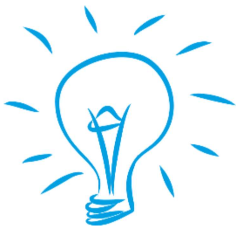
6. Introduction to Operations Research



Operations research (British English: operational research, U.S. Air Force Specialty Code: Operations Analysis), often shortened to the initialism OR, is a discipline that deals with the development and application of analytical methods to improve decision-making. The term management science is occasionally used as a synonym.

OR methods are used to analyse resource capacities, bottlenecks, lead and cycle times, demand patterns, inventory, resource distribution, maintenance, operator dispatching, product mixing, product output, reliability, resource utilization, rules and policies, schedule and dispatch efficiency, process throughput, etc. (Ueda, 2010)

Employing techniques from other mathematical sciences, such as modelling, statistics, and optimization, operations research arrives at optimal or near-optimal solutions to decision-making problems. Because of its emphasis on practical applications, operations research has overlapped with many other disciplines, notably industrial engineering and logistics, making it an integral part of their Knowledge Management Systems (KMS).

6.1 Strategic logistics planning

According to (Robinson, 2004) operations research mainly deals with the interaction among planned technical and human systems. They are characterized by variability, interdependence among components and structural as well as behavioural complexity. To manage these characteristics a wide array of methods has been devised to appropriately address them as a whole. They are used in their strategic planning to:

- enable complex what-if analysis;
- manage complexity: interdependence + variability + dynamics;
- involve less costs and interference with the process than by experimentation with a real system;
- focus on details;

- improve the understanding of a system;
- improve communication between management and experts.

Strategic logistics planning (Figure 6.1) comprises all activities which need to be performed on the strategic, tactical and operational levels in order to provide for Total quality management (TQM) (Ciampa, 1992) and Just-in-time production (JIT) (Britannica, 2023).

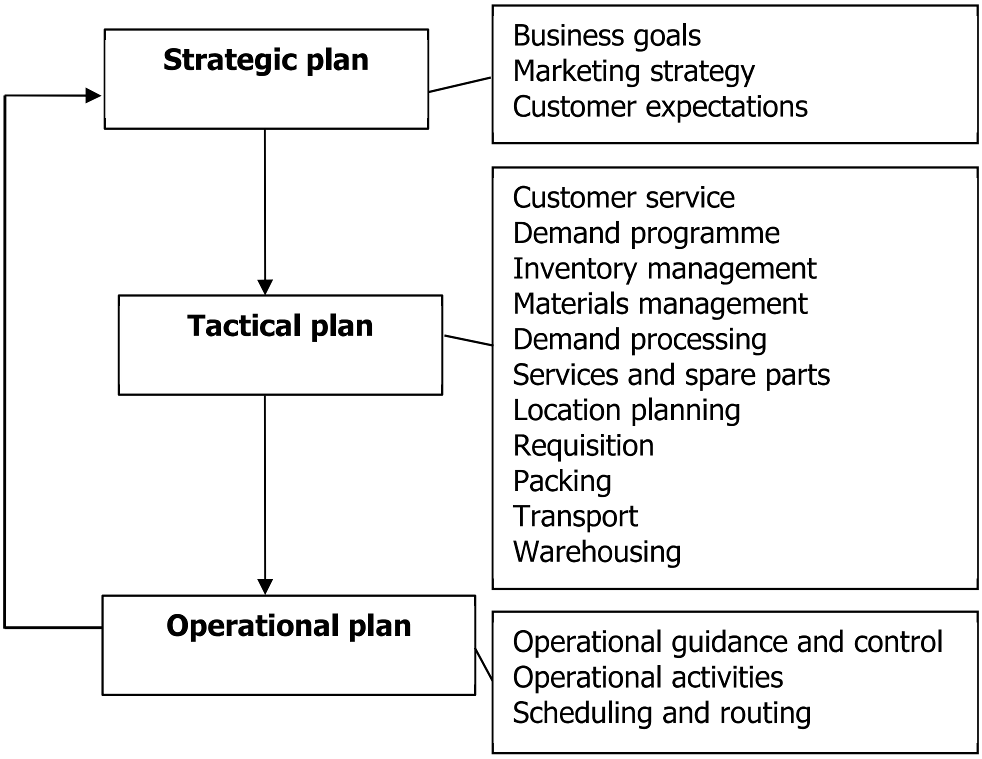
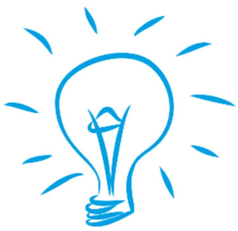


Figure 6.1 Strategic logistics planning.

6.2 Six-Sigma



In strategic logistics planning the SCOR reference model (AIMS, 2021) helps businesses evaluate and perfect supply chain management for reliability, consistency, and efficiency. It recognizes 6 major business processes — Plan, Source, Make, Deliver, Return and Enable.

The SCOR planning process comprises all activities associated with developing plans for supply chain management and improvement. Continuous efforts to achieve stable and predictable process results by reducing process variation (6-sigma) are of vital importance to business success.

DMAIC and DMADV explained

The manufacturing processes (sourcing, making, delivering, enabling, as well as handling returns) have characteristics that can be defined, measured, analysed, improved, and controlled. Hence, these phases constitute the production process management methodology, abbreviated as DMAIC.

Some practitioners have combined 6-sigma ideas with lean manufacturing to create a methodology named Lean Six Sigma (Wheat & Mills & Carnell, 2003). The Lean Six Sigma methodology considers lean manufacturing ("just-in-time" production), which addresses process efficiency, and 6-sigma, with its focus on reducing variation and waste, as complementary disciplines that promote business and operational excellence.

The DMADV methodology (define, measure, analyse, design and verify), also known as DFSS ("Design for Six Sigma"), is consistent with KBE ("Knowledge Based Engineering"). DFSS methodology's (Chowdhury, 2002) phases are:

1. Define design goals that are consistent with customer demands and the enterprise strategy.
2. Measure and identify characteristics that are Critical to Quality (CTQ), measure product capabilities, production process capacity, and measure risks.
3. Analyse to develop and design alternatives.
4. Design an improved alternative, best suited per analysis in the previous step.
5. Verify the design, set up pilot runs, implement the production process and hand it over to the process owner(s).

Six Sigma (Tennant, 2001) business improvement projects, inspired by W. Edwards Deming's "Plan–Do–Study–Act" cycle (Tague, 2005), depending on their nature, follow either of the aforementioned methodologies, each with five phases:

1. DMAIC is used for projects aimed at improving an existing business process.
2. DMADV is used for projects aimed at creating new products or process designs.

6.3 Business intelligence

Business intelligence (BI) comprises all strategies and technologies used by enterprises for the data analysis of past and current business information (Tableau, 2023). It is supported by Knowledge Management Systems (KMS) that represent the part of Logistics Information Systems (LIS) that enables experts in different fields to advise and provide support to different levels of management.

Business analytics

Business analytics (BA) is a process based on BI, enabling new insights into the business process and better strategic decision making for the future. It originates from Data Mining (DM) being the process of finding anomalies, patterns, and correlations in larger data sets, to predict the results.

The BA process is composed of:

1. Data Aggregation: prior to analysis, data must first be gathered, organized, and filtered, either through volunteered data or transactional records.
2. Data Mining: data mining sorts through large datasets using databases, statistics, and machine learning to identify trends and establish relationships.
3. Association and Sequence Identification: the identification of predictable actions that are performed in association with other actions or sequentially.
4. Text Mining: explores and organizes large, unstructured text datasets for the purpose of qualitative and quantitative analysis.
5. Forecasting: analyses historical data from a specific period in order to make informed estimates that are predictive in determining future events or behaviours.
6. Predictive Analytics: predictive business analytics uses a variety of statistical techniques to create predictive models, which extract information from datasets, identify patterns and provide predictive score for an array of organizational outcomes.

7. Optimization: once trends have been identified and predictions have been made, businesses can engage simulation techniques to test best-case scenarios.

8. Data Visualization: provides visual representations such as charts and graphs for easy and quick data analysis.

Sales and operations planning

Sales and operations planning (SOP) is a flexible tool to forecast and plan production activities. SOP steps:

1. sales plan,
2. production plan and
3. capacity planning.

SOP operates on data from different information sources throughout the company: Sales, Marketing, Production, Accounting, Human resources and Requisition. They are usually provided by the corresponding departments through the company's enterprise resource planning (ERP) system.

While SOP operates on the strategic level, ERP operates on the tactical level of a company's logistics information system. They are joined by the Demand Management program, linking the strategic sales and operations planning (SOP) and detailed production planning (Master Production Scheduling / Material Requirements Planning) on the operational level. Here the previously mentioned scheduling and simulation come into play to render a feasible and optimal production plan.

Demand management program (Figure 6.2) is composed of two types of forecasts:

1. planned independent requirements (PIR) from projected sales volumes based on marketing and
2. customer independent requirements (CIR) from data based on existing and planned sales orders.

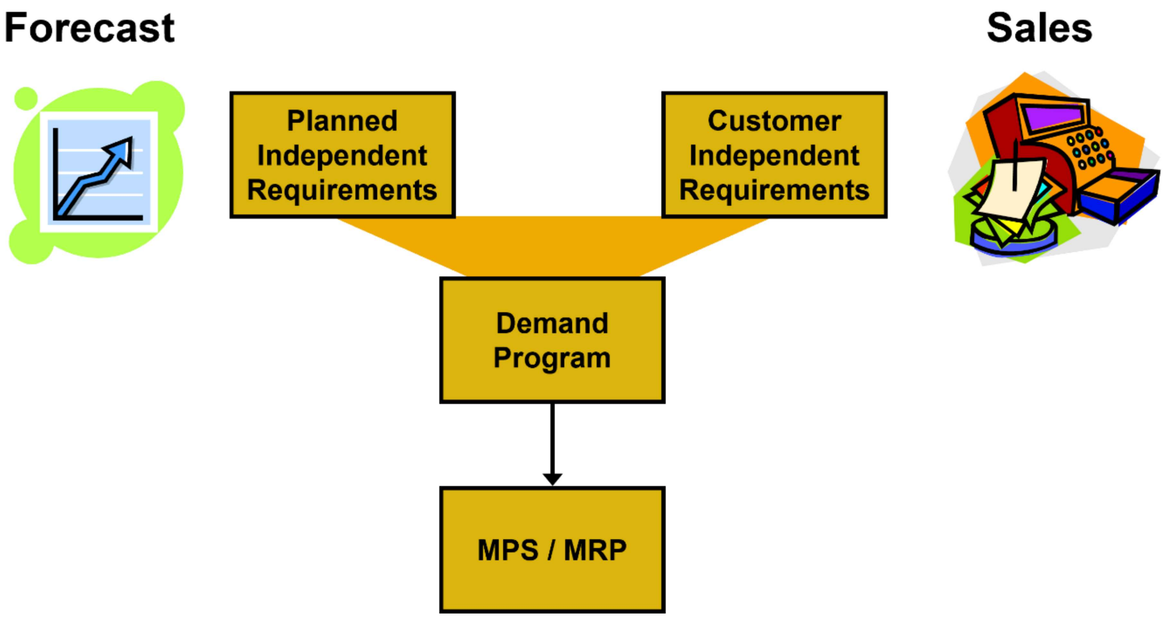


Figure 6.2 Demand management.

SOP Example

A company trades several types of products across its sales network. Sales transactions are stored centrally to be able to monitor stock status as well as perform sales analysis for demand management. They are logged in CSV (Comma Separated Values) format, which is easy to process by the company's ERP system as well as by the analytics department, which uses spreadsheets.

In sales analysis the sales transactions are initially filtered to determine whether they are complete and correctly formatted. Only then are they ready to be statistically assessed, since otherwise any missing or ill-formed data could result in misinterpretation of the results.

Date	Seller ID	Customer ID	Transaction ID	Product ID	Product Price
1.10.24	1	12	1	101	195,00 €
1.10.24	1	12	1	102	45,00 €
1.10.24	1	12	1	103	35,00 €
1.10.24	2	14	2	104	55,00 €
1.10.24	2	14	3	101	195,00 €
2.10.24	3	15	4	105	85,00 €
2.10.24	3	15	4	101	195,00 €
2.10.24	3	15	4	103	35,00 €
2.10.24	3	16	5	104	55,00 €
2.10.24	1	17	6	101	195,00 €
2.10.24	1	17	6	102	45,00 €
2.10.24	1	17	6	105	85,00 €
3.10.24	2	18	7	106	35,00 €
3.10.24	2	18	7	107	65,00 €
3.10.24	2	18	7	108	86,00 €
3.10.24	4	19	8	105	85,00 €
3.10.24	4	19	8	101	195,00 €
3.10.24	4	19	8	103	35,00 €
3.10.24	4	19	9	104	55,00 €
4.10.24	5	20	10	105	110,00 €
4.10.24	5	20	10	106	125,00 €
4.10.24	5	20	10	104	55,00 €
4.10.24	5	20	10	101	195,00 €
4.10.24	1	21	11	102	45,00 €
4.10.24	1	21	11	105	85,00 €
4.10.24	1	21	12	106	35,00 €
4.10.24	3	12	13	103	35,00 €
4.10.24	3	12	13	104	55,00 €
4.10.24	3	12	13	105	110,00 €
4.10.24	3	12	13	101	195,00 €
5.10.24	1	22	14	107	35,00 €
5.10.24	1	22	14	108	25,00 €

Figure 6.3 Weekly sales data.

Usually by analytics, various sensible insights into the collected "raw data" (Figure 6.3) are enabled. One can achieve this with pivot tables that enable to group data by chosen attributes and perform statistical analysis. In principle, any attribute (column) of input data can be considered a pivot. Hence, we are often speaking of a "data cube" of multiple dimensions. Since we cannot graphically represent more than two or three dimensions, the simplest, yet usually the most useful, representations of input data are formed from two or three pivot attributes. Based on the given data sample, some examples of pivot tables are given in the sequel.

Date	Vsota - Product Price
1.10.24	525,00 €
2.10.24	695,00 €
3.10.24	556,00 €
4.10.24	1.045,00 €
5.10.24	875,00 €
6.10.24	605,00 €
7.10.24	556,00 €
Skupaj Rezul	**4.857,00 €**

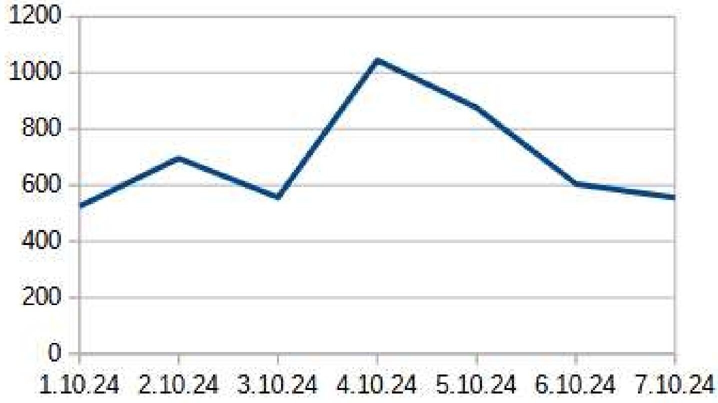


Figure 6.4 Sales statistics by weekday.

Sales statistics by weekday or month (Figure 6.4) enable insights into seasonal trends.

Seller ID	Vsota - Product Price
1	1.110,00 €
2	1.072,00 €
3	1.585,00 €
4	605,00 €
5	485,00 €
Skupaj Rezul	**4.857,00 €**

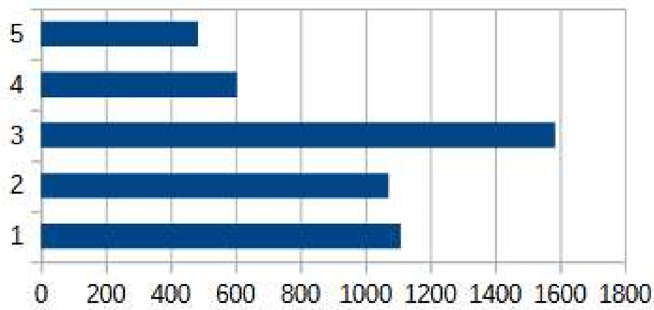


Figure 6.5 Sales statistics by sales-office.

Sales statistics by the sales office (Figure 6.5) determine which offices are the busiest and/or create the most revenue.

Product ID	Vsota - Product Price
101	1.950,00 €
102	180,00 €
103	245,00 €
104	440,00 €
105	925,00 €
106	425,00 €
107	165,00 €
108	197,00 €
109	35,00 €
110	95,00 €
111	75,00 €
112	125,00 €
Skupaj Rezult	**4.857,00 €**

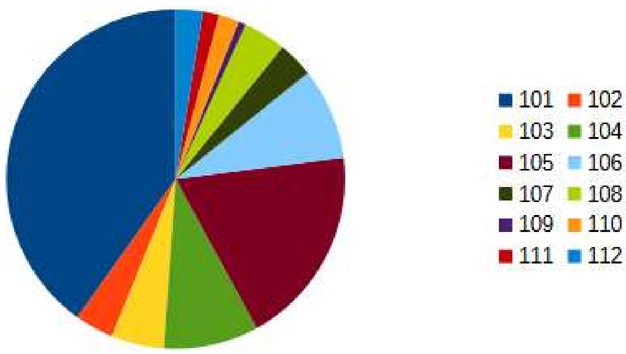


Figure 6.6 Sales statistics by product.

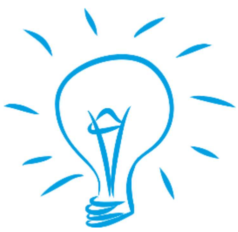
Sales statistics by product (Figure 6.6) determine the products that are most sought for or represent a significant share in the portfolio.

Date	Seller ID	Customer ID	Transaction ID	Product ID	Vsota - Produ
1.10.24	1	12	1	101	195,00 €
				102	45,00 €
				103	35,00 €
	2	14	2	104	55,00 €
			3	101	195,00 €
2.10.24	1	17	6	101	195,00 €
				102	45,00 €
				105	85,00 €
	3	15	4	101	195,00 €
				103	35,00 €
				105	85,00 €
		16	5	104	55,00 €
3.10.24	2	18	7	106	35,00 €
				107	65,00 €
				108	86,00 €
	4	19	8	101	195,00 €
				103	35,00 €
				105	85,00 €
			9	104	55,00 €

Figure 6.7 Transactions' overview.

Transaction's overview (Figure 6.7) by day, sales-office, transaction and buyer offer a structured insight into the data which is useful when solving inquiries on a certain product or sales transaction.

6.4 Decision support systems



A decision support system (DSS) is an interactive system, which assists the decision makers to use the data and models for solving unstructured or partly structured problems. An expert System (ES) is an application program or environment, which effectively supports problem solving in a specialized problem area, requiring expert knowledge and skills.

In addition to statistical and simulation methods used in BA, DSS often includes models that enable decision making, based on a set of distinctive criteria. These models may be simple (e.g., decision tables, trees, etc.) leading to a single correct solution. On the other hand, when dealing with multiple (possibly conflicting) criteria and multiple solutions, a more elaborate model is necessary. An appropriate model often used in professional and personal life is the multi-criteria decision model.

Multi criteria decision making

Multi criteria decision making (MCDM), or multiple-criteria decision analysis (MCDA) is a sub-discipline of OR that explicitly evaluates multiple (possibly) conflicting criteria in decision making over a set of candidate solutions or variants.

A MCDM decision model is composed of:

- Criteria – the parameters of input variants, critical for our design.
- Weighs – the relative importance of selected criteria.
- Utility function – the function that combines the weighted parameters of variants into a fitness value.
- Data – the data representing the variants; input data to our MCDM model.

Data types in MCDM may be:

- Quantitative – representing values that can be compared as such.
- Qualitative – representing relative comparison values (e.g., high, comfortable, low temperature, etc.) that need to be quantified to provide unique values.
- Binary – representing binary criteria; a property being fulfilled (1) or not (0).

The procedure of multi-criteria decision making:

1. Representation of variants (V) by their characteristic parameters (P): $\{V_i\ (P_{i,1}; P_{i,2}; \ldots P_{i,n});\ i=1...m\}$.
2. Normalization of parameters by calculating the relative local grade $p_{i,j}$ for each $P_{i,j}$ ($j=1...n$), with reference to the j^{th} parameter maximum $P_{i,j}$ value from all i samples:
   a) $p_{i,j}=P_{i,j}/\max\{P_{i,j}\}$ if a greater value of $P_{i,j}$ is more beneficial.
   b) $p_{i,j}=1 - P_{i,j}/\max\{P_{i,j}\}$ if a smaller value of Pi,j is more beneficial.
3. The grades are weighted according to preferences: $x_{i,j}=p_{i,j}*U_j$ for each $j=1...n$, by weighs U_j which need to sum-up to 1, i.e. 100%.

4. The weighted grades of all variants are summed up: $X_i = \sum x_{i,j}$ for each i=1...m to obtain composite grades according to our utility function.

5. The best variant is chosen $Y = \max \{X_i\}$.

MCDM Example

When choosing new equipment in a company, we must often perform multi-criteria decision making. Let us consider an example of choosing the most cost-effective (below 300 EUR) mobile platform with the Android operating system for our company. In Table 6.1 the specimens, which have been chosen from an inquiry among employees to narrow down our assortment, are listed. For each of them the parameters which have been selected as most relevant, are given. In the sequel the selected parameter data are normalized to obtain comparable values, weighted to emphasize the values that are more significant and summed up to obtain grades for the selected specimens.

Table 6.1 MCDM for a cost-effective Android mobile platform.

PARAMETERS									
	Price (€)	Grade*	Performance			Properties			Camera
Model		(1-10)	proc.speed (GHz)	RAM (GB)	int.mem. (GB)	weight (g)	size (mm3)	bat.cap. (mAh)	(MP)
Honor Magic Lite 5	263 €	2	2,2	6	128	175	94344	5100	64
Honor X7a	210 €	2,5	2,3	4	128	196	106442	6000	50
Samsung A34	297 €	1,8	2,6	8	256	199	103300	5000	48
Redmi Note 12 Pro	240 €	1,9	2,6	6	128	187	99104	5000	50
Redmi Note 12 S	224 €	1,7	2,05	8	256	176	95715	5000	108

*Vir: www.testberichte.de

PARAMETER WEIGHS									
	Price (€)	Grade	Performance			Properties			Camera
			proc.speed (GHz)	RAM (GB)	int.mem. (GB)	weight (g)	size (mm3)	bat.cap. (mAh)	(MP)
			10 %	5 %	5 %	10 %	10 %	10 %	
Utež	20 %	10 %	20 %			30 %			20 %

NORMALIZED PARAMETERS									
	Price (€)	Grade*	Performance			Properties			Camera
Model		(1-10)	proc.speed (GHz)	RAM (GB)	int.mem. (GB)	weight (g)	size (mm3)	bat.cap. (mAh)	(MP)
Honor Magic Lite 5	0,11	0,20	0,85	0,75	0,50	0,12	0,11	0,85	0,59
Honor X7a	0,29	0,00	0,88	0,50	0,50	0,02	0,00	1,00	0,46
Samsung A34	0,00	0,28	1,00	1,00	1,00	0,00	0,03	0,83	0,44
Redmi Note 12 Pro	0,19	0,24	1,00	0,75	0,50	0,06	0,07	0,83	0,46
Redmi Note 12 S	0,25	0,32	0,79	1,00	1,00	0,12	0,10	0,83	1,00

FINAL PARAMETER ASSESSMENT									
	Price (€)	Grade*	Performance			Properties			Camera
Model		(1-10)	proc.speed (GHz)	RAM (GB)	int.mem. (GB)	weight (g)	size (mm3)	bat.cap. (mAh)	(MP)
Honor Magic Lite 5	0,02	0,02	0,08	0,04	0,03	0,01	0,01	0,09	0,12
Honor X7a	0,06	0,00	0,09	0,03	0,03	0,00	0,00	0,10	0,09
Samsung A34	0,00	0,03	0,10	0,05	0,05	0,00	0,00	0,08	0,09
Redmi Note 12 Pro	0,04	0,02	0,10	0,04	0,03	0,01	0,01	0,08	0,09
Redmi Note 12 S	0,05	0,03	0,08	0,05	0,05	0,01	0,01	0,08	0,20

The end result of our analysis is the summary table (Table 6.2) and possibly a graph (Figure 6.8) which summarizes the decision-making process and presents the best choice as well as the strengths and weaknesses of individual variants. Often-times the specimen with the best grade is not the one that performed best in all categories but the one that on average best matches our selection criteria as well as weighing of the parameters. This is also the main strength of the MCDM method, since the choice by any single parameter might mislead us.

Table 6.2 MCDM summary for our mobile platform selection example.

FINAL PARAMETER ASSESSMENT						
Model	Price	Grade	Performance	Properties	Camera	TOTAL:
Honor Magic Lite 5	0,02	0,02	0,15	0,11	0,12	0,42
Honor X7a	0,06	0,00	0,14	0,10	0,09	0,39
Samsung A34	0,00	0,03	0,20	0,09	0,09	0,40
Redmi Note 12 Pro	0,04	0,02	0,16	0,10	0,09	0,41
Redmi Note 12 S	0,05	0,03	0,18	0,10	0,20	0,56

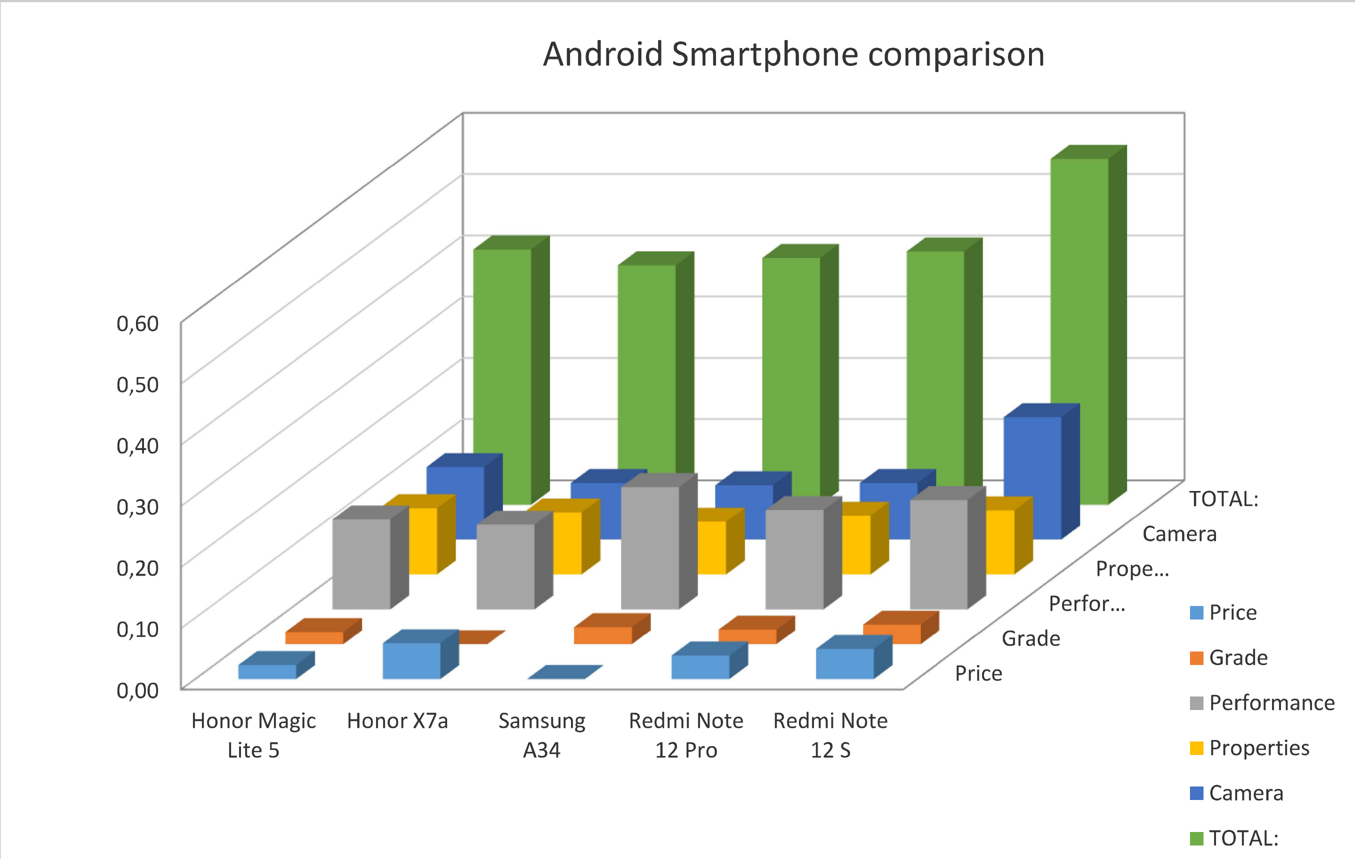


Figure 6.8 The choice of the best mobile platform.

Best choice: 0,56 (Redmi Note 12 S).

6.5 Knowledge based engineering

Knowledge Based Engineering (KBE) is an engineering methodology to integrate engineering knowledge systematically into the design system (Andersson & Larsson & Ola, 2011).

Lifecycle of experience management

The need to capture, manage, and utilize design knowledge and automate processes unique to a manufacturer's product development experience has led to the development of knowledge-based Engineering (KBE) technology (Prasad, 2005). KBE is meant to enrich institutional knowledge by experience management. The phases of experience management, according to (Andersson & Larsson & Ola, 2011) are:

1. Identify: a non-conformance with the desired state that appears in the manufacturing process due to an ill-defined product or process is selected.
2. Capture: the experience with its properties is captured.
3. Analyse: a root cause analysis of the captured experience is made to identify an appropriate remedy strategy and its re-use to prevent recurring anomalies.
4. Store: insights from the analysis are archived with the experience.
5. Search & Retrieve: the experience is searched for and retrieved.
6. Use: an element of the experience is used.
7. Reuse: concludes the cycle of knowledge management and starts a new one.

Knowledge based engineering is in general supplemented by further disciplines, whose closer consideration outreaches the scope of this chapter:

- Computer aided project management (PS).
- Computer aided design (CAD), production (CAM) and robotics (CIM).
- Computer simulation modelling and analysis (SMA).
- Computer aided detailed production planning (MPS / MRP).

6.6 Conclusion

As presented in this chapter, the main applications of BI in corporate management relate to business analytics (BA) and decision support systems (DSS). They are commonly termed operations research (OR). In addition to the underlying BI techniques, described in this chapter, in chapters 3 and 4 on data management and simulation modelling and analysis (SMA) some additional considerations on data collection, manipulation and presentation, which also support decision making, are given. In summary BI applications are found in Knowledge Management Systems (KMS), comprising:

- Decision support systems (DSS),
- Business analytics (BA) as an upgrade to Data Mining (DM) and
- Knowledge-based Engineering (KBE) as an upgrade to Computer-aided Engineering (CAE).

Based on BA, DSS and SMA results, experiences, which enhance institutional knowledge and constitute their knowledge-based expert systems (KBS), are devised. As demonstrated in (Gumzej et. al., 2023), they can be employed by KBE to introduce the "lessons-learned" principle into enterprise improvements management by strategic logistics planning.

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