. 21 f.) structure the task of development management as shown in Figure 1 into knowledge management, innovation management and process and project management.

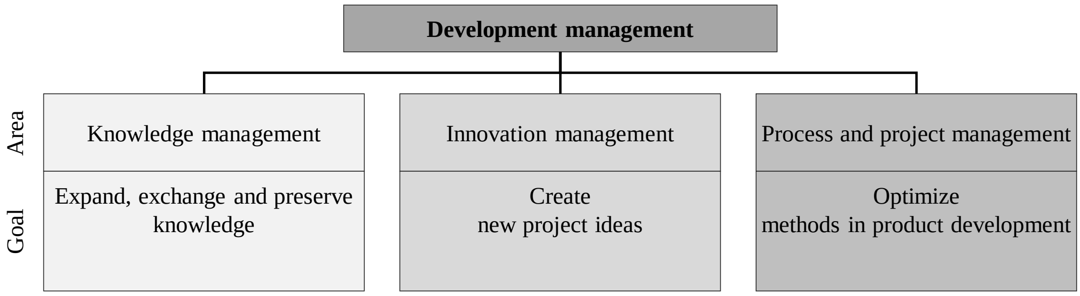

Figure 1. Development management according to Hahn et al. (2013, p. 21)

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Process and project management can be considered similar to coordinating the development efforts of a company as stated by Holzbaur. Innovation management addresses similar aspects as coordinating, the development efforts, which a company undertakes. What is different is the focus on knowledge management. In accordance with Ophey (2006, p. 19), Hahn et al. argue that the expansion, distribution and preservation of development knowledge are among the responsibilities of development management. The paper follows this logic and aims to support development managers in their task of knowledge management, which in turns supports innovation management as well as process and project management.

2.1.2. Quantitative decision support in development management

Various scientific approaches and research fields support decision-making in development management through quantitative methods. Among the fields is operations research, which according to Domschke et al. (2015, p. 1 ff.) covers quantitative decision support in a business context using mathematical models. An example of a problem covered by operations research is that of the traveling salesman, put forth by (Menger, 1932, p. 12). Other methods are proposed by Hahn et al. by presenting a framework for increased transparency in decision-making. To this end, they present an approach to estimate the project scope based on the product structure (Hahn et al., 2013, p. 73) and an approach to monitor the product quality during the development process based on development data (Hahn et al., 2013, p. 103). In this way, development managers can benefit from increased transparency during project execution and anticipate upcoming challenges.

2.2. Factor analysis

Factor analysis is an established method of reducing the dimensionality of datasets. Four approaches to factor analysis will be discussed and their differences will be highlighted. The four approaches have been selected as they represent the field of factor analysis for dimension reduction.

2.2.1. PCA and MCA

The first approach to be discussed is principal component analysis (PCA) as presented by Pearson (1901, p. 559 ff.). PCA works with numerical data. By calculating the principal components of a dataset, new dimensions are calculated, the first of which represents the highest variability of the dataset (Dunteman, 1989, p. 9). These principal components form an n-dimensional space (Michailidis, 2007, p. 783). The dataset can be reduced while retaining as much information, meaning variability of data, by only considering the first principal components (Kramer, 2013, p. 33).
With PCA being limited to numerical data, a solution for categorical data is multiple correspondence analysis (MCA) (Greenacre, 1991, p. 195). MCA can be considered an application of PCA to categorical data, as demonstrated by Pagès (2004, p. 95 ff.) and by Gower (2011, p. 365). However, the two approaches rely on datasets to be either completely numerical in the case of PCA or completely categorical in the case of MCA. This is not true for the project data provided by past development projects. Approaches have been presented to categorize numerical data to turn mixed data into completely categorical data, however this is associated with a loss of information (Wedel and Kamakura, 2001, p. 515).

2.2.2. MFA

An approach to address mixed data is multiple factor analysis (MFA) as presented by Greenacre (2006). MFA is devoted to analysing observations described by groups of variables. Within a group of variables, data can be numerical, categorical or both. The methodology hence is valuable to the analysis of surveys. However, MFA depends on the variables being grouped, which is a prerequisite missing from project data.

2.2.3. FAMD

A second approach to address mixed dataset is factor analysis of mixed data (FAMD), presented by Escofier (1979) and by Saporta (1990). The exploratory approach can be considered a combination of

PCA and MCA in that it acts towards numerical data as if it were a PCA and towards categorical data as if it were a MCA as shown by Pagès (2004, p. 95 ff.). FAMD works by representing the numerical data as they are and representing the categorical data by two numerical data tables. After combining all three numerical data tables, singular value decomposition is applied to the combined dataset (Pagès, 2015, p. 71). In this way, it becomes possible to reduce the dimensionality of mixed datasets as required for the analysis of project data.

This potential of FAMD is used already in various applications, including the clinical analysis of COVID-19 clusters (Han et al., 2021). Another application is the detection of anomalies in datasets (Davidow and Matteson, 2020). Own research is conducted in the field of development management (Riesener et al., 2022b).

2.3. Intuition

Intuition is defined by Rowan (1986, p. 96) as knowledge obtained without rational thought. It is the result a subconscious process of pattern recognition, hard to grasp or observe (Shirley and Langan-Fox, 1996, p. 564; Hodgkinson et al., 2008, p. 19). Along these lines, enhanced intuition is considered to be databased patterns from past observations which are informative for the decision-making process. The degree to which these observations are representative of reality is the degree to which databased intuition can be considered valid.

2.4. Research deficit

The research presented in this section demonstrates a need for improved support of development management, for which factor analysis is an established tool. As opposed to operations research, it does not require an analytical problem statement. With knowledge management being a task of development management, it is becoming increasingly relevant to access the potentials of project data to address the challenge of decision complexity going beyond the scope of human cognition.

There is a deficit however with regard to the applicability to existing approaches such as FAMD. For decision makers in developing companies, the result of a FAMD analysis may not be accessible, due to a gap in decision maker's data science background. Training every decision maker in detail on the required data science approaches is not feasible or in fact efficient to many developing companies. An approach is needed to effectively reduce the dimensionality of dataset of project data while preserving the available information. This gap is to be addressed through the proposed extension of the FAMD methodology.

3. Concept for an extension of FAMD

To address the research deficit highlighted in section 2, an extended FAMD methodology is presented in section 3. The goal of the methodology is to enable enhanced intuition for development management through the retention of original variables during dimensionality reduction, rather than forming new dimensions as is the status quo of FAMD.

Section 3.1 provides a methodical overview, followed by detailed descriptions of the extended FAMD methodology in section 3.2 and 3.3. Suggestions for the application of the approach in development management are provided in Section 4.

3.1. Overview of methodology

Transferring the concept of intuition to exploratory data analysis using FAMD, the suggested methodology aims to reduce the dimensionality of a dataset of project data while retaining a subset of the original and therefore interpretable project attributes. The methodology displayed in Figure 2 achieves this by identifying the informational value of each original variable and reducing the dataset to a set of the original variables with the highest informational value.

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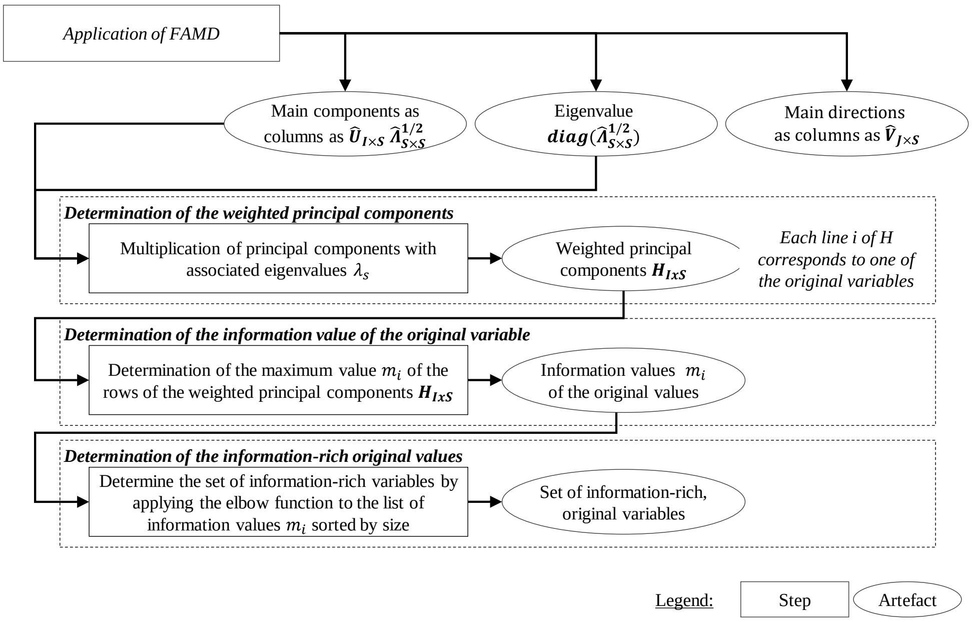

Figure 2. Extended FAMD for knowledge discovery in development management

The methodology consists of three primary steps as shown in Figure 2 and utilizes the principal components identified using the existing FAMD methodology. The first two steps aim to create transparency regarding the informational value of each of the original variables of the dataset. To this end, the weighted contributions of each original variable to each principal component are calculated. In the following step, the informational value of each original variable is derived. With this insight, the dataset is reduced in a third step to then only contain the original variables of the highest informational value. The steps are detailed further in following subsections.

3.2. Calculating weighted principal components

One result of applying FAMD to a dataset is to receive the eigenvalues of the principal components. They represent the informational value of the corresponding principal component. The eigenvalues of a sample dataset are shown in Figure 3. The i-th principle component, marked as "Dim. i" in the figure, is a vector comprising the contributions of original variables to the i-th principal component. It is apparent from Figure 3 that these contributions are not equally relevant: with A and B being original variables of the sample dataset, if A contributes twice as much to principal component 24 as B, but B contributes twice as much to principal component 1 than A, with all else being equal it can be stated that the informational value of A is far lower than that of B, as the eigenvalue of Dim. 24 is much lower than the eigenvalue of Dim. 1. Therefore, the contributions of the original variables are multiplied with the corresponding eigenvalues to receive weighted contributions of the original variables.

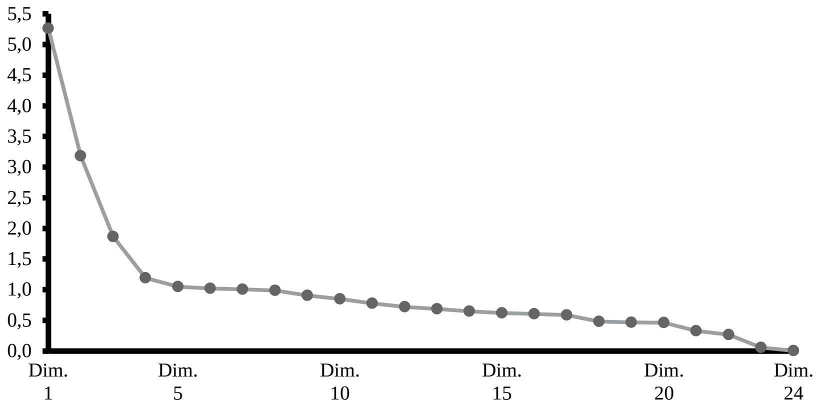

Figure 3. Eigenvalues (on the vertical axis) of the principal components shown as Dim i

3.3. Identifying informational values

The weighted contributions of the sample dataset are displayed in Figure 4. Each row represents an original variable, each column represents a principal component from one through 24 as shown in Figure 3. The figure shows a clear shift in the distribution of major contributions towards the left side, namely to the most relevant principal components. This is in accordance with the purpose of step one and confirms the effectiveness of the step. To reduce the dataset in step three, the informational value of each original variable needs to be derived from the weighted contributions. Experiments with sample datasets and preliminary industrial datasets showed the maximum value to be the most relevant indicator of informational value, as opposed to i.e. the sum of each row. In Figure 4, the contributions representing the informational value of the corresponding original variable are shown in black.

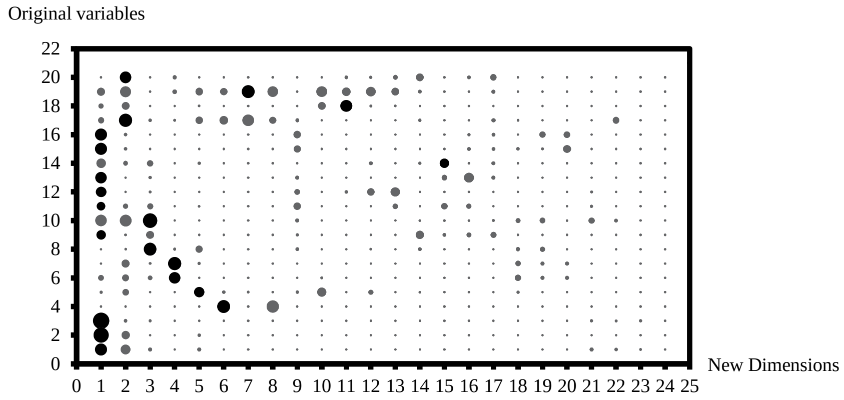

Figure 4. Informational value of original variables

3.4. Reduction of dataset

To use the previous insights for the reduction of the dataset, an elbow function is employed as shown in Figure 5. The objective is to separate original variables with high informational value from original variables with low informational value. To this end, Figure 5 shows the original variables sorted by their informational value. As the range of informational values is continuous and the bars can decrease arbitrarily, no definitive threshold of i.e. 80 % is feasible. Hence, the threshold is chosen as the bar, which has the furthest distance from a line connecting the first to the last bar. Original variables left of the threshold are chosen as the reduced dataset, original variables on the right of the threshold are discarded. In the example of Figure 5, it is apparent that the threshold, original variable 17, is more akin to the discarded variable. If the threshold is below the line connecting the first to the last bar, it is discarded. If it is above the line, it is considered part of the reduced dataset. It is to be noted, that according to the proposed methodology, while meaningfully reducing the dataset, the cumulative informational value can become low.

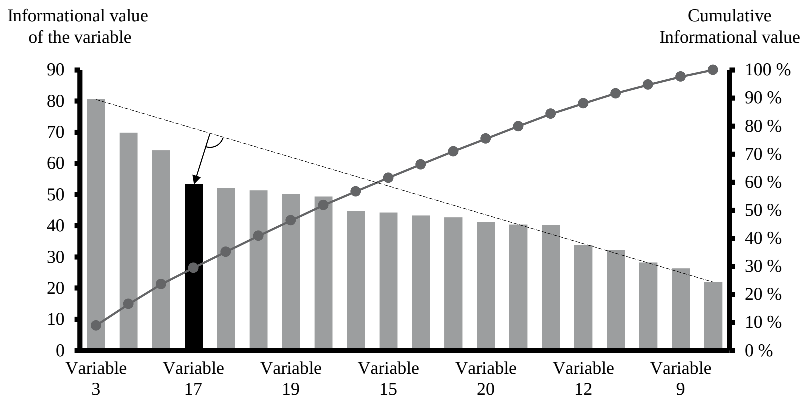

Figure 5. Selection of variables with high informational value

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4. Application of concept in development management

Section 4 covers the application of the methodology and its results in development management. This includes an analysis for knowledge discovery as well as steps to use insights for project definition and for auditing project proposals.

4.1. Knowledge discovery in reduced datasets for development management

It is to be underlined that the methodology addresses project metadata. Original variables can be various project attributes such as budget, team size or the locations at which development took place, but also the disciplines involved in the project or the cumulative project experience of the team (Riesener et al., 2022a, p. 261).

To assist in the decision-making process shaping a project, either before it starts or during its execution, patterns are to be discovered among past projects. To this end, the degree to which a project meets its goal is considered as a measure of project success. Using clustering of past projects in the space of relevant project attributes resulting from the application of extended FAMD, such patterns can be discovered. As the amount of attributes can be vast and the number of projects for which data exists may be limited, preselection combined with extended FAMD works as a method to reduce the dimensionality of space, within which clusters are to be found. Because spaces get sparse as dimensionality increases, this is crucial for reliable results.

Using cluster analysis as shown in Figure 6, heuristics, i.e. guidelines which can be applied under limited knowledge, can be determined of what to seek or avoid in defining a project. Each point in the figure represents a past project, with the darkness of the points indicating the degree to which a project has met its goals. The use of such heuristics for defining and auditing projects will be discussed subsequently.

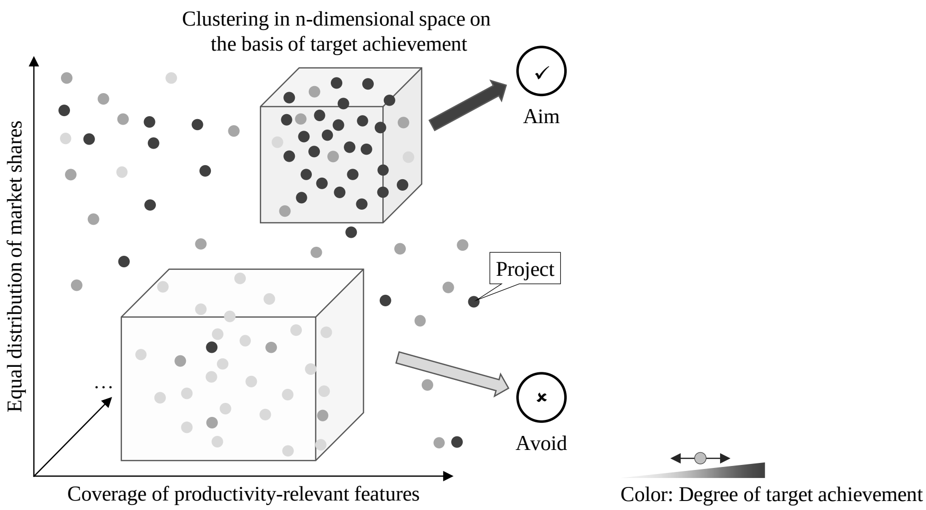

Figure 6. Application of methodology for knowledge discovery in development management

4.2. Definition of new development projects

A situation will be discussed where a development project is being defined. In this situation, many decisions are made which have a major impact on whether the project will succeed in or fail to meet its goals. Having used the extended FAMD methodology and the identification of heuristics, a first step is to verify that heuristics can be applied. This depends on the project being similar to past projects in the aspects addressed by the heuristics as well as data availability. While there may have been similar projects in the past, it needs to be verified that reliable data has been collected.

If relevant heuristics exist, it needs to be verified that the heuristics do not contradict each other. If all heuristics are compatible with other, they can be implemented during project definition. If not, conflicts need to be resolved. A possible source of conflicting heuristics are conflicting project goals. Reaching the start of production in time can be in conflict with the project scope and available resources. In this case, project goals are to be prioritized to be able to select a matching heuristic to implement.

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4.3. Auditing development projects

The situation and the approach are different, if a project proposal exists already. Nevertheless, the dataspace stemming from the application of the extended FAMD methodology can be used in this decision-making process as well.

As before, the first step is to verify the applicability, focusing on the availability of data from similar projects in the past. Only with such data can reliable insights be gained, as discussed when introducing enhanced intuition. As opposed to the case of project definition however, it is not necessary to identify heuristics prior to auditing a project proposal. Only the project data itself is used in this decision-making scenario. With attributes of the new project defined in the proposal to be audited, the project can be located in the n-dimensional space of project attributes, which in turn is the result of applying the extended FAMD methodology. Now that the project to be audited is located in this space, the past projects in its vicinity can be observed. For each objective of the new project, the degrees to which the past projects have fulfilled that objective are present as data. This allows for an estimation of objective fulfilment using kernel density estimation. What can be gained from this are insights into the degree, to which similar projects have fulfilled their objectives. This way, the company's specific constraints are incorporated into the estimation.

With these insights, both a decision on whether to confirm or to deny the project and measures to improve the project can be derived. The decision on project confirmation can be based on the estimated fulfilment of project objectives. Measures can be derived by observation of similar projects. If it is possible to change attributes of the project in a way that will move the project closer to successful past projects, this forms a measure to improve the project setting.

4.4. Limitations

In this section, the limits of the extended FAMD methodology and its use in development management will be discussed. A first limit is the methodology's conceptual stage. The methodology will be validated using industrial data in the future. Only after the industrial validation can the benefit to developing companies be certain.

The validation as well as the current application is limited by data availability. It is not yet standard in developing companies to automatically collect project metadata in a comparable way, such that extended FAMD is applicable. Employees are commonly required to aggregate such data manually, resulting in sparse data obtained with high efforts. However, with the increase in project management software it can be estimated, that both challenges to the application of the extended FAMD methodology in development management are temporary.

Regarding the potential insights, only such insights can be derived, which concern similar past projects or project aspects. If the scope of development efforts shifts, either by change of development methodology or product portfolio, insights may not be transferable. This is to be considered during data aggregation with regard to how far back in time data is to be considered.

In addition, the methodology does not prevent the cumulative informational value from becoming low.

5. Conclusion

The paper presents a concept for using an extended FAMD methodology to gain enhanced intuition for development management. The need for such methods increases with the complexity of decision scenarios, just as the potential increases with the availability of data from past development projects. The methodology is in a conceptual phase, validation with industrial datasets is pending. The methodology works by identifying the relevance of original variables and reducing the dataset to the most relevant original variables. This way, the interpretability of results is increased for decision makers without a data science background, to whom principal components may not be helpful in deciding whether the current team size and composition is suitable. In addition to presenting the extension of the FAMD methodology, possibilities for the application of the approach are presented for defining new projects as well as for auditing project proposals. The limitations of the methodology are discussed. Subsequent research will focus on validating and detailing the approach as well as on deriving the heuristics for development management. These can be considered as a form of enhanced intuition.

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References

Bender, B. and Gericke, K. (Eds.) (2021), *Pahl/Beitz Konstruktionslehre*, Springer Berlin Heidelberg, Berlin, Heidelberg.

Cowan, N. (2001), "The magical number 4 in short-term memory. a reconsideration of mental storage capacity", *The Behavioral and brain sciences*, Vol. 24 No. 1, 87-114; discussion 114-85. https://dx.doi.org/10.1017/s0140525x01003922.

Davidow, M. and Matteson, D.S. (2020), *Factor Analysis of Mixed Data for Anomaly Detection*, available at: http://arxiv.org/pdf/2005.12129v1.

Domschke, W., Drexl, A., Klein, R. and Scholl, A. (2015), *Einführung in Operations Research*, 9. Auflage, Springer Berlin Heidelberg, Berlin, Heidelberg.

Dunteman, G.H. (1989), *Principal components analysis, Sage University papers Quantitative applications in the social sciences*, Vol. 69, SAGE Publications, Newbury Park, Calif. https://dx.doi.org/10.4135/9781412985475.

Escofier, B. (1979), "Traitement simultané de variables qualitatives et quantitatives en analyse factorielle", *Les cahiers de l'analyse des données*, Vol. 4 No. 2, pp. 137–146.

Fricke, G. and Lohse, G. (1997), *Entwicklungsmanagement*, Springer Berlin Heidelberg, Berlin, Heidelberg. https://dx.doi.org/10.1007/978-3-642-59075-7.

Gower, J.C. (2011), "Multiple Correspondence Analysis", in Gower, J.C., Le Roux, N. and Lubbe, S. (Eds.), *Understanding biplots*, Wiley-Blackwell, Oxford, pp. 365–403. https://dx.doi.org/10.1002/9780470973196.ch8.

Greenacre, M.J. (1991), "Interpreting multiple correspondence analysis", *Applied Stochastic Models and Data Analysis*, Vol. 7 No. 2, pp. 195–210. https://dx.doi.org/10.1002/asm.3150070208.

Greenacre, M.J. (2006), *Multiple Correspondence Analysis and Related Methods, Chapman and Hall/CRC Statistics in the Social and Behavioral Sciences Ser*, 1. Auflage, CRC Press LLC, London.

Hahn, A., Häusler, S. and große Austing, S. (2013), *Quantitatives Entwicklungsmanagement*, Springer Berlin Heidelberg, Berlin, Heidelberg. https://dx.doi.org/10.1007/978-3-642-34510-4.

Han, L., Shen, P., Yan, J., Huang, Y., Ba, X., Lin, W., Wang, H., Huang, Y., Qin, K., Wang, Y., Chen, Z. and Tu, S. (2021), "Exploring the Clinical Characteristics of COVID-19 Clusters Identified Using Factor Analysis of Mixed Data-Based Cluster Analysis", *Frontiers in medicine*, Vol. 8. https://dx.doi.org/10.3389/fmed.2021.644724.

Hodgkinson, G.P., Langan-Fox, J. and Sadler-Smith, E. (2008), "Intuition: a fundamental bridging construct in the behavioural sciences", *British journal of psychology (London, England 1953)*, Vol. 99 No. 1, pp. 1–27. https://dx.doi.org/10.1348/000712607X216666.

Holzbaur, U. (2007), *Entwicklungsmanagement: Mit hervorragenden Produkten zum Markterfolg*, Springer Berlin Heidelberg, Berlin, Heidelberg.

Kramer, O. (2013), *Dimensionality Reduction with Unsupervised Nearest Neighbors, Intelligent Systems Reference Library*, v.51, 1. Auflage, Springer Berlin Heidelberg, Berlin, Heidelberg.

Krzywinski, J. and Wölfel, C. (2021), "Industriedesign und nutzerzentrierte Produktentwicklung", in Bender, B. and Gericke, K. (Eds.), *Pahl/Beitz Konstruktionslehre*, Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 684–703.

Lauth, E. and Scholz, S.G. (2023), "Introduction and Evaluation of a Project Management Software Tool in the Context of the Administration of Science and Research Projects", in Scholz, S.G., Howlett, R.J. and Setchi, R. (Eds.), *Sustainable Design and Manufacturing, Smart Innovation, Systems and Technologies*, Vol. 338, Springer Nature Singapore, Singapore, pp. 11–20. https://dx.doi.org/10.1007/978-981-19-9205-6_2.

Menger, K. (1932), "Das Botenproblem", *Ergebnisse eines Mathematischen Kolloquiums*, No. 2, pp. 11–12.

Michailidis, G. (2007), "Principle Component Analysis", in Salkind, N.J. and Rasmussen, K. (Eds.), *Encyclopedia of measurement and statistics*, SAGE Publications, Thousand Oaks, Calif., pp. 783–786.

Oluyisola, O.E., Bhalla, S., Sgarbossa, F. and Strandhagen, J.O. (2022), "Designing and developing smart production planning and control systems in the industry 4.0 era: a methodology and case study", *Journal of Intelligent Manufacturing*, Vol. 33 No. 1, pp. 311–332. https://dx.doi.org/10.1007/s10845-021-01808-w.

Ophey, L. (2006), *Entwicklungsmanagement, VDI-Buch*, Springer, Dordrecht.

Pagès, J. (2004), "Analyse factorielle de données mixtes", *Revue de statistique appliquée*, Vol. 52 No. 4, pp. 93–111.

Pagès, J. (2015), *Multiple factor analysis by example using R*, *Chapman & Hall/CRC the R series*, CRC Press, Boca Raton, FL. https://dx.doi.org/10.1201/b17700.

Pearson, K. (1901), "LIII. On lines and planes of closest fit to systems of points in space", *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, Vol. 2 No. 11, pp. 559–572. https://dx.doi.org/10.1080/14786440109462720.

Riesener, M., Dölle, C., Keuper, A. and Schuh, G. (2021a), "Understand and Control Complexity in Cyber-Physical Systems by Analyzing Complexity Drivers", in *4th IEEE International Conference on Industrial Cyber-Physical Systems (ICPS): Online*, *10-13 May*, *2021*, *5/10/2021 - 5/12/2021*, *Victoria*, *BC*, *Canada*, IEEE, Piscataway, NJ, pp. 255–260. https://dx.doi.org/10.1109/ICPS49255.2021.9468255.

Riesener, M., Dölle, C., Perau, S., Lossie, P. and Schuh, G. (2021b), "Methodology for iterative system modeling in agile product development", *Procedia CIRP*, Vol. 100, pp. 439–444. https://dx.doi.org/10.1016/j.procir.2021.05.101.

Riesener, M., Kuhn, M., Keuper, A., Lender, B. and Schuh, G. (2022a), "Framework for FAMD-Based Identification of RCPSP-Constraints for Improved Project Scheduling", *Proceedings of the Design Society*, Vol. 2, pp. 253–262. https://dx.doi.org/10.1017/pds.2022.27.

Riesener, M., Kuhn, M., Lender, B. and Schuh, G. (2022b), "Concept for Databased Identification of Heuristics for Development Management using FAMD", in *IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, *07.-10.12.*, *Kuala Lumpur*, *Malaysia*, IEEE, pp. 1281–1285. https://dx.doi.org/10.1109/IEEM55944.2022.9989972.

Rowan, R. (1986), *The intuitive manager*, 1. Auflage, Little Brown, Boston, MA.

Sabadka, D., Molnár, V. and Fedorko, G. (2019), "Shortening of Life Cycle and Complexity Impact on the Automotive Industry", *TEM Journal*, Vol. 8 No. 4, pp. 1295–1301. https://dx.doi.org/10.18421/TEM84-27.

Saporta, G. (1990), "Simultaneous Analysis of Qualitative and Quantitative Data", *Atti della XXXV riunione scientifica; società italiana di Statistica*, pp. 63–72.

Schuh, G. and Dölle, C. (2021), *Sustainable Innovation*, Springer Berlin Heidelberg, Berlin, Heidelberg. https://dx.doi.org/10.1007/978-3-662-61910-0.

Schuh, G., Dölle, C., Breunig, S. and Becker, A. (2019), "Gestaltungsmodell zur Steigerung der Wirtschaftlichkeit von Baukästen mechatronischer Produkte", *Zeitschrift für wirtschaftlichen Fabrikbetrieb*, Vol. 114 No. 6, pp. 367–371. https://dx.doi.org/10.3139/104.112095.

Shirley, D.A. and Langan-Fox, J. (1996), "Intuition: A Review of the Literature", *Psychological Reports*, Vol. 79 No. 2, pp. 563–584. https://dx.doi.org/10.2466/pr0.1996.79.2.563.

Wedel, M. and Kamakura, W.A. (2001), "Factor analysis with (mixed) observed and latent variables in the exponential family", *Psychometrika*, Vol. 66 No. 4, pp. 515–530. https://dx.doi.org/10.1007/BF02296193.