

Data & AI Literacy

Framework & Applications

30.11.2022 EMOS

katharina.schueller@stat-up.com



Overview



EMOS





HFD Data Literacy Framework

2019: Systematic Review, Research Report, Competence Framework

2020: English version







CHARTA^(§)

Data Literacy Charter

Stifterverband, DStatG and many more

>100 signatories from the beginning

German & English version



Stadt | Land | DatenFluss



Stadt | Land | DatenFluss

Ed.: DVV, sponsored by BMBF

Patronage of the Federal Chancellor

Awards:

- App of the month July (German Academy for Children's and Youth *Literature*)
- Comenius-EduMedia-Award (Society) for Pedagogics, Information and Media e. V.)
- Shortlist for "Innovation of the year", German OnlineCommunication Award
- German Design Award





Data-Informed Decision Making in a Pandemic

2nd Ideas Competition, Focus: Data Literacy

Development of ~15 new MOOCs







Project Authorization Request

Standard for Data & Al Literacy, Skills, and Readiness

Partners a.o.: DStatG, FENStatS, Stifterverband, KI-Campus, PARISC:

Statistical Consulting & Data Science



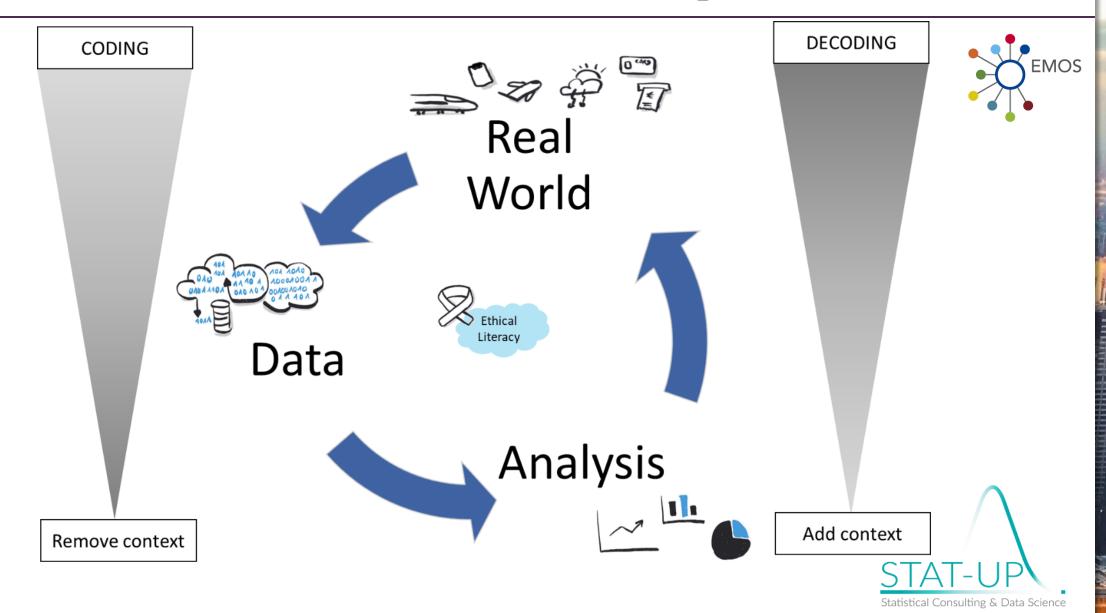
Research

The HFD Data Literacy Framework



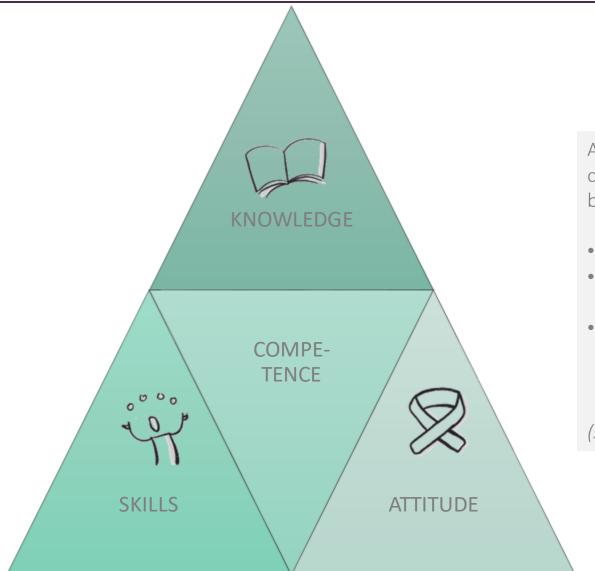
Data-informed Decision Making





Dimensions of Future Skills







According to the KSAVE-model, Future Skills comprise three competence dimensions that must be represented in all competence areas:

- specific knowledge ("knowledge"),
- the abilities and skills to apply this knowledge ("skills") and
- the willingness to do so, i.e., the corresponding value attitude ("attitudes, values, ethics").

(see Data-Literacy-Charta)



Industry: Predictive Maintenancy





Requirement

Requirements document for maintenance object

- Use standardized terms
- Collect data in an automated process
- Merge unstructured data from different data procurers
- Dealing with (un-)
 structured data
- Checking assumptions and data quality
- Safe handling of databases

N

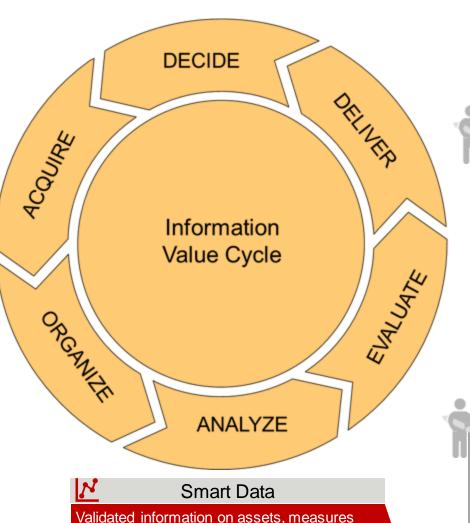
Raw Data

Factual data table with structured data; delta between ideal and real maintenance measures

- Prepare structured data
- Clean and transform data
- Detect outliers, missing/implausible data, etc.
- Knowledge of maintenance strategy
- Data management and data validation
- Data enrichment, e.g. geodata, weather data







carried out incl. maintenance history,

associated location data

Recommendation on maintenance cycles and storage related to maintenance strategy

N Actionable

- Derive different maintenance strategies (e.g. maintenance cycles, optimal stock level)
- Evaluate costs

- Understanding technical relations
- Knowledge of maintenance processes
- Planning competence

Relations between property features, location characteristics, etc.; forecasts of maintenance requirements



Knowledge

- Determine factors affecting maintenance requirements
- Failure forecasts
- Time forecast for repairs

- Knowledge of components and repair process
- Modelling competence
- Visualization and communication of complex models



Requirements for a Framework





Competence Framework

Stages & Dimensions

- All stages of the knowledge/value creation process from data
- Competence dimensions:
 - 1. Knowledge,
 - 2. Skills,
 - 3. Attitudes, Values, Ethics

Operationalizability

 Allows the competencies to be translated into specific and testable learning or competency objectives



Measurement



Areas & stages

- Cognitive and affective learning areas
- Learning stages:
 - 1. Reaction,
 - 2. Learning success,
 - 3. Behavior,
 - 4. Result

Applicability

- Transparency regarding the possibilities and limitations of inferring competencies from observable behavior.
- Validity, reliability and objectivity
- Cost-benefit ratio (money, time, required skills of examiners)

Reflection of interdisciplinarity



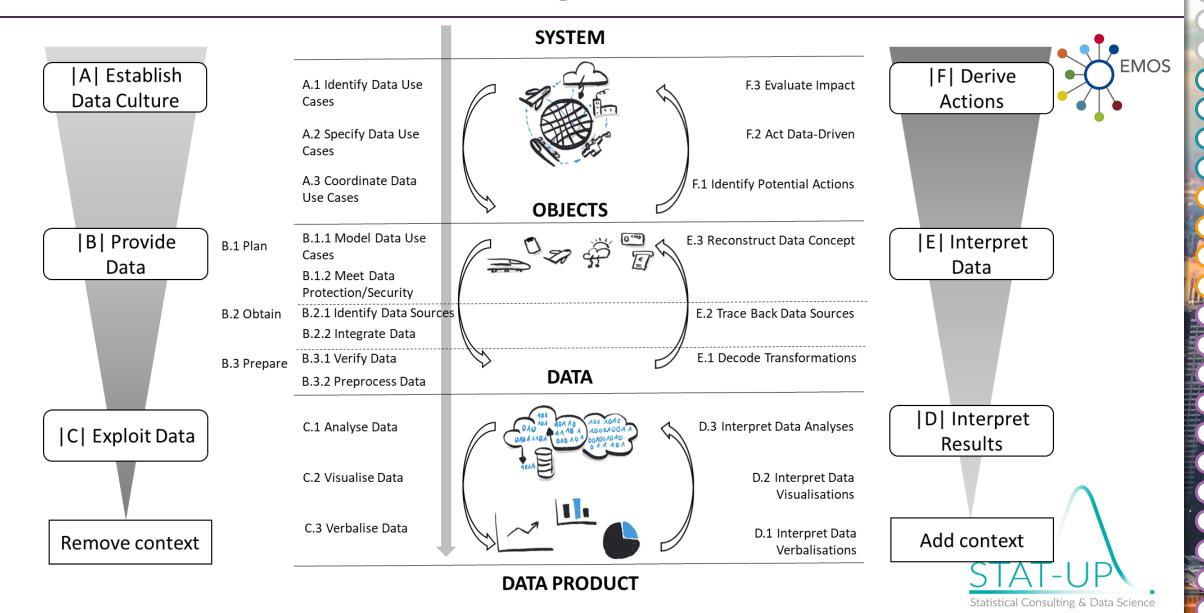
- 1. What do I want? (Domain expert)
- 2. What can I do? (Data expert)
- 3. What am I allowed to do? (Data protection expert)
- 4. What should I do? (Data ethicist)



The HFD Data Literacy Framework







Example Cl: Analyse Data



Levels

Examples of



- Knowledge about estimation methods and algorithms
- Knowledge
 about possible
 causes of
 artifacts

Competence Labelling Description C.1: Uses analysis **Analysing** methods from various data statistics, analytics, nine ing), **Ability to** represent measurable relationshipsin osemodels ited **Ability to** anticipate future uses of analysis

results

The skill to map Knowledge of procedures for measurable different tasks relationships in (description, models exploration, The ability to prognosis) as well identify and select as their appropriate requirements, analytical methods based on the issue "Analytical fairness" as a basic attitude, i.e. willingness not to perform analyses if the risk of misuse is

high

Dimensions

Examples of

knowledge

Examples of

skills

process

hods Sceptical basic
assue attitude in data
analysis

Willingness to
y weigh up and
accept
g. information losses
in the analysis
process

Villingness to
comply with
"good analytics
standards", even if

Examples of

Willingness to

implement and

adapt models in

an iterative and

often time-

consuming

attitude

ascending levels (1) Can handle basic statistical methods such as mean value and standard deviation (2) Can handle and use more complex models, can assess which methods provide meaningful results for which questions and data, and recognises the limitations of analytical results (3) Masters and uses highly complex models

and recognises
Statistical Consulting & Data Science

Example D1: Interpret Data Analyses



Knowledge of statistical terminology

contextual

knowledge

Knowledge of statistical fallacies (e.g. correlation vs. causality)

Tildel bile		C Data Allo		
	Competence		Dimensions	
	Labelling	Descriptio n	Examples of knowledge	Examples of skills
	D.1: an draw	Interprets	Knowledge of statistical key figures such as mean values,	Can draw conclusions ab which characteristics
w te	onclusions a hich charac eristics of da	- ita a	points,	the data a key figure/ makes statements ab
st	ey figure ma atements a an question	bout the	and limitations Knowledge of the	Understands which key figu palise
w in	hat extent terpretatio	ly n of ed	 Openness new findin even if the 	igs,
	esults deper n one's own		contradict previous	, teloti

Examples of Examples of ascending levels attitude Willingness to (1) Can question explicitly understand simple bout statistical communicated, cs of terminology and given interpretations in interpret its relation to data. data verbalisations knows basic forms bout Willingness to of manipulation by search for and statistics and question implicitly ures reports and the ed) communicated criteria to be interpretations observed Willingness to (2) Has an question one's advanced own contextual cial understanding of knowledge terminology and the regarding its convictions can differentiate

Levels

clearly between





Applications (I)

Stadt | Land | Datenfluss



Target Groups and Motivation

#

EMOS

Stadt | Land | DatenFluss

Data is used everywherebut what do I Data and get out of it? information...

Aren't they

the same

thing?

constantly

reading AI,

IoT, Big

Data... What

is that

actually?

WHAT are the technologies behind digitization?

✓ **Drivers:** Big Data, AI, IoT, Data Flow/ Communication ...

WHERE does change through digitization take place?

✓ **Fields of application:** Health, mobility/smart city, work/economy...

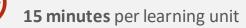
> **HOW** can we act confidently in a digitized world?

✓ **Digital skills:** especially data literacy

I know what Big Data and AI are... but how do they affect my life and my job?



12 lessons of 3 learning units each + basic module basic knowledge + outlooks

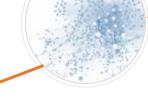


10 weeks total duration when working on one learning unit/day











Adaption of Competence Fields

#

Stadt | Land | DatenFluss

Establish $\overline{\forall}$

Provide B

|C| Exploit Data

_			
ure		A.1 Identify Data Use Cases	F.3 Evaluate Impact
Data Culture		A.2 Specify Data Use Cases	F.2 Act Data-Driven
Dat		A.3 Coordinate Data Use Cases	F.1 Identify Potential Actions
	lan	B.1.1 Model Data Use Cases	E.3 Reconstruct Data Concept
σ,	B.1 Plan	B.1.2 Meet Data Protection/Security	
Data	B.2 Obtain	B.2.1 Identify Data Sources B.2.2 Integrate Data	E.2 Trace Back Data Sources
	B.3 Prepare	B.3.1 Verify Data B.3.2 Preprocess Data	E.1 Decode Transformations
	8.6	C.1 Analyse Data	D.3 Interpret Data Analyses
		C.2 Visualise Data	D.2 Interpret Data Visualisations
i - -		C.3 Verbalise Data	D.1 Interpret Data Verbalisations

|F| Derive Actions

Interpret

Interpret

Results

Data sovereignty: What can, should, may happen with my data?

Acting on data |A|+|F|

> What does data do, how do man and machine complement each other?

Consciously share data: How do I decide on my own responsibility about my data?



Use and protect data |B|+|C|

> Gain data and information: How do you learn from data?

Classify data and information |D|+|E|

Questioning data: Which information is in the data, which is not?

DATA

LITERACY:

3 AREAS

Interpret information: What do results mean in context?



Data culture:

Learning Objectives

	7		
ц			
Æ			7

	LEADING OLIECTION	LINDEDSTAND [km quidedee]	ADDIV [akilla]	EVALUATE fothitudel
	LEADING QUESTION	UNDERSTAND [knowledge]	APPLY [skills]	EVALUATE [attitude]
ACT ON DATA	What can, should, may happen with my data?	a. Knows opportunities for using data in various application areasb. Knows details of current developments in data use	a. Identifies obvious opportunities for data use in the work environment and in private lifeb. Identifies innovative opportunities for data use in the w.e. and in private life	a. Is critical-open-minded about data use in the application areasb. Reflects on data use with regard to several criteria (e.g., benefits and costs)
	What does data do, how do man and machine complement each other?	a. Knows basics of current technologies and methodsb. Knows central strengths and weaknesses of the technologies	a. Finds out about new technologies in a targeted mannerb. Develops first own ideas for the use of new technologies	a. Shows interest in the opportunities of new technologiesb. Questions technologies with regard to potential risks
CLASSIFY DATA AND INFOR- MATION	Which information is in the data, which is not?	a. Differentiates key terms (e.g., date vs. information)b. Differentiates a wider range of technical terms	a. Can assess the significance of data in simple casesb. Can assess the significance of data also in more complex situations	a. Reflects on and evaluates the significance of datab. Distinguishes clearly between facts and interpretations
	What do results mean in context?	a. Recognizes that data and analysis must always be viewed in contextb. Knows different techniques of contextualization	a. Can classify data and evaluations in the obvious contextb. Classifies data and evaluations in a diff. manner in various contexts	a. Questions evaluations in front of the respective contextb. Questions evaluations in different contexts, according to several criteria
USE AND PROTECT DATA	How do I decide on my own responsibility about my data?	a. Knows the basic principles of data protectionb. Knows essential rules of data protection	a. Detects privacy compliance in simple casesb. Anticipates impending, more subtle privacy issues	a. Recognizes the value of data privacy and securityb. Weighs where the release of own data is justified
EMC	How do you learn OS ^{from} data?	a. Knows basic principles of how knowledge is created from datab. Knows possible causes of erroneous conclusions during evaluation	a. Can find and use nearby data sourcesb. Combines data and recognizes correlations	a. Reflects on the strengths and weaknesses of data sourcesb. Reflects on possible fallacies from data

Structure and Content

* 15

Stadt | Land | DatenFluss



ACTING ON DATA

CLASSIFY DATA AND INFORMATION

USE AND PROTECT DATA

ARTIFICIAL INTELLIGENCE

BIG DATA

DATA FLOW AND DIGITAL COMMUNICATION

INTERNET OF THINGS



MONITORING OF BODY DATA

HEALTH INFORMATION ON THE NET

THE DIGITAL HEALTH SYSTEM

THE DIGITAL HEALTH SYSTEM



DYNAMICALLY OPTIMIZED
TRAFFIC FLOW

DYNAMICALLY OPTIMIZED PUBLIC TRANSPORT

THE SMART PUBLIC SPACE

ASSISTANCE SYSTEMS
IN THE CAR



THE FLEXIBLE WORKPLACE

DIGITAL LEARNING IN THE WORK PROCESS

INTELLIGENT RECRUITING

SMART FACTORY

[understand]

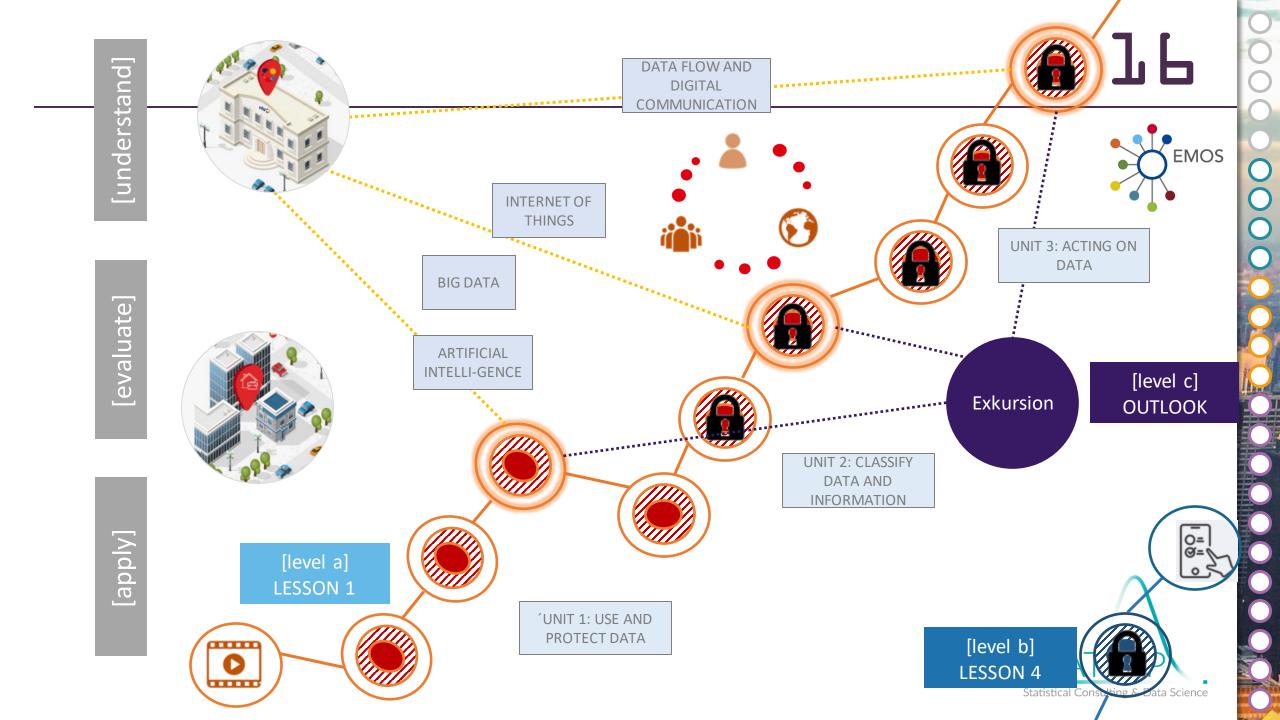
[apply]

[evaluate]



[level 1]

[level 2]





Lernangebote / Stadt | Land | DatenFluss

Ein KI-Campus-Spezial in Zusammenarbeit mit



Der Kurs "Stadt | Land | DatenFluss" sensibilisiert für einen souveränen Umgang mit Daten in einer digitalisierten Welt und we tengestützten Technologien, Er ist kostenlos unter der Lizenz CC BY-SA 4.0 verfügbar und basiert auf der gleichnamigen App, an Volkshochschul-Verband (DVV) entwickelt hat. Schirmherrin der App ist Bundeskanzlerin Dr. Angela Merkel.

Willkommen bei Stadt | Land | DatenFluss



der Kapitel gelesen



gelöst

Hintergrund und zentrale Themen











Hintergrund und zentrale Themen



Stadt | Land | DatenFluss

spitel	Aufgoben
l-Compus-Spezial zu Stadt [Land] atenFluss	-
tadt Land DatenFlumer of the für mohr D	

Künstliche Intelligenz

Auf	gobon	Kapital	Aufge
1	-	Was worde ich erreichen?	
		Basiswissen zu Künstlicher	
	-	Intelligenz	
À.		KI im täglichen Leben	
		Wie Kluns im Alltog unterstützt	
9		Der Mensch und KI	
		Wie geht as weiter mit KIP	



Kopital	Aufgaber
Was worde ich erreichen?	-
Basiswissen zum Internet der Dinge	0/
Smarte Geräte im Alltag	0/1
Smart Society und Smart Economy	0/2
Smarte Vernetzung – Anwendungsbeispiele	0/2
6 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8	



ži.	algobien	Kopitel
h erreichen?	-	Was werde ich erreichen?
nt Big Data?	0/1	Kurze Geschichte der
ig Data so beconders?	0/2	Kommunikationstechnologie
lltog	0/2	Vor- und Nachteile digitaler Kommunikation
Dotenschutz	0/2	Digitale Kommunikation - Schnelle
veiter mit Big Data?	0/2	Kommunikotion
		Vielfalt digitaler Kommunikation
		E-Government und digitale



Kapitel	Autgober
Was werde ich erreichen?	-
Kurze Geschichte der Kommunikationstechnologie	ah
Vor- und Nachteile digitaler Kommunikation	0/2
Digitale Kommunikation - Schnelle Kommunikation	0/2
Vielfalt digitaler Kommunikation	0/2
E-Government und digitale Kommunikation	0/2

Daten: Fragen und Antworten





Kopitel	Aufgoben
Was werde ich erreichen?	-
Persönliche Daten sind überall	0/1
Smarte Geräte und persönliche Daten	0/2
Persönliche Daten im Alltag	0/2
Persönliche Daten in Social Media und E-Gommerce	0/2
Online-Gaming und persönliche Daten	0/2



Was leisten Daten, wie ergänzen sich Mensch und

Kapitel	Autgober
Was werde ich erreichen?	
Roboter im Labor	o/
Roboter im Alltag	oja
Augmented Reality	0/2
Virtual Reality	0/:
Autonomes Fahren	0/3



Welche Information steckt in

Kopitel	Aufgober
Was werde ich erreichen?	
Wie kann man überhaupt en Daten gelangen?	0/1
Die Quelle der Doten muss zum Anliegen passen	0/2
Was können Daten überhaupt aussagen – und was nicht?	0/2
Die Darstellung von Daten beeinflusst die Wahrnehmung	0/2
Informationen im Kontext richtig Interpretieren	0/2





Campus: Home-

page





ELEKTRONISCHE DATENSAMMLUNG

Monitoring von Körperdaten

Ipsum tator tum poen legum odioque civiuda. Et tam neque pecun modut est neque nonor et imper ned met, consectetur adipiscing elit, sed ut labore et dolore magna aliquam makes one.

Herr L. geht zur Routineuntersuchung zum Arzt. Dieser bemerkt, dass Herr L. eine Smartwatch der neuesten Generation trägt. Beide kommen darüber ins Gespräch - Herr L. ist erstaunt, dass er viele Funktionen der Uhr noch gar nicht kannte. So verfügt das Wearable über eine EKG-Funktion (sie ist als Medizinprodukt zugelassen), eine Notfallfunktion bei Stürzen und vieles mehr.











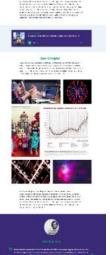
A 0 0





AI-Campus: Chapter









20



App vs.
Web

IMPLEMENTATION AS AN APP

ACCESS

- Download from the app stores
- Easy access (without login)
- Storage of learning status on end device

LEARNING SITUATION

- Affective approach: Playing
- Short learning units
- Desire for entertainment
- Selective learning of content

FUNCTIONALITY

- "Everyday life" in design and approach
- Short texts (optimized for smartphone display)
- App-appropriate graphic design
- Predefined learning paths
- Animations

ACCESS

Accessibility via website of the KI-Campus

IMPLEMENTATION AS BROWSER VERSION

- Integration in platform (optional login)
- Central storage of learning status

LEARNING SITUATION

- Cognitive approach: Learning
- Focused, longer learning sessions
- Need for concentration
- Linking content to context

FUNCTIONALITY

- Reduced graphics prevent distraction
- Links to web content
- Embedding options (e.g. Wikipedia)
- Extension with didactic scenarios (tutoring, peer learning)
- Optional deepening (advanced courses)





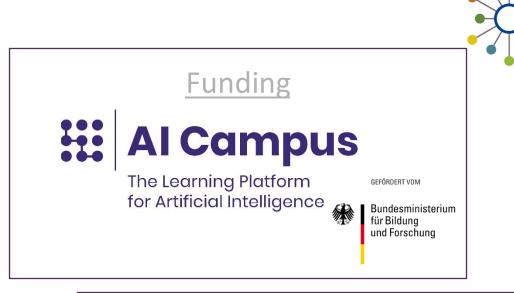
Applications (II)

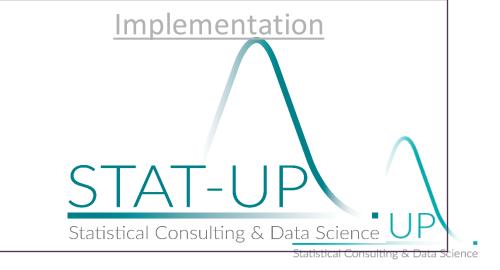
Data-Informed Decision Making in a Pandemic



DIDMP: European Cooperation Project # 22







EMOS

Not Another Paper, Please

‡ 23

During the Covid 19 pandemic, decision-makers in politics and business were in trouble.

- Many, sometimes conflicting, interests had to be weighed against each other
- in order to find compromises that would minimize the damage in all areas of public and private life.

In order to support these decisions, **insights** gained from data were used.

- → FENStatS Covid-19 WG collected best practices from Europe / rest of the world...
- → ... but who would read that?





Develop an **online course** to allow users explore

- how exactly data-driven decisions are made
- what the limitations of using data in complex decision-making situations are



Goals and Intended Target Groups





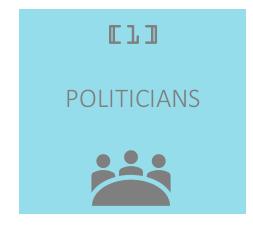




Show how data can be used to improve and support decision-making



Understand the principles, opportunities and limitations of data decision-making













Course Contents





Data and information must always be embedded in a context

[2] Establish a Data Culture

Planning on what information and data is important, as well as planning on what can be left out



[3] Provide Data

How to collect the necessary data and get to know different ways to do



[4] Exploit Data

How to generate useful data and to avoid the misuse of visualisations

[8] Recapitulation

Data can support decisionmakers, but it cannot – should not – replace them

[7] Derive Actions

Evaluate the direct and indirect impact of your decisions

[6] Interpret Data

Evaluate the relevance and reliability of your data by taking into account its origin

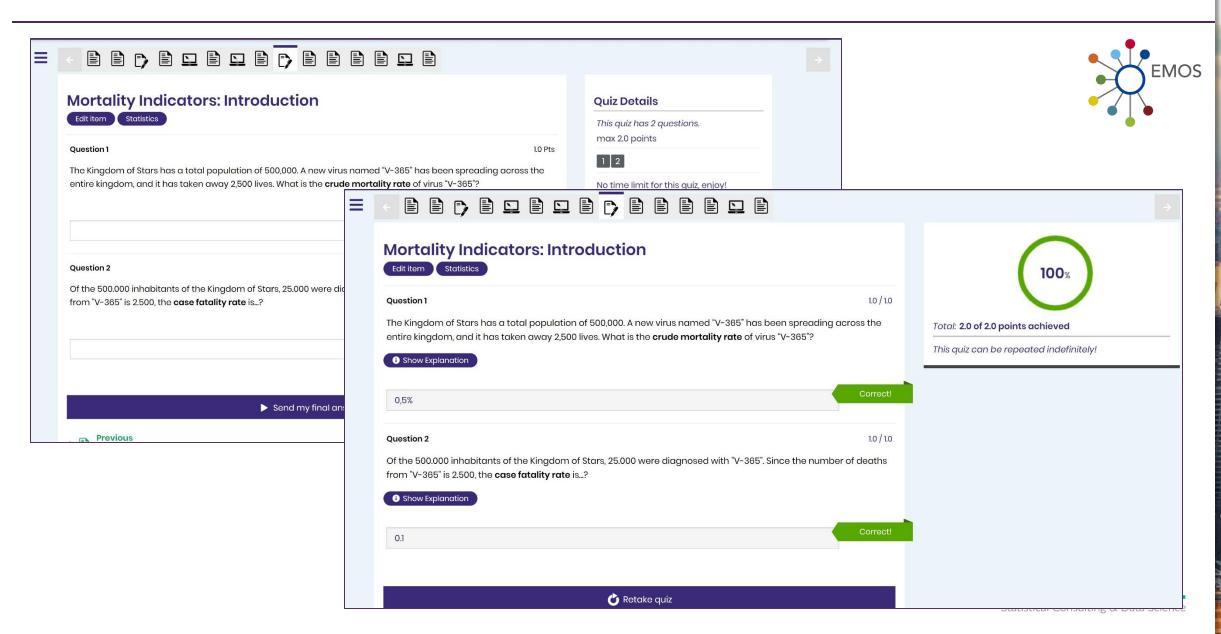
[5] Interpret Results

Learn to interpret the data product and how it needs to be distinguished from facts



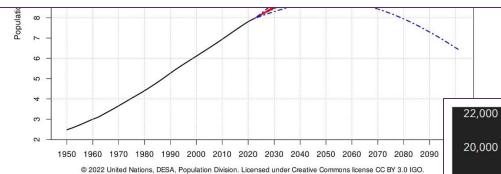
The Role of Indicators





Forecasts and their Limits





United Nations, DESA, Population Division, World Population Prospects 2022, http://population.un.org/wpp/

The future population growth according to different scenarios and assumptions based on previous develo Different levels of uncertainty are visualized here. The median scenario estimates a population of about 11 billion influential factors which were accounted for, there is an 80% probability that the population size will be between (dashed red lines, 80% prediction interval). United Nations Population Division; accessed on 27.03.202

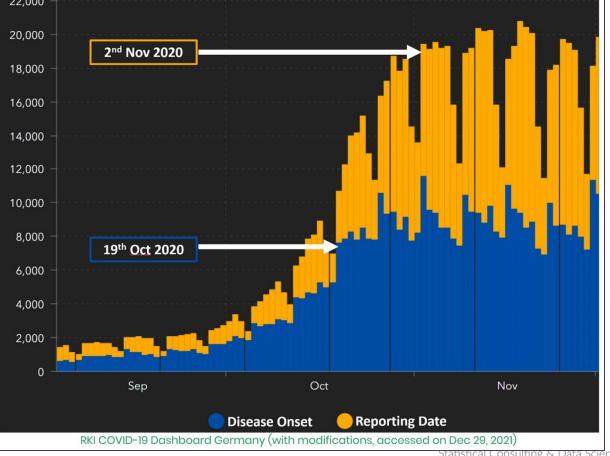
What can and can't forecasts do?

Forecasts are statistically estimated, future values of a target variable.

Regular observations of a process over time are often stored in the form of data as a time series. Statistical and used to create forecasts based on these past events.

However, as the definition states, forecasts are only estimates. A forecast is not a prediction about the future th hundred percent certainty. It only makes statements about the range in which certain values (e.g. the size of the probably develop in the future, if circumstances stay as they are in the present or in predefined scenarios. No with absolute certainty - even if some like to claim that.





Definitions determine Data



Short-Time Working Policies in Germany

In Germany, short-time working was one of the main state interventions to prevent a rising unemployment rate during lockdowns. Basically, the German government provided partial compensation of lost wages for people whose working hours had to be reduced. This enabled employers to reduce their employees' working hours instead of firing them altogether.



We want to address two general issues here:

- Different methods of analyzing the same data can lead to different results. For instandal poverty rate, if you take the same income data but use different definitions of "poverty"
- "You can't manage what you don't measure". Our simulation depends on a lot of assured the effects of short-time working policies was not high, and thus the amount of relicities very limited. This makes it difficult for decision makers to assess if the policies are enough.

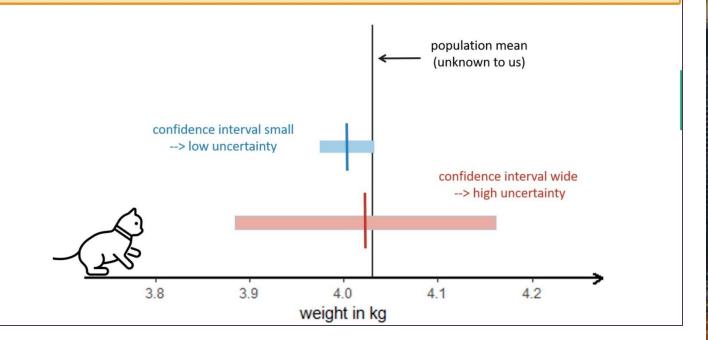
We will now start with an introduction to statistical definitions of poverty:

A person is considered *poor*, if their income is below a certain threshold (a *poverty l* line is called *poverty rate*.

Definitions of poverty differ mainly in how the poverty line is defined. They can be sorted in poverty

0

- A larger sample size leads to less uncertainty (i.e. a smaller confidence interval).
- A higher variability inside the sample leads to more uncertainty (i.e. a wider confidence interval). And vice versa.



Inference from Samples



Consider the chicken example again:

Perfect equality

Maximum inequality

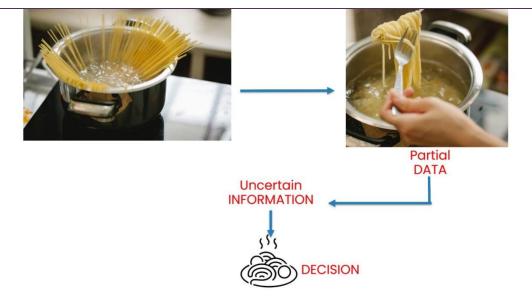






According to what you've just learned, which of these two chicken distributions has the higher variability?

- Perfect equality
- Maximum inequality



Have you ever started cooking spaghetti and thrown away the package before checking the recommended cooking time?

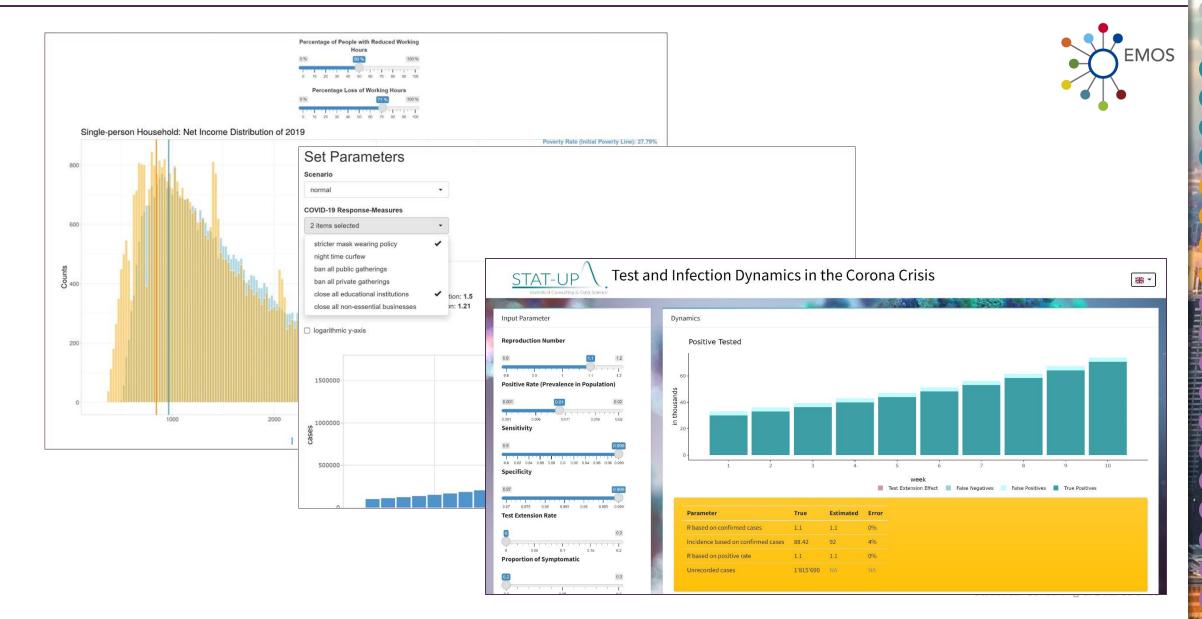
How do we know when the spaghetti is ready? What should we do? It would be **impractical to taste the entire pot of spaghetti**. Although we are interested in the readiness of every single spaghetto, trying the entire pot would obviously miss the point.

Yet all we need to do is pick up and taste one random spaghetto - this is our sample data. Then, we generalize the sample data to the entire pot and decide whether or not to turn off the stove. This is drawing inference!



App: Test and Infection Dynamics

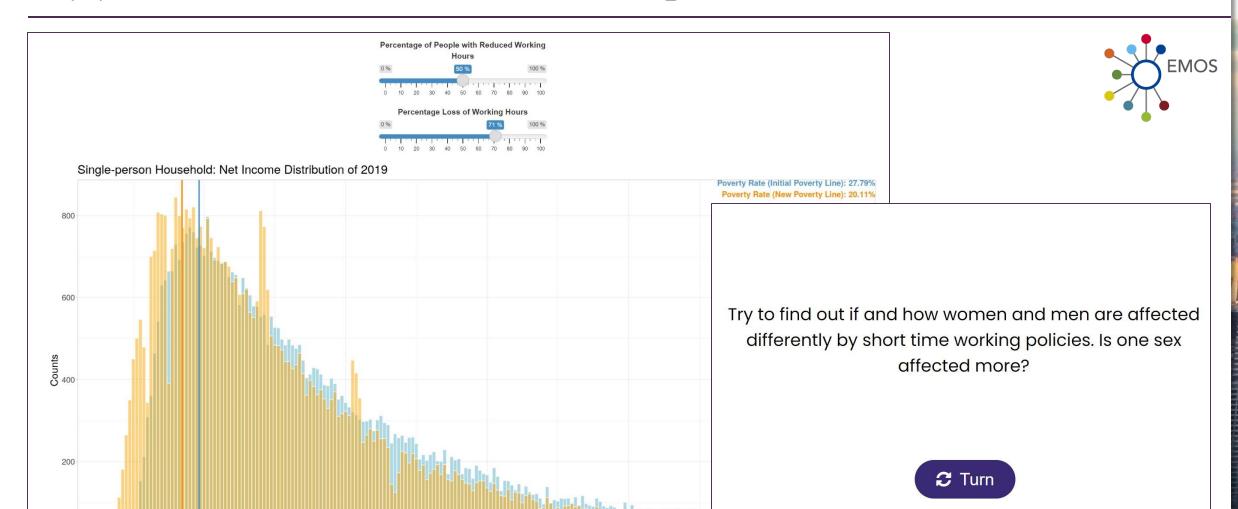




App: Short Time Working Policies

2000

Initial Poverty Line: €965.15 New Poverty Line: €844.25

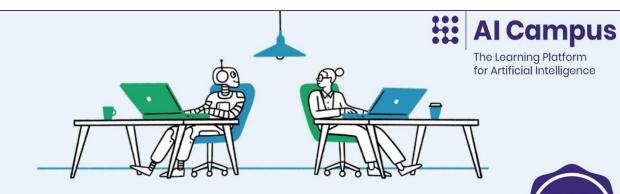


5000



Certificate: Record of Achievement







RECORD OF ACHIEVEMENT

Learning outcomes

- Understanding the functional principles, possibilities and limitations of data-informed decision-making.
- Understanding the role of data, statistics, forecasts and mathematical models in the COVID-19 pandemic.
- Developing a critical, but open-minded attitude towards data in complex decision processes.

has successfully participated in:

Data-Informed Decision-Making in a Pandemic





By completing the exercises and achieving at least 60% of the total points in this course, the requirements for obtaining the certificate have been fulfilled.

Total result

Florian Rampelt

Office Manager, Al-Campus



Outlook

The Data Literacy Charter

Data & Al Literacy Standard





Data Literacy Charter (shortened)



EMOS



PREAMBLE

With the Data Literacy Charter, the signatories express their common understanding of data literacy in the sense of comprehensive data literacy and its overall importance in educational processes.

Data literacy enables people, businesses, and scientific institutions as well as governmental or civil society organizations,

- to actively participate in opportunities to use data:
- to deal confidently and responsibly with one's own and other people's data;
- to use new drivers and technologies such as Big Data, Artificial Intelligence or Internet of Things to meet individual needs, address societal challenges and solve global problems.



21st century.

GUIDING PRINCIPLES



- Use and protect data
- Classify data and information derived from it
- Act in a data-driven way
- (5) DL must include knowledge, skills, and values for a conscious and ethically sound handling of data. Data ethics is a central component of any set of data-related skills and competencies, reflected in all sub-areas of DL.
- (1) DL must be accessible to all people. We are committed to ensuring that DL and the respective set of skills and competencies are widely taught and can be acquired by all people.
- (2) DL must be taught throughout life in all areas of education: in curricula and educational standards of schools, teacher training and higher education, and in DL programmes for extracurricular and vocational training.
- (3) DL must be taught as a transdisciplinary competence across all subjects from three **perspectives:** the application-oriented (What is to be done?), the technical-methodological (How is it to be done?) and the socio-cultural (What is *it to be done for?*)



CLOSING

- Reference to further information
- List of signatories (incl. photos & citations)

Statistical Consulting & Data Science

On the way to a Global Standard

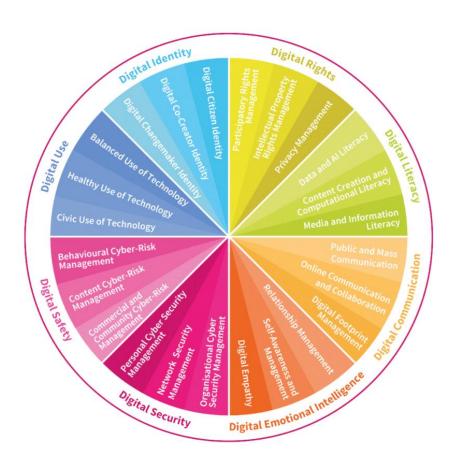








DQ Global Standards (IEEE 3527.1™)

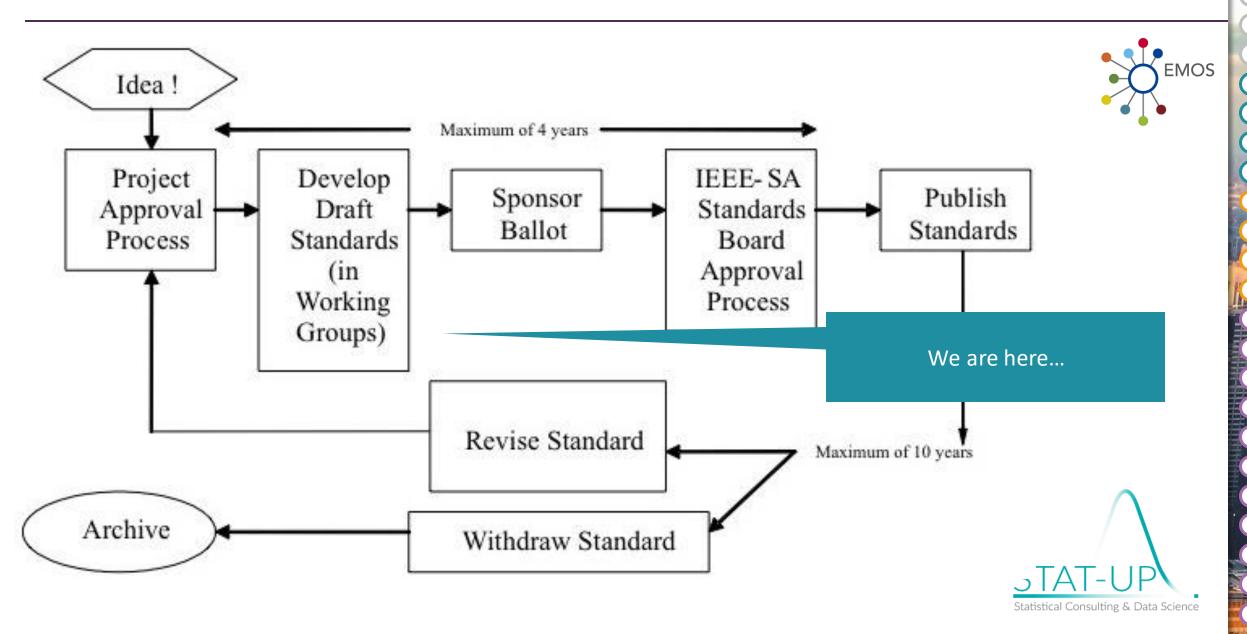


- Data and AI literacy is the ability to collect, manage, evaluate, and apply data and to develop, use, and apply artificial intelligence (AI) and related algorithmic tools and strategies in a critical manner, in order to guide informed, optimized, and contextually relevant decision-making processes.
- Scope: **establish a global standard** that encompasses a common framework to ensure that data and Al literacy building efforts are coordinated globally
- Standard is built upon the Data Literacy Framework (DLF) of Hochschulforum Digitalisierung / Stifterverband and the Data Literacy Charter (DLC)
- Combines perspectives from academia & industry, different disciplines and cultures



The Standard Process





First steps: Systematic Review



ELEMENT	HFD-DLF	SLDF-DLF	DQ-DAILF	AH-DCF	LM-AILF	FWM-AIL	CBM-AIL
Stakeholders / roles and their needs	No	Yes (2 groups)	No	Yes (5 groups)	Yes (2 groups)	Yes (4 groups)	Yes (3 groups)
Activities / tasks ordered within a process	Yes (not systematically associated wi roles)	Yes (associated with roles)	Yes (ac ies) / No (process; mentions "c making proces	No	Yes (activities) / No (overarching process)	Yes (activities) / No (overarching process)	Yes (activities) / No (overarching process)
Competence demonstrators according to KSAVE	Yes	Yes	Yes "We h	(German) Scien ave to research th		No	No (demonstrators) / Yes (distinguishes between mental
Competence		erican) Practi is not a study		Yes (competencies	Yes	Yes	state, understanding, and behavior) Yes
levels	syst associated with	with roles)	associated with roles)	are associated with roles, but no definition of levels within competencies)	(competencies are associated with roles, but no definition of levels within competencies)		(competencies are associated with roles, but no definition of levels within competencies)

Working on the Draft



Certain words (shall, should, may, can) have a special meaning

Pre-determined structure,

standardized content (e.g. definitions,

sbbreviations, acronyms...)

Sie sind im Vorschlagsmodus

P7015™/D1

Draft Standard for Data and Artificial Intelligence (AI) Literacy, Skills, and Readiness

Developed by the

Artificial Intelligence Standards Committee of the

IEEE Computer Society

Approved < Date Approved>

IEEE SA Standards Board

Copyright © 2022 by The Institute of Electrical and Electronics Engineers, Inc. Three Park Avenue

New York, New York 10016-5997, USA

All rights reserved.

This document is an unapproved draft of a proposed IEEE Standard. As such, this document is subject to

index: A composite set of measures that reflect a concept such as well-being. An example of an index is the OECD Better Life Index [REF]. Some use the term indicator and index synonymously.

NOTE—For the purposes of IEEE Std 7010, the terms should not be used synonymously.

indicator [statistical]: A measure of a discrete element of a domain. One domain can have one or more indicators.

P7015/D1 March 2022
Draft Standard for Data and Artificial Intelligence (Al) Literacy, Skills, and Readiness

The word shall indicates mandatory requirements strictly to be followed in order to conform to

standard and from which no deviation is permitted (shall equals is required to). 7,8

The word *should* indicates that among several possibilities one is recommended as particularly suitable, without mentioning or excluding others; or that a certain course of action is preferred but not necessarily required (*should* equals is recommended that).

The word may is used to indicate a course of action permissible within the limits of the standard (may equals is permitted to).

The word *can* is used for statements of possibility and capability, whether material, physical, or causal (*can* equals *is able to*).

2. Normative references

The following referenced documents are indispensable for the application of this document (i.e., they must be understood and used, so each referenced document is cited in text and its relationship to this document is explained). For dated references, only the edition cited applies. For undated references, the latest edition of the referenced document (including any amendments or corrigenda) applies.

Definitions, acronyms, and abbreviations

2.1 Definitions

For the purposes of this document, the following terms and definitions apply. The *IEEE Standards Dictionary Online* should be consulted for terms not defined in this clause. ⁹

Statistics ≠ Computer Science: If for information only Indicator ← → Measure? stems and software

stems and software ed periodically as a 'ocabulary) database

and is publicly accessible at <computer.org/sevocab>.

NOTE 3—ISO publications are available from the ISO Central Secretariat (https://www.iso.org/). ISO publications are also available in the United States from the American National Standards Institute (https://www.ansi.org/).



Sneak Preview: Our Draft



4.1 Field of competence A: Establishing a data and Al culture – from systems to measurable objects

Activity: Coding Input: System

Output: Objects and their relations

Product: Requirements

New definiton "Competence Demonstrator" (> "Value Demonstrator", IEEE 7000-2021)



Revised table structure

Apolog

Competenci we established that they are all profes wills. In terms of general Al literacy, there are





Identify knowledge gaps and background information, identify specific problems that can be solved with the help of data and/or algorithmic tools and strategies, evaluate potential value contribution of data and algorithms

Demonstrators: Knowledge	Demonstrators: Skills	Demonstrators: Attitudes
Possess theoretical and practical knowledge of the field of application or the discipline and, if applicable, related	Identify and assess relevant gaps in knowledge regarding the potential value of data, algorithmic tools and strategies	Ready to learn from data by questioning existing rules and processes and by admitting and accepting knowledge gaps
Oversee relevant literature and professional requirements (norms, rules, quality standards,	Distinguish relevant from irrelevant information about the system with respect to the potential application	Open to answer specific questions with the help of data, algorithmic tools and strategies
processes, restrictions) related to data & Al use cases in the respective discipline	Evaluate organizational context to identify demands, roles and responsibilities of potential stakeholders, domain	Evaluate externalities on customers, society, and environment, including ethical considerations
Understand how data and algorithmic tools and	experts, and project sponsors	
strategies can be used for decision-making in the respective discipline	Enable decision makers to select a use case by facilitating discussions	



Howard Deiner 18:17 7. Sept.

This is an excellent point. We are trying to help people understand why things like targeted marketing occur. And Google searches are biased by company and client concerns: you are not the customer. Does trustworthiness come into

Know the organizational context (departments, roles, potential stakeholders, current and past data/Al projects)	between different stakeholders, evaluating feasibility and impact, and drafting a business case			
Examples of ascending levels				

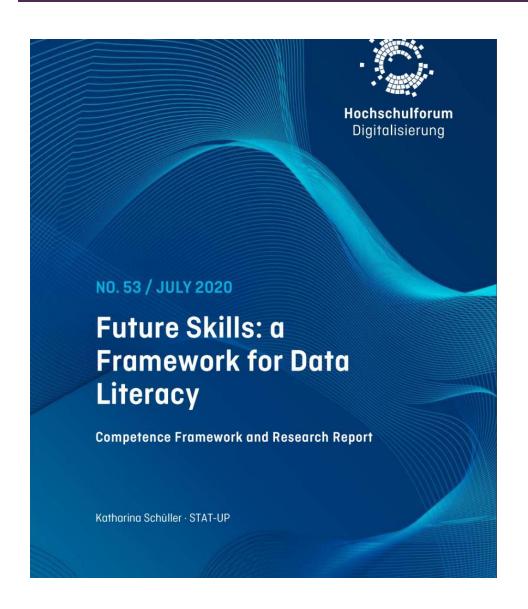
Examples of ascending levels				
Examples: Basic	Examples: Advanced	Examples: Expert		
Identify obvious use cases, e.g., through copying published use cases for typical problems with standard data sources/ algorithms	Identify innovative use cases, e.g., through creative recombination of standard applications	Identify disruptive use cases, e.g., through anticipating new algorithmic technologies, data sources, user groups		



Further Reading



Statistical Consulting & Data Science



- Deutscher Volkshochschul-Verband (2021)
 Stadt | Land | DatenFluss: Die App für mehr
 Datenkompetenz. https://stadt-land-datenfluss.de/
- Schüller, K., Koch, H. & Rampelt F. (2021). Data-Literacy-Charter. Berlin: Stifterverband. https://www.stifterverband.org/sites/default/files/dataliteracy-charter.pdf
- Schüller, K. (2020). Future Skills: a Framework for Data Literacy. Competence Framework and Research Report. Arbeitspapier Nr. 53. Berlin: Hochschulforum Digitalisierung.
- Schüller, K., Busch, P., Hindinger, C. (2019). Future Skills: Ein Framework für Data Literacy – Kompetenzrahmen und Forschungsbericht. Arbeitspapier Nr. 47. Berlin: Hochschulforum Digitalisierung. DOI: 10.5281/zenodo.3349865
- Schüller, K., Busch, P. (2019). Data Literacy: Ein Systematic Review zu Begriffsdefinition, Kompetenzrahmen und Testinstrumenten. Arbeitspapier Nr. 46. Berlin: Hochschulforum Digitalisierung. DOI: STAT

