A Further Step Towards Sustainable Development – Re-evaluating and Expanding Cognitive-Affective Mapping for Technology Acceptance Prediction

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All data presented and used in this thesis, including datasets, materials and results, can be retrieved from the OSF-project via the following link: https://osf.io/v3g7z/?view_only=afe535e892414589be7672f0fb79c8ba

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Abstract

In 2010, Canadian philosopher Paul Thagard introduced cognitive-affective mapping, a method to visualize cognitive contents and their affective evaluations. Since then, there has been a steadily increasing number of researchers applying Cognitive-Affective Maps (CAMs) in psychological settings (Kreil, 2018; Mansell et al., in press; Reuter et al., 2021), shifting questions regarding the methodological quality of CAMs more into the center of attention.

Thus, the thesis at hand is a first attempt to replicate former findings and, thereby, contribute to the understanding of CAMs' reliability. In 2020, Ricken studied the acceptance of two scenarios of life-like materials systems using CAMs to assess the ratings of 32 basal attributes. One year later, we reiterated Rickens study and compared the results of both samples. While doing so, we found little evidence for different assessments, identifying CAMs as a reliable research method. In addition, while trying to expand the application of CAMs, we found first indicators for CAM parameters being valid predictors for scenario-related outcomes.

Keywords: Cognitive-Affective Maps, acceptance of life-like materials systems, replication study, reliability

Zusammenfassung

Im Jahr 2010 führte der kanadische Philosoph Paul Thagard Cognitive-Affective Mapping ein, eine Methode zur Visualisierung kognitiver Inhalte mitsamt affektiver Bewertung. Seitdem ließ sich eine konstant wachsende Anzahl an Forschern dabei beobachten, wie sie Cognitive-Affective Maps (CAMs) in psychologischen Settings einsetzten, was wiederum Fragen zur methodischen Qualität von CAMs stärker in den Fokus der Aufmerksamkeit rückt.

Daher ist die vorliegende Thesis ein erster Versuch, bereits bestehende Ergebnisse zu replizieren und dadurch zum Verständnis über die Reliabilität von CAMs beizutragen. Im Jahr 2020 untersuchte Ricken die Akzeptanz von zwei Szenarien lebensähnlicher Materialsysteme, wobei er Bewertungen zu 32 grundlegenden Attributen mithilfe von CAMs erfasste. Ein Jahr später wurde Rickens Studie wiederholt und die Ergebnisse aus beiden Stichproben verglichen. Hierbei wurden kaum Hinweise auf unterschiedliche Bewertungen gefunden, wodurch CAMs als reliable Forschungsmethode identifiziert werden konnten. Zusätzlich konnten bei dem Versuch, die Anwendung von CAMs zu erweitern, erste Anzeichen dafür gefunden werden, dass CAM-Parameter valide Prädiktoren für szenariobezogene Ergebnisvorhersagen sind.

Schlüsselwörter: Cognitive-Affective Maps, Akzeptanz von lebensähnlichen Materialsystemen, Replikationsstudie, Reliabilität

Introduction

During the early 2010's, various events raised people's awareness of an ongoing methodological crisis affecting the replicability of well-known scientific findings which resulted in the term *replication crisis* rising to prominence in the social sciences, most notably in psychology (Pashler & Wagenmakers, 2012). As a countermeasure, a large-scale open science project was formed with the goal to replicate existing results. However, the participating researchers were only able to replicate 36% of the significant results that were originally reported in 100 prominent psychological studies (Open Science Collaboration, 2015). Since then, possible reasons like the *publication bias*, the tendency to favour the publication of significant over non-significant results, questionable research practices or even outright misconduct have been discussed (John et al., 2012; Pashler & Wagenmakers, 2012).

Considering that decisions concerning sustainability pose a long-term impact on the environment as well as on future generations, it becomes obvious that these decisions should be made in accordance with the latest scientific methodologies, providing stable and reliable findings. Similar to the above mentioned Open Science Collaboration Project, we intend to contribute to the research of sustainable development by studying the stability of a relatively young research method, namely *cognitive-affective mapping*. We will do so by rerunning an earlier study utilizing this method by Ricken (2020) and comparing the results of both samples with each other.

Like Ricken's (2020), the study at hand has been conducted as a part of the excellence cluster *Living, Adaptive and Energy-autonomous Materials Systems* (*liv*MatS) of the University of Freiburg. As the name implies, *liv*MatS' research is dedicated to the development of novel, biological inspired and energy-autonomous materials systems, which have the potential to be of value for the society (Albert-Ludwigs-Universität, n.d.). One of the focal points of the psychological partial project (research area D) is the social acceptance of such systems (Reuter, 2019). Hereby, *cognitive-affective maps* (CAMs) act as a communication tool through which the exchange between scientific and non-scientific stakeholders can be channeled and fostered (Möller et al., 2021).

In the following, we will examine how subjects rate the attributes of two scenarios of sustainable materials systems and compare the results to those found in Ricken (2020). For this purpose, we will first present the CAM method, explain how the graphs are visualized and show in which fields they are applied. Furthermore, we will introduce two scenarios of materials systems. Based on this we develop our research hypotheses. Afterwards, we will describe the method of the study at hand before we will present its results. Conclusively, in the last part of the thesis we will discuss these results and provide an outlook onto possible future implications and research designs.

Theoretical Background

Cognitive-Affective Maps

According to Thagard (2010) a CAM is a graphic representation of emotional evaluations of a group of interconnected concepts. Therefore, CAMs allow individuals to depict complex networks of cognitive as well as affective concepts of a specific subject in a visuo-spatial way (Homer-Dixon et al., 2013; 2014; Kreil, 2018; Ricken, 2020). At the same time, CAMs are to be differentiated from so-called *mind* or *concept maps* that indeed hold a cognitive component but do not offer the possibility to evaluate the affective component of the presented concepts (Möller et al., 2021; Thagard, 2010). However, affective assessments are central to human thinking (Thagard, 2010). Thagard (2006) even argues that cognition and emotion are inseparable from each other. Thus, *cognitive-affective mapping* offers users the opportunity to represent important aspects of the world and, simultaneously, to assign an emotional value (valence) to them.

It is worth noting that CAMs are not created arbitrarily (Homer-Dixon et al., 2013). Rather, a CAM's construction follows a stepwise *multiple constraint process* in which the individual's concepts, beliefs or goals are mentally represented bit by bit (Milkoreit, 2013; Thagard, 2000; 2006). Consequently, concepts in a CAM are only added or removed if this would contribute to a more coherent depiction of the topic at hand in regard to the person's existing belief system (Homer-Dixon et al., 2013; Thagard, 2000).

Graph Semantics and Visual Representation

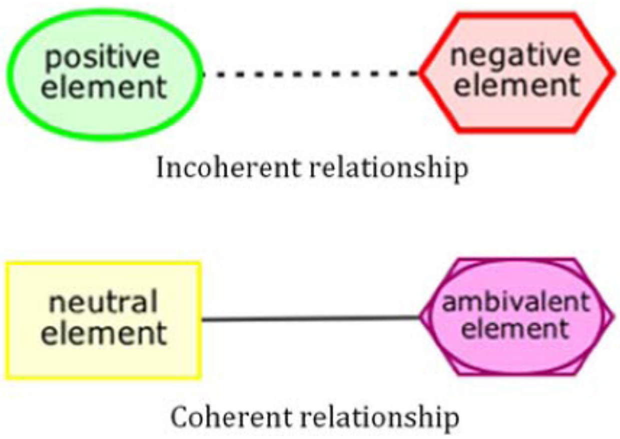
A central part of CAMs are the so-called *knots* (synonymously called *vertices* or *nodes* in graph theory; Diestel, 2017), which represent the concepts. Thagard (2010) describes concepts as important cognitive elements such as goals, actions or ideas. More generally, the concepts can display any form of content like thoughts, knowledge or even events in a written way (Reuter et al., 2021). Furthermore, every concept can be emotionally evaluated, which then influences the knot's graphical representation by changing its color and shape (Reuter et al., 2021).

Depending on each concept's valence, the knot is either depicted as a rectangle, an oval or a hexagon (Thagard, 2010). Neutral concepts are depicted as yellow rectangles, positive concepts as green ovals and negative concepts as red hexagons (Thagard, 2010; 2020). Moreover, an ambivalent concept, that has positive as well as negative aspects, is represented as a purple oval inside a purple hexagon (Homer-Dixon et al., 2013; 2014). The strength of the emotional evaluation is indicated by the thickness of the line surrounding the concept (Thagard, 2010). Thereby, three levels of intensity can be distinguished; thicker lines indicating a higher intensity affect. Examples for what can be subsumed under the valence or affect component are emotions, mood or motivation (Thagard, 2012b).

Additionally, a pair of concepts can be connected to each other if they are related. These connections between the concepts are called *edges* (Thagard, 2010). A solid link indicates a coherent relationship where two concepts mutually support each other, a dotted link indicates an incoherent relationship where two concepts inhibit each other (Thagard, 2010). Analogous to the knots, the edges' thickness indicates the strength of the connection (Thagard, 2010). CAMs can be digitally drawn by means of computer programs like *Valence* developed by Rhea et al. (2020). Figure 1 shows the conventions for the construction of CAMs following the procedure outlined above.

Figure 1

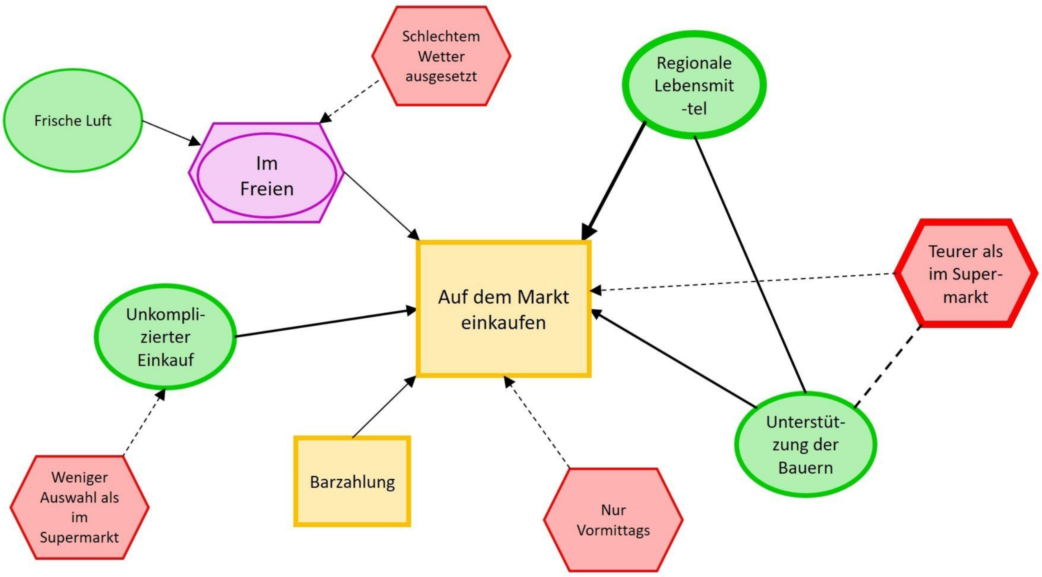
Conventions for the Construction of CAMs (Homer-Dixon et al., 2014, p. 4)



When developing the rules for cognitive-affective mapping, Thagard (2010) initially did not intend the graph edges to include a representation of causality. Nevertheless, like Ricken (2020), we followed Kreil's (2018) recommendation and decided to give participants the option to indicate causal connections between concepts with arrows. Edges with an arrowhead indicate a one sided effect of one concept on the other and edges without them indicate a mutual causal connection (Ricken, 2020). Figure 2 depicts an exemplary CAM that makes use of causal arrows.

Figure 2

Exemplary CAM About 'Shopping at the Farmers Market' in the Original German Language



Application Fields

The application fields of CAMs are widespread. Some of them are cross-cultural understanding, literary analysis or cognitive modelling (Thagard, 2010). Originally, however, the primary intention of CAMs is the analysis and exploration of conflicts (Thagard, 2010). CAMs can be used to mediate between two conflicting parties. To do so, every party has to draw two CAMs: One of their own views and beliefs and one of the views and beliefs they assume in their opponent (Ricken, 2020; Thagard, 2010). CAMs that have been created in that manner, can then easily be compared and analysed for similarities and differences (Ricken, 2020; Thagard, 2010). On this basis, recommendations can be drawn on which aspects the parties should concentrate on to resolve their conflict (Homer-Dixon et al., 2014; Thagard, 2010; 2015). More recently, CAMs have been applied to graphically represent individual attitudes and their changes (Reuter et al., 2021, Thagard, 2012a; 2012b; 2018).

Hence, in this work we are going to apply cognitive-affective mapping as a research tool since we aim to capture the cognitive and affective components of people's evaluations towards scenarios of life-like materials systems. It has been shown for the first time by Kreil

(2018) that CAMs are a suitable approach to obtain data directly from subjects in psychological empirical research settings. In her study, Kreil applied CAMs to investigate the subjects' motivation to engage in specific behaviour, namely stair climbing or elevator riding, and came to the conclusion that CAMs yielded similar results to those that have been found in qualitative interviews (2018).

Therefore, CAMs combine features of qualitative as well as quantitative methods (Kreil, 2018; Möller et al., 2021). Yet, CAMs offer specific advantages over the commonly used approaches. While CAMs, when compared to interviews, save time and effort since there is no transcript to be made, they are also able to depict much higher levels of cohesion and, thus, offer an additional value, when compared to conventional questionnaires (Möller et al., 2021; Ricken, 2020). Additionally, due to CAMs being editable, subjects have more control over their data and are not restricted to linear answers as in many of the more usual methods (Kreil, 2018).

To conclude, CAMs provide an immediate gestalt of the individual's belief system as well as the connections and interactions between its parts (Homer-Dixon et al., 2014). Möller et al. (2021) describe them as a "versatile tool, [that] can be used for data collection, analysis and communication of results" (p. 59). Hence, the cognitive and affective assessments of the attributes of possible materials systems can be analysed by CAMs in a visual way (Ricken, 2020). Further studies have since then successfully applied CAMs as a research tool (Kreil, 2018; Mansell et al., in press; Reuter et al., 2021; Ricken, 2020).

Scenarios of Life-Like Materials Systems

To assess the acceptance of life-like materials systems via CAMs, Ricken (2020) developed two exemplary biological inspired scenarios. Both scenarios, although they are of hypothetical nature, were created in consideration of their ability to serve as a "probabilistic context" (Ricken, 2020, p. 18). With regard to the *liv*MatS setting, Ricken describes a nanoparticle parka (*NanoPat*) that is adaptive to inner and outer circumstances as well as an ocean-microplastic collecting system (*PlastGat*) that pulls its energy from the collected plastics. The complete scenarios can be found in Appendix A and B. Both scenario descriptions are built around 32 basal attributes that can be found in Table 1. These attributes were selected by Ricken (2020) from a list of attributes that are likely to be found in novel technologies, which was compiled in interviews with 14 experts from the interdisciplinary research team of *liv*MatS by Reuter (2019).

Table 1

Attribute Preset that was Given to the Subjects in German Language

English	German
Adaptive	Adaptiv
Autonomous	Autonom
Bio-inspired	Bio-inspiriert
Dynamic	Dynamisch
Energy autonomous	Energieautonom
Contains Cadmium	Enthält Cadmium
Remote controllable	Fernsteuerbar
Poisonous	Giftig
Innovative	Innovativ
Intelligent	Intelligent
Clacking	Klackend
Complex	Komplex
Slow	Langsam
Loud	Laut
Capable of learning	Lernfähig
Microelectromechanical	Mikroelektromechanisch
Molecular	Molekular
Containing nanoparticles	Nanopartikel enthaltend
Can not be turned on/off	Nicht an/ausschaltbar
Not compostable	Nicht kompostierbar
Ecological	Ökologisch
Reflective	Reflektierend
Self-luminous	Selbstleuchtend
Stiff	Steif
Whirring	Surrend
Unpleasantly smelling	Unangenehm riechend
Unknown	Unbekannt
Unexpected	Unerwartet
Bulky	Unförmig
Reliable	Verlässlich
Versatile	Vielseitig verwendbar
Maintenance-intensive	Wartungsintensiv

Hypotheses

The main goal of this thesis is to reevaluate cognitive-affective mapping as an assessment method for predicting technology acceptance. A year ago, the study of Ricken (2020) piloted in the research of societal evaluation of life-like materials systems. Hence, we aim to replicate the results of Ricken. If we are able to do so, this would indicate that CAMs can indeed be a reliable and stable method to assess beliefs and attitudes.

First of all, we hypothesize that there is no difference in the ratings of the basal attributes between Ricken's 2020 sample and the newly collected sample of 2021. This assumption of no differences applies to both the comparison between the scenarios (NanoPat vs. PlastGat) and the comparison between the survey methods (CAM vs. Questionnaire).

Additionally, concerning both scenarios in the new sample of 2021, we want to investigate if the mean valence of a CAM is a valid predictor for the following outcomes: For the NanoPat, this would be whether the subjects are willing to purchase the product. For the PlastGat, the outcome variable would be whether subjects agree to governmental funding. Furthermore, we take a general, explorative look at the network properties of the CAMs (i.e., the relative frequency of positive, negative, ambivalent and neutral knots and the mean valences of the CAMs) of Ricken's (2020) sample as well as our sample.

For the purpose of a better understanding, the following work is split into three parts. First, we describe and reanalyse the sample drawn from Ricken's work in 2020 (for this sample we also use the term 'old sample' synonymously). Second, we compare our newly collected data from 2021 ('new sample') with the results of Ricken's sample from 2020. Third and finally, we expand the possible data analyses of both the new and the old sample. Detailed descriptions of those parts will follow below.

Part 1: Reanalysis of Sample 2020

Method

As a starting point, we first examined the data of Ricken (2020) and reviewed his work. Given the comparative nature of our approach, the reprocessing of the already existing data is a necessary prerequisite for the comparison with the newly collected data.

That being said, our thesis' focus lies on the comparison between the samples rather than on solely reiterating Ricken's (2020) work. Such a practice would exceed the scope of this thesis. Besides, it would not add any significant value since our method, that is described in detail at a later point, only slightly deviates from Ricken's. Therefore, we rather want to highlight the changes we undertook. Note that, however, an exact description of the method applied in the former study can be found in the original work (Ricken, 2020).

Sample

Regarding the existing raw data, we merged the two data sets that originated from two survey periods into one data set and likewise treated it as one sample (Ricken, 2020). In the process of reanalysing Ricken's data, we decided to introduce an additional inclusion criterion to Ricken's only original criterion whereupon CAMs must include at least eight non-neutral concepts. Thus, we implemented a second criterion according to which questionnaires must have at least 50% of questions answered and, analogously, at least 50% of the default concepts must remain in any CAM. The addition of this second criterion resulted in one CAM and one questionnaire to be excluded for further analysis.

Hence, we included $N = 105$ subjects ($M_{\text{age}} = 26.82$ years, $SD_{\text{age}} = 8.83$ years) into our reanalysis of which 54.29% ($n = 57$) were female. 47.62% of the subjects ($n = 50$) rated the basal attributes by means of the CAM method, accordingly, 52.38% ($n = 55$) used a questionnaire. With $n = 56$ (53.33%) more than half of the participants indicated German as their mother tongue followed by Polish (n = 18, 17.14%), Greek (n = 5, 4.76%) and others (n = 26, 24.76%). The distribution to study conditions and the sample's demographic data is depicted in Table 2.

Table 2

Overview of Participants' Distribution to Survey Condition and Demographic Data

Survey condition	n	Gender		M_{age}	SD_{age}
		female	male		
CAM – NanoPat	25	11	14	24.56	4.43
CAM – PlastGat	25	13	12	25.40	6.78
Questionnaire – NanoPat	27	16	10	26.85	8.86
Questionnaire – PlastGat	28	17	10	30.07	12.19

Note. One person in each questionnaire condition indicated their gender to be 'diverse'. These persons are included in the total calculation of the M_{age} and SD_{age} as well as in n.

Data Analysis

We used *JASP* (version 0.14.1) to compute the statistical analyses, which is a free open source software with a user-friendly interface. JASP includes the possibility to perform Bayesian statistics as well as classical inference testing (JASP Team, 2020).

Since we ideally wanted to replicate Ricken's (2020) findings even after we applied stricter exclusion criteria, we, too, performed group comparisons. Nonetheless, contrary to Ricken, we did not compute two one-way Bayesian ANOVAs. Instead, we computed a 2x2 Bayesian ANOVA with the factors *method* (CAM vs. Questionnaire) and *scenario* (NanoPat vs. PlastGat) serving as independent variables. The 2x2 ANOVA design has the advantage of a higher statistical power compared to the one-way ANOVA approach and, thus, offers a higher possibility to detect an effect while, simultaneously, maintaining a lower possibility for beta-errors (Leonhart, 2017). The prior for the distributions was set to 0.5 for fixed factors, which is the default setting in JASP. This setting is, in turn, among others based on the work of Rouder et al. (2012; 2016) who tried to work out robust default settings to compute Bayes factors for ANOVA designs.

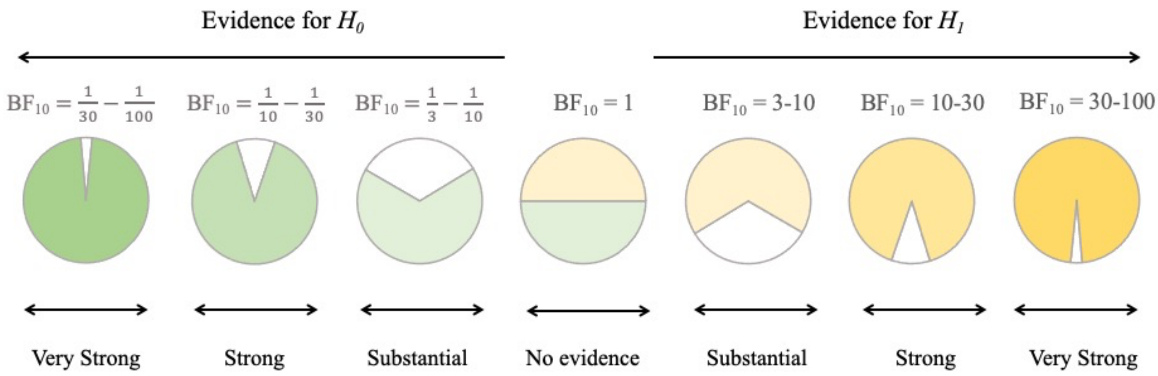
The advantages of Bayesian statistics for hypothesis testing and parameter estimation compared to classical inference are numerous (for more details on Bayesian inference see Etz et al., 2018; Jeffreys, 1961; Wagenmakers et al., 2018). In case of hypothesis testing for example, the Bayes factor (BF) enables users to quantify evidence in favour of the null hypothesis, which is not possible when simply reporting the *p*-value (Morey & Rouder, 2011; Wagenmakers et al., 2018). Moreover, it is not necessary to discard one hypothesis over the other, as the evidence that the data provides for H_1 vs. H_0 is quantifiable with either the BF_{10}, which is used to report evidence for the alternative hypothesis, or the BF_{01} for the null hypothesis respectively (van Doorn et al., 2020; Wagenmakers et al., 2018).

As the BF is a likelihood ratio of two competing models, the BF_{10} results from the model for H_1 being in the numerator and the model for H_0 being in the denominator, thus, $BF_{01} = \frac{1}{BF_{10}}$ (Marsman & Wagenmakers, 2017). To assess our observed BFs we used the classification scheme that Jeffreys (1961) suggested but adapted the modulated wording from Wagenmakers et al. (2011), replacing the label ‘worth no more than a bare mention’ for ‘anecdotal’.

Therefore, a $BF_{10} = 1$ indicates ‘no evidence’, meaning the data provides no proof of supporting one model over the other. A $BF_{10} = 1$ - 3 is labelled as ‘anecdotal’ evidence or in other words provides inconclusive evidence. A $BF_{10} > 3$ indicates ‘substantial’ evidence, i.e. that, under the observed data, the alternative hypothesis is > 3 times more likely than the null hypothesis. A $BF_{10} > 10$ indicates ‘strong evidence’ and a $BF_{10} > 100$ indicates ‘decisive evidence’ for the alternative hypothesis. Consequently, a $BF_{10} = ⅓/BF_{01} > 3$ indicates substantial evidence for the null hypothesis, continuing in the same way. For an overview of the classification see Figure 3.

Figure 3

Classification Scheme According to Jeffreys (1961) (Adapted From van Doorn et al., 2020)



Results

Before presenting our results, we want to specify how we dealt with missing values. Although subjects in the questionnaire conditions had the possibility to skip questions, we observed only a small number of participants (*n* = 2) with missing values. While one participant had a total number of *n* = 16 attributes missing, the other had only one missing value. The former answered either the positivity or negativity question, but skipped the respective other one. Therefore, we assumed that the data was not missing at random (NMAR). We replaced the missing values of both test persons with the attribute medians of the corresponding condition since they are less susceptible against outliers (Leonhart, 2017). Further, as our dataset is rather small and only includes the most relevant variables, more complex procedures such as multiple imputation were no reasonable options because the dataset did not contain enough information to compute such procedures.

In the CAM conditions, *n* = 3 participants showed missing values. Those occured due to attribute knots being deleted by the subjects from the given preset. As they were statistically independent, we treated the missing values as missing completely at random (MCAR). On top of the aforementioned rationale, we assumed that this behavior was indeed intentional and, therefore, decided to not replace them.

In our 2x2 Bayesian ANOVA we detected at least substantial evidence for the alternative hypothesis (H_1) in our Bayes Factors for seven attributes within the factor *scenario*. For example, for the attribute 'Autonomous' we found a $BF_{10} = 56.62$ with a higher mean, i.e. a more positive valence, for the PlastGat in both the CAM and the Questionnaire condition (labelled 'Quest' in statistical reporting for clarity reasons) ($M_{\text{CAM-PlastGat}} = 1.72$, $SD_{\text{CAM-PlastGat}} = 0.94$; $M_{\text{Quest-PlastGat}} = 2.00$, $SD_{\text{Quest-PlastGat}} = 1.12$ vs. $M_{\text{CAM-NanoPat}} = 0.96$, $SD_{\text{CAM-NanoPat}} = 1.14$; $M_{\text{Quest-NanoPat}} = 1.11$, $SD_{\text{Quest-NanoPat}} = 1.34$), meaning the alternative hypothesis is 57 times more likely than the null hypothesis, given the observed data.

The strongest evidence for the alternative hypothesis was found for the attribute 'Remote controllable' with a $BF_{10} = 791.80$, with a higher mean for the PlastGat ($M_{\text{CAM-PlastGat}} = 1.80$, $SD_{\text{CAM-PlastGat}} = 1.08$; $M_{\text{Quest-PlastGat}} = 1.61$, $SD_{\text{Quest-PlasGat}} = 1.71$ vs. $M_{\text{CAM-NanoPat}} = 0.40$, $SD_{\text{CAM-NanoPat}} = 1.23$; $M_{\text{Quest-NanoPat}} = 0.48$, $SD_{\text{Quest-NanoPat}} = 1.58$). For 15 attributes we found substantial evidence for the null hypothesis, indicating that, under the observed data, it is more likely that there is no difference in the ratings between the presented context (i.e. scenarios) than a difference in ratings. The highest $BF_{01} = 6.67$ was found for both 'Contains cadmium' and 'Can not be turned on/off' ('Contains cadmium': $M_{\text{CAM-NanoPat}} = -1.72$, $SD_{\text{CAM-NanoPat}} = 1.10$; $M_{\text{Quest-NanoPat}} = -1.52$, $SD_{\text{Quest-NanoPat}} = 1.70$ vs. $M_{\text{CAM-PlastGat}} = -1.56$, $SD_{\text{CAM-PlastGat}} = 1.36$; $M_{\text{Quest-PlastGat}} = -1.54$, $SD_{\text{Quest-PlastGat}} = 1.37$), indicating a roughly seven times higher likelihood for the null hypothesis than the alternative hypothesis. For the remaining 10 attributes we found only anecdotal evidence for either the alternative or the null hypothesis, with most BFs close to 1, meaning that no evident statement can be made in favour of one model over the other.

Within the factor *method* we found only four attributes with BFs providing substantial evidence for the alternative hypothesis, with the highest $BF_{10} = 9.08$ for the attribute 'Bio-inspired' with a higher mean in both scenarios for the Questionnaire ($M_{NanoPat\text{-}Quest}$ = 1.78, $SD_{NanoPat\text{-}Quest}$ = 1.37; $M_{PlastGat\text{-}Quest}$ = 2.07, $SD_{PlastGat\text{-}Quest}$ = 0.77 vs. $M_{NanoPat\text{-}CAM}$ = 1.00, $SD_{NanoPat\text{-}CAM}$ = 1.04; $M_{PlastGat\text{-}CAM}$ = 1.56, $SD_{PlastGat\text{-}CAM}$ = 1.08). For 19 attributes we found substantial evidence for the null hypothesis, meaning there was a higher likelihood that there is no observable difference in the assessment method, given the data. The highest BF_{01} in this range was found for the attribute 'Can not be turned on/off' with BF_{01} = 6.71, indicating a seven times higher likelihood for the null model than the alternative model, again, given the data ($M_{NanoPat\text{-}CAM}$ = -1.16, $SD_{NanoPat\text{-}CAM}$ = 1.11; $M_{NanoPat\text{-}Quest}$ = -0.85, $SD_{NanoPat\text{-}Quest}$ = 1.75 vs. $M_{PlastGat\text{-}CAM}$ = -0.88, $SD_{PlastGat\text{-}CAM}$ = 0.78; $M_{PlastGat\text{-}Quest}$ = -1.18, $SD_{PlastGat\text{-}Quest}$ = 1.52). For the remaining 10 attributes we found only anecdotal evidence for either the H_1 or H_0, with most BFs close to 1.

For the interaction between *scenario* and *method*, we found no substantial evidence for a possible interaction of both factors. On the contrary, we found substantial to strong evidence for the null hypothesis for most attributes. For a full description of the results for all attributes see Table 3. Further, for a full presentation of the descriptive values (*M*, *SD*, *n*, lower and upper bound for the *CI*) see Appendix C.

Table 3

Results of the Bayesian ANOVAs for the Basal Attributes in the Old Sample

Attributes	BF_{10}		
	Scenario	Method	Scenario*Method
Adaptive	0.23	0.21	0.08
Autonomous	56.62	0.27	0.27
Bio-inspired	1.04	9.08	0.65
Dynamic	0.40	1.28	0.39
Energy autonomous	5.75	0.25	0.23
Contains Cadmium	0.15	0.16	0.04
Remote controllable	791.80	0.18	0.21
Poisonous	0.21	4.29	0.21
Innovative	0.65	0.80	0.27
Intelligent	0.17	0.21	0.07
Clacking	0.16	0.33	0.12
Complex	0.22	2.38	0.42
Slow	0.17	0.21	0.13
Loud	0.24	0.39	0.38
Capable of learning	0.56	0.56	0.22
Microelectromechanical	0.79	0.16	0.10
Molecular	0.45	0.37	0.14
Containing nanoparticles	0.22	0.31	0.09
Can not be turned on/off	0.15	0.15	0.06
Not compostable	0.64	0.17	0.08
Ecological	0.47	0.28	0.13
Reflective	16.27	0.33	0.31
Self-luminous	0.23	0.22	0.09
Stiff	4.46	0.37	0.34
Whirring	0.19	0.20	0.05
Unpleasantly smelling	6.74	0.32	0.54
Unknown	0.20	0.24	0.13
Unexpected	0.17	0.67	0.11
Bulky	28.33	1.30	0.74
Reliable	1.38	0.21	0.25
Versatile	0.34	0.15	0.07
Maintenance-intensive	0.26	3.86	0.22

Note. Values colored in green indicate evidence for the H_0, the darker the stronger. Vice versa, values colored in yellow indicate evidence for the H_1, again, the darker the stronger. For a more detailed description of our color coding and on how to interpret the results, see Appendix D.

Part 2: Sample 2020 vs. Sample 2021

Method

After reviewing Rickens data from 2020 and recalculating key figures, we focused on comparing these with the results of our sample collected in 2021. Yet, this is not a direct replication study in a narrow sense rather than a conceptual replication due to some adjustments being made. The few deviations will be highlighted in the following, though our study follows mainly the same method as Ricken's (2020).

Sample

We recruited our sample via *Prolific*, an online platform where people can register and participate in online experiments from their homes. In total, our sample included 141 participants (M_{age} = 29.88 years, SD_{age} = 10.85 years) of which 48.23% (n = 68) were female. The CAM method was used by n = 71 subjects (50.35%) to evaluate the basal attributes, while n = 70 participants (49.65%) evaluated them by using a Questionnaire. With n = 65 subjects (46.10%) slightly less than half of the participants indicated German as their mother tongue, followed by English (n = 20, 14.18%), Polish (n = 15, 10.64%) and others (n = 41, 29.07%). Subjects were rewarded with £6.88 (~8€). For an overview, see Table 4.

Table 4

Overview of Participants' Distribution to Survey Condition and Demographic Data

Survey condition	n	Gender		M_{age}	SD_{age}
		female	male		
CAM – NanoPat	34	15	18	28.53	8.21
CAM – PlastGat	37	20	17	31.05	11.03
Questionnaire – NanoPat	35	17	18	31.22	12.12
Questionnaire – PlastGat	35	16	19	28.60	11.70

Note. One person in the questionnaire – PlastGat condition indicated their gender to be 'diverse'. This person is included in the total calculation of the M_{age} and SD_{age} as well as in n.

For a CAM or Questionnaire to be included into the analyses, the inclusion criteria were set, exactly as described in Part 1: Reanalysis of Sample 2020. In total, n = 20 data sets did not meet these criteria and were therefore not included for further analyses. Additional dropout reasons were no available data (n = 65) or technical problems (n = 5).

Materials

All materials used in this survey were presented on a computer screen and consisted of the instructions on how to draw a CAM, the two scenarios mentioned above, the Valence software to draw CAMs as well as a research related questionnaire and a post-research questionnaire. The materials are described in detail in the following.

Instructions. The instructions in our reassessment study are solely text-based. Although Ricken's design distinguished between text and video based instructions for the CAM method, he did not evaluate them differently due to findings of Koloczek (2020), according to which there are no significant differences in both instruction types regarding the usability of CAMs. Since Ricken neglected the instruction type in his analyses, we decided to use text based instructions only. Moreover, we did not use Ricken's original instructions on how to draw a CAM as they were revised within the last year.

Based on the fictional example of 'Julia shopping at the farmers market', participants were introduced to the logic and usage of the different components of a CAM. We presented the instruction example using screenshots of the software interface, so the participants would get familiar both with the features of the software as well as the logic on how to draw a CAM at the same time. For an excerpt of the used instructions in the original language (German), see Figure 4.

Figure 4

Excerpt of the Instructions Used

In his original work, Ricken split the instructions in several parts, using the *Rapid Assessment* method to ask comprehension questions in between parts (Ricken, 2020; Yeh, 2006). We did not follow this procedure, and presented the instructions all at once on one page within the survey window. Still on the same page, we instructed participants on how to register and log in onto the website for the Valence software and gave a final summary of the rules on how to draw a CAM (see Appendix E). The full instructions can be retrieved from the OSF-project (see 'Author note').

Scenarios. The scenarios we utilized to test the reliability of CAMs in regard to the evaluation of basal attributes were adopted in exactly the same form in which they were applied by Ricken (2020). Ricken developed the scenarios iteratively, describing it as "a converging process, in the area of tension between objectivity, creativity and credibility" (Ricken, 2020, p. 25). Both materials systems were described using the 32 basal attributes listed earlier in the Scenarios of Life-Like Materials Systems chapter. By implication, both scenarios are quite similar, however, they vary in one basic characteristic, namely their proximity to the individual.

Under the assumption that the attributes are rated differently according to this characteristic, the NanoPat scenario was designed to represent an object close to humans, whereas the PlastGat was designed to be spatially as far away as possible from human interaction.

Questionnaire. Similarly to the scenarios, we also employed the same questionnaire design to assess the attributes' valence. Subjects were asked to evaluate each of the 32 basal attributes with three questions. As a consequence, the questionnaire consisted of 96 questions in total. For each attribute, participants were asked to rate the positivity as well as the negativity of the attribute on a 4-point scale, ranging from 0 = *neutral* to 3 = *strong*. Finally, they were asked to assess the importance of the attribute in terms of importance for the overall scenario, again on the identical 4-point scale. Please see Appendix F for an example.

Afterwards, those subjects who were assigned to draw a CAM were presented with a final questionnaire. In this questionnaire, subjects were among other things asked to rate the usefulness of the instructions as well as the usefulness of the CAM method to properly display their attitudes and beliefs towards the scenario.

Study Procedure

It took about 40-60 minutes to complete the full experiment. Since we recruited our participants via Prolific, the survey started on this platform and participants were then redirected to *Unipark*, a website for building and conducting online surveys. In the preliminary part, participants read and agreed to the consent form and answered a few demographic questions about age, gender and native language.

Subsequently, they were distributed to the four survey conditions which are as follows: Subjects in Condition 1 were allocated to the NanoPat scenario and had to create a CAM, in Condition 2 subjects had to create a CAM about the PlastGat scenario. Subjects in Condition 3 and 4 got allocated to the NanoPat and PlastGat respectively but filled in the Questionnaire after reading the specific scenario. The Questionnaire, however, took only a few minutes to be completed. In order to keep the time required stable in each condition, the subjects in Condition 3 and 4 were also given a short CAM task unrelated to the study at hand after completing the Questionnaire. For an overview of the survey conditions, see Table 5.

Table 5

Overview of Survey Conditions

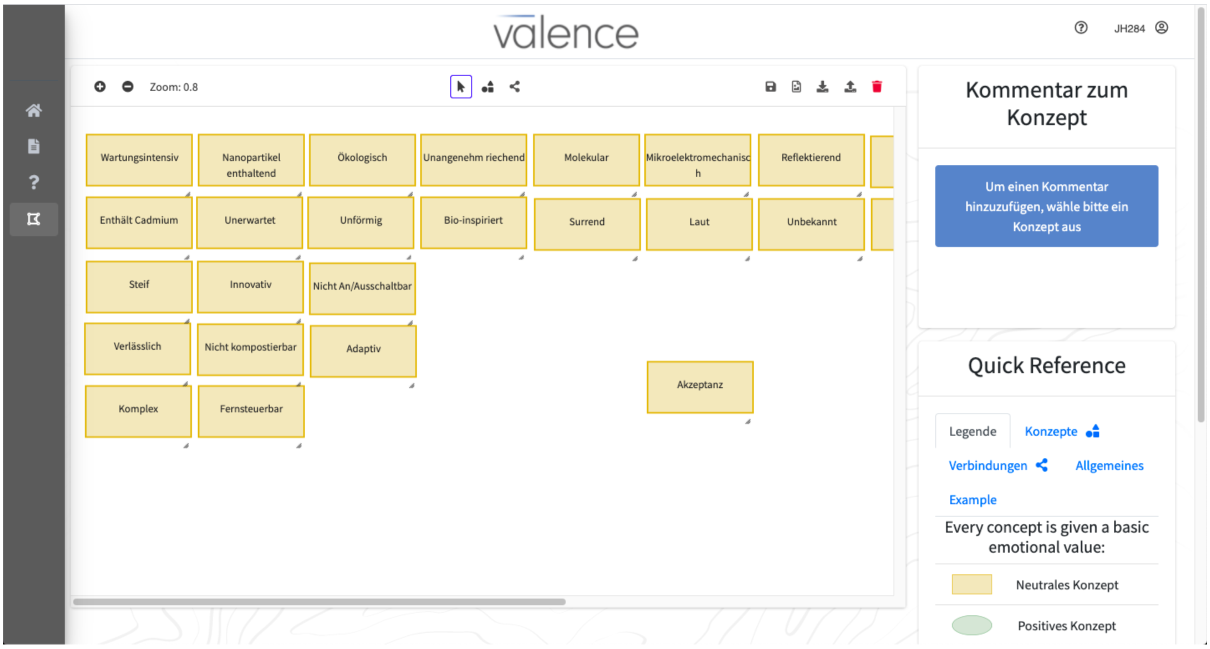
Scenario	Survey method	Condition
NanoPat	CAM	1
	Questionnaire	2
PlastGat	CAM	3
	Questionnaire	4

In Condition 1 and 2, the subjects were first presented with the instructions on how to create a CAM. After reading the instructions, they read either one of the two scenarios and directly answered two questions. They were asked to give an overall rating of the NanoPat (or PlastGat respectively) on a 7-point Likert scale ranging from '*very good*' ('*sehr gut*' in German) to '*very bad*' ('*sehr schlecht*'). Moreover, we assessed their willingness to either buy (in the case of the NanoPat) or support governmental funding for (in the case of the PlastGat) the object presented in the scenario. Both questions were answered with either '*yes*' ('*Ja*') or '*no*' ('*Nein*').

Participants then got an explanation on how to register and log in to the Valence software for creating their own CAM. Following this, they found a summary of the rules and components for the CAM construction. This was all shown in one page and subjects were instructed to leave this window open the whole time while creating their individual CAM. On the Valence software itself, they were presented with the 32 attributes in neutral knots that they were supposed to create their CAM with (see Figure 6). After completing their CAM, subjects were asked to save it and return to the instruction page to proceed with the survey.

Figure 6

Initial Screen Participants Found When Logging in to the Valence Software



In Condition 3 and 4, subjects were directly presented with the scenario after completing the demographic part. Subsequently, they were asked to answer the same two questions as in Condition 1 and 2 before proceeding with the Questionnaire to rate the attributes. As mentioned before, upon finishing the Questionnaire, participants were then presented with the same CAM instructions. However, they were assigned to a different CAM creating task. Those CAMs were not analysed in this thesis in any way.

Data Analysis

Again, we used JASP to analyse our data (JASP Team, 2020). Therefore, we exported the CAM data from the Valence software. Like Ricken (2020), we split the analyses according to the 32 attributes. To use them in statistical calculations, we had to transform the affective word description into a numerical value (see Table 6). The valence rating of each attribute served as its own dependent variable. For every attribute there was a stand-alone analysis. The Questionnaire data was exported from Unipark and transformed similarly to represent a 7-point Likert scale from -3 to 3. The assessment of importance was not included.

Table 6

Transformation of Valence Word Descriptions Into Valence Values

Valence word description	Valence value
Negative strong	-3
Negative	-2
Negative weak	-1
Neutral	0
Positive weak	1
Positive	2
Positive strong	3
Ambivalent	(-1.5 + 1.5)/2 = 0

Note. As ambivalent ratings have both a negative and a positive component, we processed them as having two ratings with the values of -1.5 and +1.5. However, for further aggregation we considered them as one rating (-1.5 + 1.5)/2 = 0.

Afterwards, we combined the data from the sample of 2020 with our data from 2021. Therefore, *dataset* became an additional factor with two groups (Old vs. New) in our expanded 2x2x2 Bayesian ANOVA design. The remaining two factors were, as before, *scenario* (NanoPat vs. PlastGat) and *method* (CAM vs. Questionnaire). The prior was also set to 0.5 which is the default setting of JASP.

Results

Since in the Questionnaire condition subjects had to answer every question and, therefore, could not proceed without giving a rating, we did not observe any missing values in this condition. Unfortunately, we observed a much higher number of missing values in the CAM condition. In total, n = 21 participants had CAMs with missing values, i.e. deleted knots. The number of missing values ranged from n = 1 to n = 15 missing attributes. We classified the missing knots statistically as MCAR. However, as we wanted to keep the datasets comparable and also saw an intention in deleting the knots, we did not replace them and treated them again with listwise deletion.

Within this 2x2x2 ANOVA we focused mainly on the detection of possible differences in the factor *dataset*, which is why we concentrate on reporting these BFs and, if necessary, the corresponding interactions (e.g., *dataset*method*). We found only one $BF_{10} = 16.76$ for the attribute 'Microelectromechanical', indicating strong evidence for the alternative hypothesis and, thus, different ratings between the old and the new dataset. However, there was also a substantial $BF_{10} = 4.56$ for the interaction effect of *dataset*method* with a higher mean, i.e., a more positive rating, in the Questionnaire condition in the new sample for both scenarios while the CAM rating was relatively stable over both datasets ($M_{\text{New-NanoPat-CAM}} = 0.30$, $SD_{\text{New-NanoPat-CAM}} = 0.75$; $M_{\text{New-NanoPat-Quest}} = 1.06$, $SD_{\text{New-NanoPat-Quest}} = 1.21$; $M_{\text{New-PlastGat-CAM}} = 0.56$, $SD_{\text{New-PlastGat-CAM}} = 1.08$; $M_{\text{New-PlastGat-Quest}} = 1.23$, $SD_{\text{New-PlastGat-Quest}} = 1.22$ vs. $M_{\text{Old-NanoPat-CAM}} = 0.12$, $SD_{\text{Old-NanoPat-CAM}} = 0.53$; $M_{\text{Old-NanoPat-Quest}} = 0.19$, $SD_{\text{Old-NanoPat-Quest}} = 1.52$; $M_{\text{Old-PlastGat-CAM}} = 0.56$, $SD_{\text{Old-PlastGat-CAM}} = 0.92$; $M_{\text{Old-PlastGat-Quest}} = 0.57$, $SD_{\text{Old-PlastGat-Quest}} = 1.10$).

For 12 attributes we found strong evidence supporting the H_0, with the highest $BF_{01} = 17.24$ for the attribute 'Self-luminous', indicating that no difference was found in the rating between old and new sample. Moreover, the interactions provided strong to decisive evidence for the H_0, too, with a $BF_{01} = 50$ for the interaction *dataset*scenario*, a $BF_{01} = 47.62$ for the interaction *dataset*method* and a $BF_{01} = 1000$ for *dataset*method*scenario* ($M_{\text{New-NanoPat-CAM}} = 1.00$, $SD_{\text{New-NanoPat-CAM}} = 0.88$; $M_{\text{New-NanoPat-Quest}} = 1.51$, $SD_{\text{New-NanoPat-Quest}} = 1.52$; $M_{\text{New-PlastGat-CAM}} = 0.94$, $SD_{\text{New-PlastGat-CAM}} = 1.32$; $M_{\text{New-PlastGat-Quest}} = 1.03$, $SD_{\text{New-PlastGat-Quest}} = 1.29$ vs. $M_{\text{Old-NanoPat-CAM}} = 0.96$, $SD_{\text{Old-NanoPat-CAM}} = 1.24$; $M_{\text{Old-NanoPat-Quest}} = 1.48$, $SD_{\text{Old-NanoPat-Quest}} = 1.22$; $M_{\text{Old-PlastGat-CAM}} = 1.00$, $SD_{\text{Old-PlastGat-CAM}} = 1.04$; $M_{\text{Old-PlastGat-Quest}} = 0.96$, $SD_{\text{Old-PlastGat-Quest}} = 1.67$).

In addition, we found substantial evidence for the null hypothesis compared to the alternative hypothesis for 16 attributes, with the highest BF in this range for the attribute 'Not compostable' with BF_{01} = 9.62 indicating an approximately 10 times higher likelihood for the null model to be true compared to the alternative model ($M_{New\text{-}NanoPat\text{-}CAM}$ = -2.00, $SD_{New\text{-}NanoPat\text{-}CAM}$ = 0.99; $M_{New\text{-}NanoPat\text{-}Quest}$ = -1.43, $SD_{New\text{-}NanoPat\text{-}Quest}$ = 1.67; $M_{New\text{-}PlastGat\text{-}CAM}$ = -1.97, $SD_{New\text{-}PlastGat\text{-}CAM}$ = 1.03; $M_{New\text{-}PlastGat\text{-}Quest}$ = -1.29, $SD_{New\text{-}PlastGat\text{-}Quest}$ = 1.25 vs. $M_{Old\text{-}NanoPat\text{-}CAM}$ = -1.40, $SD_{Old\text{-}NanoPat\text{-}CAM}$ = 1.04; $M_{Old\text{-}NanoPat\text{-}Quest}$ = -1.41, $SD_{Old\text{-}NanoPat\text{-}Quest}$ = 1.65; $M_{Old\text{-}PlastGat\text{-}CAM}$ = -1.80, $SD_{Old\text{-}PlastGat\text{-}CAM}$ = 0.87; $M_{Old\text{-}PlastGat\text{-}Quest}$ = -1.86, $SD_{Old\text{-}PlastGat\text{-}Quest}$ = 1.15).

For three attributes we found only anecdotal evidence, with the attribute 'Ecological' having a BF_{10} = 1.20 (respectively BF_{01} = 0.83) close to 1, indicating that no evident statement can be made in favour of one model over the other. This can also be seen in varying *M*s and *SD*s within the descriptive statistics of the attribute ($M_{New\text{-}NanoPat\text{-}CAM}$ = 1.58, $SD_{New\text{-}NanoPat\text{-}CAM}$ = 1.41; $M_{New\text{-}NanoPat\text{-}Quest}$ = 0.54, $SD_{New\text{-}NanoPat\text{-}Quest}$ = 2.13; $M_{New\text{-}PlastGat\text{-}CAM}$ = 2.42, $SD_{New\text{-}PlastGat\text{-}CAM}$ = 0.91; $M_{New\text{-}PlastGat\text{-}Quest}$ = 1.91, $SD_{New\text{-}PlastGat\text{-}Quest}$ = 1.36 vs. $M_{Old\text{-}NanoPat\text{-}CAM}$ = 2.00, $SD_{Old\text{-}NanoPat\text{-}CAM}$ = 1.04; $M_{Old\text{-}NanoPat\text{-}Quest}$ = 1.59, $SD_{Old\text{-}NanoPat\text{-}Quest}$ = 1.74; $M_{Old\text{-}PlastGat\text{-}CAM}$ = 2.28, $SD_{Old\text{-}PlastGat\text{-}CAM}$ = 0.98; $M_{Old\text{-}PlastGat\text{-}Quest}$ = 2.11, $SD_{Old\text{-}PlastGat\text{-}Quest}$ = 1.17).

As stated above, our focus lies mainly on possible differences in the factor *dataset*. On top of this, the analyses of Ricken (2020) as well as our reanalysis of his data have already shown that there are rating differences for some attributes both within the factor *scenario* and the factor *method*. Hence, we will not specifically report these factors. They are presented in detail in Table 7, including all BFs for the factor *dataset* as well as all possible interactions. For a better overview we highlighted them in the same fashion as we did with the resulting BFs in the first part. Appendix C provides all *M*s, *SD*s, *n*s and *CI*s for all attributes in all groups.

Table 7

Results of the Bayesian ANOVAs for the Basal Attributes Comparing Both Samples

Attributes	BF_{10}						
	Dataset	Dataset* Scenario	Dataset* Method	Dataset* Scenario* Method	Scenario	Method	Scenario* Method
Adaptive	0.20	0.22	0.04	0.01	2.76	0.07	0.08
Autonomous	0.06	0.06	0.02	0.00	8220.45	0.12	0.09
Bio-inspired	0.14	0.11	0.42	0.03	6.06	0.19	0.12
Dynamic	0.13	0.05	0.09	0.02	0.24	0.60	0.68
Energy autonomous	0.19	0.26	0.03	0.00	7.42	0.09	0.08
Contains Cadmium	0.26	0.25	0.85	0.06	0.55	9.37	0.24
Remote controllable	0.06	0.05	0.01	8.397e −4	2.906e +7	0.07	0.05
Poisonous	0.10	0.02	0.08	0.00	0.07	6.71	0.05
Innovative	0.47	0.10	0.13	0.00	0.15	0.14	0.04
Intelligent	0.06	0.02	0.02	3.971e −4	0.11	0.13	0.04
Clacking	0.09	0.15	0.10	0.14	0.38	2.99	0.25
Complex	0.06	0.01	0.07	0.00	0.08	272.49	0.10
Slow	0.12	0.04	0.16	0.04	0.09	1.70	0.08
Loud	0.20	0.03	0.41	0.06	0.07	67.55	0.07
Capable of learning	0.09	0.07	0.04	0.00	2.42	0.24	0.16
Microelectromechanical	16.76	0.32	4.56	0.08	0.60	9.30	0.27
Molecular	0.09	0.06	0.15	0.01	0.89	32.89	0.32
Containing nanoparticles	0.09	0.02	0.19	0.01	0.08	27.47	0.12
Can not be turned on/off	0.12	0.02	0.07	0.00	0.08	0.18	0.02
Not compostable	0.10	0.05	0.24	0.01	0.09	0.56	0.05
Ecological	1.20	1.49	0.65	0.14	784.62	6.92	0.69
Reflective	0.36	0.20	0.25	0.01	6457.01	2.47	0.39
Self-luminous	0.06	0.02	0.02	0.00	0.20	0.21	0.12
Stiff	0.19	0.17	0.06	0.01	6249.36	0.24	0.15
Whirring	0.12	0.09	0.19	0.01	0.61	2.20	0.26
Unpleasantly smelling	0.18	0.20	0.44	0.10	22550.68	15.10	0.43
Unknown	0.06	0.01	0.01	4.587e −4	0.06	0.09	0.01
Unexpected	0.08	0.01	0.06	5.488e −4	0.06	1.34	0.05
Bulky	0.15	0.12	0.09	0.01	10438.66	0.48	0.40
Reliable	0.09	0.06	0.14	0.02	0.77	0.21	0.15
Versatile	0.12	0.08	0.02	0.00	1.15	0.07	0.07
Maintenance-intensive	0.12	0.04	0.33	0.02	0.27	3.441e +6	0.24

Note. Values colored in green indicate evidence for the H_0, the darker the stronger. Vice versa, values colored in yellow indicate evidence for the H_1, again, the darker the stronger. For a more detailed description of our color coding and on how to interpret the results, see Appendix D.

Part 3: Expanding the Application of Cognitive-Affective Maps

Method

Up to this point, our thesis was primarily dedicated to reevaluating already existing results. In the following, we hope to expand the application of CAMs in research settings by (a) examining if specific CAM components can be used to predict different outcomes depending on the scenario used and (b) taking an explorative look, both on participant and attribute level, at the relative number of valent knots in the CAMs. This especially allows us to investigate the amount of ambivalent knots, which were treated as '0' in the former statistical analyses and, hence, equal to 'neutral' ratings.

Regarding the former, we wanted to predict if people are willing to buy the NanoPat parka or to support governmental funding for the PlastGat system respectively. Both questions could be answered with '*yes*' ('*Ja*') or '*no*' ('*Nein*'). Hence, we focused our analysis for (a) on the new sample (for more details see Part 2: Sample 2020 vs. Sample 2021), and our analysis for (b) on both samples, old and new (see also Part 1: Reanalysis of Sample 2020). We did not further include or exclude any data that has not already been described up to this point. Thus, we refrain from describing the sample once again.

Data Analysis

Since the main characteristic that differentiates CAMs from other semantic networks is their ability to display affective evaluations (Möller et al., 2021; Thagard, 2010), we focused on the valence component for further analyses. Thus, we first calculated the CAMs' mean valences for every participant, using the rating of each of the 32 attributes. Even though we were mainly interested in the predictive value of the CAMs, we also computed the mean valences of both Questionnaire conditions. That way, we were able to distinguish (a) the predictive value of the CAMs alone and (b) the predictive value of the CAMs compared to the Questionnaire. Those mean valences served as our predictor, or in other words, were our independent variables which we labelled as follows depending on the scenario (NanoPat vs. PlastGat) and condition (CAM vs. Quest): *MVal-NanoPat-CAM*, *MVal-NanoPat-Quest*, *MVal-PlastGat-CAM* and, finally, *MVal-PlastGat-Quest*.

In the next step, as our outcome variables were binary ('*yes*' = 1 or '*no*' = 0), we computed logistic regressions to investigate if the valences of both, CAMs and Questionnaires, impact the respective scenario outcomes. Therefore, correspondingly to the independent variables, we labelled the dependent variables for each regression as *Outcome-NanoPat-CAM*, *Outcome-NanoPat-Quest*, *Outcome-PlastGat-CAM* and *Outcome-PlastGat-Quest*. For the inclusion of the predictor variables we used the preset method 'Enter' as we had only one predictor. Further, we analysed the residuals to detect possible outliers.

To get a first descriptive impression of the valent knots' relative proportions, both for every CAM and for every attribute, we first reviewed the ambivalent knots for each CAM and replaced those ratings that were formerly treated as '0' with the value '4'. This served as an indicator value to be able to differentiate between the real neutral and the ambivalent rating. Subsequently, we calculated the relative frequencies of positive, negative, neutral and ambivalent knots. However, we did not differentiate between the three possible gradations for positive (1 to 3) and negative ratings (-1 to -3).

Results

The analysis for the first model, the regression of *Outcome-NanoPat-CAM* on *MVal-NanoPat-CAM* indicated that the model as a whole was significant (x^2 (1, n = 34) = 24.63, p < .001, Nagelkerke's R^2 = 1) and points out an appropriate goodness-of-fit. The coefficient variable, though, was not significant (β = 270.61, df = 1, p = .99). No outliers were detected. Therefore, no prediction can be made about the probability of buying the parka, depending on a change of one unit in the mean valence of the CAM.

The regression of *Outcome-NanoPat-Quest* on *MVal-NanoPat-Quest* indicated that both the model (x^2 (1, n = 35) = 10.87, p < .001, Nagelkerke's R^2 = .406) and the coefficient were significant (β = 3.01, df = 1, p = .01). That means, if the mean valence in the Questionnaire increases, i.e., becomes more positively rated, the relative probability of a person willing to buy the NanoPat-Parka increases by 20 times.

For the regression of *Outcome-PlastGat-CAM* on *MVal-PlastGat-CAM* we observed both a significant model with an appropriate goodness-of-fit (x^2 (1, n = 37) = 9.56, p = .002, Nagelkerke's R^2 = 0.367) as well as a significant coefficient (β = 5.17, df = 1, p = .02). If the mean valence of a CAM in the PlastGat scenario increases, i.e, gets an overall more positive rating, the willingness to agree to funding increases by 176 times. However, we observed one case with standard residuals > 2 which should, therefore, be treated as outliers.

In our last analysis, the regression model of *Outcome-PlastGat-Quest* on *MVal-PlastGat-Quest* was not significant (x^2 (1, n = 35) = 1.864, p = .172), neither was the coefficient variable. This analysis also showed two outliers with standard residuals > 2. For an overview see Table 8.

Table 8

Results of the Logistic Regression of the Mean Valence of Each CAM/Questionnaire on the Outcome Variable

Model	β	*SE*	Odds Ratio	*df*	*p*	95% *CI*	
						Lower	Upper
NanoPat – CAM	270.62	1.8E+05	3.37E+117	1	.99	-3.5E+05	3.5E+05
NanoPat – Quest	3.01	1.21	20.37	1	.01	0.65	5.38
PlastGat – CAM	5.17	2.21	176.13	1	.02	0.83	9.51
PlastGat – Quest	1.81	1.40	6.08	1	.19	-0.94	4.55

Our calculation of the knots' relative frequencies in both samples for each CAM/participant showed an average of 38.92% of positive knots. A separate calculation for the old and the new sample revealed almost no differences with 38.99% average positive knots for the new, and 38.82% average positive knots for the old sample. As the 2x2 and the 2x2x2 ANOVAs already indicated some differences, we did not further distinguish the analyses for scenario or method. For the negative knots, we observed an overall mean percentage of 36.05% and also did not find a noteworthy difference between the old and the new dataset (36.79% and 35.01% respectively).

The analysis of the neutral knots showed a similar pattern with 17.03% overall, 17.60% for the new and 16.22% for the old dataset. The proportion of ambivalent knots, however, differed relatively stronger between the old and the new sample. The overall relative frequency of ambivalent knots is 8%. The proportion in the new dataset shows an average of 6.62% while the old dataset boasts a share of 9.95%. An overview for each participant, including the mean valence and *SD* valence, can be found in Appendix G. Note that we accounted for deleted knots while calculating the relative frequencies, as not every participant rated all 32 attributes. Hence, the results display the proportion of knots including all present knots in each CAM.

Since we have also performed the same calculations for the attributes, we will now briefly present these results as well. However, we only want to focus our report on the most salient attributes in terms of the proportion of knots and/or missing values. In this analysis, we did not distinguish between *dataset*, *method* or *scenario*. Our calculations indicated that 'Reliable', with a percentage of 96.55%, has the highest proportion of positive knots (3.45% neutral knots, no negative or ambivalent knots). The attribute with the highest proportion of negative knots is 'Maintenance-intensive' with 91.60% (0.84% of positive knots, 4.20% of neutral knots and 3.36% of ambivalent knots). The highest proportion of neutral knots was found for the attribute 'Microelectromechanical' with 49.11% (27.68% of positive knots, 3.57% of negative knots and 19.64% of ambivalent knots). The attribute 'Complex' indicated the highest proportion of ambivalent knots, with a percentage of 34.19% (5.13% positive knots, 33.33% negative knots and 27.35% neutral knots).

Note that in this calculation we accounted for deleted knots, too. This revealed that the attribute 'Unknown' had the highest number of deleted knots (15 deleted knots) followed by 'Unexpected' (13) and 'Stiff' (12).

Discussion

In the scope of this thesis we analysed if the ratings of basal attributes of two scenarios of life-like materials systems found in a study from 2020 could be replicated in an independent sample from 2021. By doing so, our goal was to contribute to the knowledge on the application of CAMs in research settings, especially regarding their reliability in iterated study designs.

In terms of reviewing Ricken's (2020) data, we found only small differences in regard to the BFs that he reported, even after applying stricter exclusion criteria. In general, although we could not report the exact same BFs, they are going in the same direction as Ricken's and, therefore, the overall resshow the same pattern. Thus, we are confident that we fulfilled the necessary prerequisite to test our hypothesis regarding the comparison of both samples.

Speaking of which, our 2x2x2 Bayesian ANOVA showed substantial or strong evidence for the null hypothesis for 28 of the 32 attributes regarding the factor *dataset*, indicating that there are similarities in the ratings between the old and the new sample. At least anecdotal evidence for the H_0 was found for the attributes 'Innovative' and 'Reflective'. Conversely, the results showed anecdotal evidence for the H_1 for the attribute 'Ecological'. Moreover, for the attribute 'Microelectromechanical' the data indicated strong evidence for the alternative hypothesis and, thus, suggest that the ratings differ in both samples. However, a possible explanation for this could be that this specific attribute is possibly harder to grasp or imagine for most people, hindering reliable assessments. This assumption is backed up by the highest proportion of neutral (roughly 50%) and the third highest proportion of ambivalent ratings (roughly 20%) for 'Microelectromechanical' out of all attributes. To summarize, the strong majority of evidence indicating similar results in both datasets leads us to the conclusion that our hypothesis is largely supported.

Concerning our further research question we found inconsistent results. Looking at the CAM conditions, our results indicated that the mean valence was able to predict the willingness to support governmental funding for the PlastGat system, meaning that basic CAM components can be valid predictors for real-life outcomes. Unfortunately, we did not find similar results for the NanoPat scenario, in which the mean valence failed to predict the willingness to buy the parka. However, since the parka combines unfavourable attributes for a piece of clothing like e.g. 'Unpleasantly smelling', 'Stiff' or 'Bulky' only four people out of 34 indicated a willingness to buy the parka at all, potentially distorting our results.

If we take a comparative look at the Questionnaire conditions, prediction of mean valences on willingness to support funding failed statistical significance. Yet, descriptive data at least indicated a trend into the expected direction. Interestingly enough, contrary to the CAM conditions, the Questionnaires' mean valences allowed for a prediction of willingness to buy the parka. Here, a higher share of eight out of 35 subjects indicated a willingness to buy. This finding suggests that a prediction of mean valence on this specific outcome is generally possible. Yet, we must conclude that our data does not definitively answer if CAMs' mean valences are able to predict scenario related outcomes. Please be reminded that this was a first explorative attempt to determine if it might be possible to make predictions based on CAM parameters. Our sample size of roughly n = 35 in each regression was way too small, and we, therefore, had a completely underpowered analysis (Bujang et al., 2018; Hsieh, 1989). However, our first results are encouraging and the analyses should be repeated with larger samples.

Furthermore, the explorative calculation of the knots' relative proportions on CAM and attribute level showed mostly similar results for both the old and the new sample, backing up the findings regarding the factor *dataset* in our 2x2x2 ANOVA. It also became clear that people seem to have an either positive or negative attitude towards most of the presented attributes. However, as we subsumed all gradations of positive and negative knots, it is possible that a CAM shows a higher proportion of positive knots although they are predominantly rated as 'positive weak' or, contrary, a lower proportion of negative knots although they are largely rated as 'negative strong'. Therefore, the calculations of the knots' relative proportion could be squared with the mean valence of each CAM to see if they are reflected in this parameter.

As we already laid out for the attribute 'Microelectromechanical', some attributes seem harder to grasp, which is reflected in a high proportion of neutral, ambivalent or even deleted knots. For example, the attribute 'Unknown' has the highest number of deleted knots and at the same time one of the highest proportions of ambivalent knots. Future goals of *liv*MatS are to develop (a) a model to predict the acceptance of life-like materials systems (Reuter, 2019) but also (b) to improve the communication between scientists and laypersons (Möller et al., 2021). Thus, it might be of advantage to assess the comprehensibility of the communicated attributes for the general population, as they were derived from interviews with experts in the respective research field (Reuter, 2019).

Limitations

Although the statistical analyses revealed CAMs as reliable, findings should be interpreted cautiously due to the experimental design having some limitations. Möller et al. (2021) state that CAMs offer the "advantage of depicting complex interrelationships, including the intensity of the emotional valence of the concepts as well as supporting and inhibiting connections" (p. 59). Yet, it is difficult to create a questionnaire that mirrors these possibilities. For example, like Ricken (2020) before us, we could not include a specific question that obtains a value comparable to the thickness of a connecting line. Adding to this, participants in the Questionnaire condition had to answer every question to avoid missing values, whereas subjects in the CAM condition (due to technical restrictions of the Valence software) could, at least theoretically, delete as many knots as they wanted. Moreover, subjects in the Questionnaire conditions were not explicitly instructed on how to indicate ambivalence, contrary to subjects in the CAM conditions. While this again highlights that CAMs offer an additional value in comparison to questionnaires (Ricken, 2020), comparability of both methods is compromised.

Speaking of ambivalence, we found this specific emotion hard to display and analyse statistically since it presents a positive as well as a negative attitude towards an attribute to the same degree. For example, ‘Complex’ would often be rated as ambivalent due to it being associated with complexity but also sophistication, meaning that the subject could value it positively (e.g. +2) and negatively (-2) at the same time. We, therefore, decided to label ambivalent ratings accordingly with a value of zero. This led to a further problem since we could not distinguish it statistically from neutral knots although ambivalence conveys a different message contentwise.

Outlook

Despite these limitations our results are, to the best of our knowledge, the first that indicate a general replicability and, therefore, reliability of cognitive-affective mapping when employed as a research tool to assess beliefs and attitudes. Thereby, our findings open up a vast amount of future research opportunities, some of them we want to discuss in the following.

First of all, due to both samples originating mainly from Prolific, our findings can only be generalized to corresponding samples. We, therefore, want to highlight the necessity to expand the study at hand to more samples that differ in composition and way of acquisition. In this respect, a replication with a sample speaking a different language (e.g., something similar to German, like English, or something very different like Chinese), would also be conceivable.

Moreover, since we focused our analyses on the main characteristic that distinguishes CAMs from comparable semantic networks: the affective component (Möller et al., 2021; Thagard, 2010), we did only little research concerning other components. For example, the analysis of network properties comes with a vast amount of possible research questions considering the sheer amount of different types of edges (one sided arrow, two-sided arrow, solid vs. dashed, thickness). Hence, to contribute to the understanding of the reliability of CAMs even further, a replication focusing on the CAMs' edges could be addressed in future studies.

In view of the fact that CAMs are still a relatively novel method in psychological science and research is still scarce, we hope that our promising results on the reliability and replicability of CAMs help to build confidence in the method. Consequently, we want to encourage more researchers to apply this unique approach, in particular because we would agree that CAMs indeed offer an additional value in comparison to conventional questionnaires (Möller et al., 2021; Ricken, 2020). To conclude, we hope that this thesis did the intended further step towards sustainable development.

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Appendix A

Scenario NanoPat in Original Language (German)

Angeregt von den Eigenschaften der Pomelo-Frucht entwickelte die Albert-Ludwigs-Universität Freiburg in Kooperation mit weiteren Instituten den Nano-Pat-Parka.

Der bio-inspirierte Nano-Pat-Parka besteht aus einer ökologischen Daunen-Innenjacke sowie einer verlässlichen und vielseitig verwendbaren Wetterschutz-Außenjacke. Die Außenjacke enthält Cadmium, einen Stoff der giftig ist. Daher ist der Nano-Pat-Parka nicht kompostierbar. Der Nano-Pat-Parka ist innovativ und autonom. Er kann sich mithilfe komplexer Technologien an verschiedene äußere und innere Bedingungen anpassen. Dabei können laute, klackende Geräusche entstehen und es kann unter Umständen unerwartet zu unförmig aussehenden Erscheinungen kommen.

Bei Reibung, z.B. durch das Tragen eines Rucksacks, wird das verwebte, molekulare N100pX-Laminat steif, dies kann zu unangenehmen Gerüchen führen. Kommt es zur Berührung von Felsen oder Gegenständen, können die mikroelektromechanischen Einsätze im Unterarm und Rückenbereich dynamisch als Protektoren dienen.

Durch die intelligente Technologie und enthaltenen Nanopartikel ist der Nano-Pat-Parka lernfähig. Das Anpassen an die äußeren Gegebenheiten ist fernsteuerbar und zunächst langsam. An- und Ausschaltbar sind diese Prozesse nicht. Was mit fortlaufendem Gebrauch der Jacke möglich wird, ist bisher unbekannt. Durch ihre selbstleuchtende und reflektierende Oberfläche ist die Außenjacke gut sichtbar, dabei ist sie vollkommen energieautonom. Der Nano-Pat-Parka ist relativ wartungsintensiv. Beispielsweise kann es sein, dass die eingebaute Technologie zu surren beginnt, was man beheben muss.

Appendix B

Scenario PlastGat in Original Language (German)

Angeregt von den Eigenschaften fleischfressender Pflanzen, insbesondere der Venusfliegenfalle, entwickelte die Albert-Ludwigs-Universität Freiburg in Kooperation mit weiteren Instituten den PlastGat.

Der bio-inspirierte PlastGat steht für Plastic Gathering und dient dem Zweck, das Mikroplastik aus den Meeren der Welt aufzusammeln. Dabei bezieht er seine benötigte Energie aus dem gesammelten Plastik und ist somit komplett energieautonom. Dahinter stecken komplexe, mikroelektromechanische und molekulare Vorgänge.

Der PlastGat ist autonom und kann sich durch kleine Motoren an Kunststoffe verschiedener Zusammensetzungen und Formen anpassen. Dies geschieht oft unerwartet. Unter Wasser führt dies zu lauten, klackernden Geräuschen. Diese intelligente Technologie ist wartungsintensiv. Beispielsweise kann es sein, dass die eingebaute Technologie zu surren beginnt, was man beheben muss. Durch enthaltene Nanopartikel wird verlässlich zwischen Kunststoff und Biomasse unterschieden.

Der Abbauprozess des gesammelten Plastiks ist ökologisch, wenngleich auch unangenehm riechend. Die dabei abfallenden Produkte sind für den Stoffwechselkreislauf im Meer vielseitig verwendbar. Der PlastGat enthält Cadmium, einen Stoff der giftig ist. Daher ist der PlastGat nicht kompostierbar.

Der PlastGat ist fernsteuerbar. An- und ausschaltbar ist er nicht, da er sonst sinken würde. Aufgrund innovativer Technologie ist er lernfähig und dynamisch. Das Anpassen an die äußeren Gegebenheiten geschieht zunächst langsam, jedoch ist bisher unbekannt, was mit zunehmendem Einsatz möglich wird. Um im Meer gut sichtbar zu sein, ist er selbstleuchtend und seine unförmige, steife Oberfläche reflektierend

Appendix C

Corresponding *M*, *SD*, *n* and *Credible Interval* of the New and the Old Dataset

Attributes	New Dataset																			
	NanoPat										PlastGat									
	CAM					Questionnaire					CAM					Questionnaire				
				CI					*CI*					*CI*					*CI*	
	M	*SD*	*n*	Lower	Upper	*M*	*SD*	*n*	Lower	Upper	*M*	*SD*	*n*	Lower	Upper	*M*	*SD*	*n*	Lower	Upper
Adaptive	1.4	1.0	32	1.1	1.8	1.4	1.5	35	0.9	1.9	2.1	0.9	37	1.8	2.4	1.9	1.2	35	1.4	2.3
Autonomous	0.9	0.8	31	0.6	1.2	1.2	1.2	35	0.8	1.6	1.8	1.2	34	1.4	2.2	1.8	1.3	35	1.3	2.3
Bio-inspired	1.5	1.1	31	1.1	1.9	1.1	1.6	35	0.6	1.7	1.9	1.1	36	1.5	2.3	1.8	1.2	35	1.4	2.2
Dynamic	1.0	1.1	27	0.5	1.4	1.6	1.1	35	1.2	2.0	1.5	1.1	37	1.1	1.8	1.3	1.2	35	0.8	1.7
Energy autonomous	1.6	1.2	32	1.2	2.0	1.7	1.4	35	1.2	2.2	2.2	1.2	36	1.8	2.6	1.9	1.5	35	1.4	2.4
Contains Cadmium	-2.4	1.0	34	-2.8	-2.1	-1.7	1.3	35	-2.1	-1.2	-2.0	1.4	34	-2.5	-1.5	-0.9	1.5	35	-1.4	-0.4
Remote controllable	0.5	1.3	31	0.0	1.0	0.5	1.5	35	0.0	1.0	1.6	1.0	37	1.3	2.0	1.7	1.6	35	1.1	2.2
Poisonous	-2.5	1.0	32	-2.9	-2.1	-2.1	1.5	35	-2.7	-1.6	-2.4	1.1	36	-2.7	-2.0	-1.9	1.4	35	-2.4	-1.4
Innovative	1.9	1.1	33	1.5	2.3	1.9	1.2	35	1.5	2.4	2.0	0.9	36	1.7	2.3	2.0	1.2	35	1.6	2.4
Intelligent	1.6	1.1	31	1.2	2.0	1.6	1.3	35	1.1	2.0	2.0	1.2	36	1.6	2.4	1.7	1.3	35	1.3	2.1
Clacking	-1.4	1.0	30	-1.8	-1.0	-1.3	1.5	35	-1.8	-0.8	-1.3	1.0	35	-1.7	-1.0	-0.3	1.4	35	-0.8	0.2
Complex	-0.5	1.0	31	-0.8	-0.1	0.2	1.4	35	-0.2	0.7	-0.3	1.0	36	-0.6	0.0	0.4	1.2	35	0.0	0.8
Slow	-1.2	1.1	29	-1.6	-0.8	-0.8	1.1	35	-1.2	-0.4	-1.1	1.0	35	-1.4	-0.7	-0.4	1.1	35	-0.8	0.0
Loud	-1.7	1.0	30	-2.1	-1.3	-1.1	1.6	35	-1.7	-0.6	-2.0	0.9	37	-2.3	-1.7	-0.9	1.4	35	-1.3	-0.4
Capable of learning	1.5	1.1	33	1.2	1.9	1.6	1.1	35	1.2	2.0	2.1	1.0	36	1.8	2.5	1.9	1.3	35	1.4	2.3
Microelectromechanical	0.3	0.8	30	0.0	0.6	1.1	1.2	35	0.6	1.5	0.6	1.1	32	0.2	1.0	1.2	1.2	35	0.8	1.6
Molecular	-0.1	1.0	27	-0.5	0.2	0.7	1.3	35	0.3	1.1	0.3	1.0	33	0.0	0.7	0.9	1.0	35	0.6	1.3
Contains nanoparticles	-0.2	1.3	32	-0.7	0.2	0.4	1.8	35	-0.3	1.0	-0.7	1.4	34	-1.2	-0.2	0.7	1.8	35	0.1	1.3
Cannot be turned on/off	-1.5	1.1	33	-1.9	-1.2	-1.2	1.5	35	-1.7	-0.7	-1.4	1.2	35	-1.8	-1.0	-0.8	1.3	35	-1.3	-0.4
Not compostable	-2.0	1.0	34	-2.3	-1.7	-1.4	1.7	35	-2.0	-0.9	-2.0	1.0	36	-2.3	-1.6	-1.3	1.3	35	-1.7	-0.9
Ecological	1.6	1.4	31	1.1	2.1	0.5	2.1	35	-0.2	1.3	2.4	0.9	36	2.1	2.7	1.9	1.4	35	1.4	2.4
Reflective	1.3	1.0	30	0.9	1.7	1.8	1.2	35	1.4	2.3	0.4	1.1	33	0.0	0.8	1.0	1.5	35	0.5	1.5
Self-luminous	1.0	0.9	32	0.7	1.3	1.5	1.5	35	1.0	2.0	0.9	1.3	34	0.5	1.4	1.0	1.3	35	0.6	1.5
Stiff	-1.2	1.3	30	-1.7	-0.7	-1.2	1.3	35	-1.7	-0.8	-0.6	0.9	29	-0.9	-0.2	-0.1	1.1	35	-0.5	0.2
Whirring	-1.5	1.1	31	-2.0	-1.1	-1.1	1.4	35	-1.6	-0.6	-1.2	1.0	35	-1.6	-0.9	-0.5	1.3	35	-0.9	0.0
Unpleasantly smelling	-2.3	0.8	32	-2.6	-2.1	-1.7	1.7	35	-2.3	-1.1	-1.5	1.1	35	-1.9	-1.1	-0.4	1.6	35	-1.0	0.1
Unknown	-0.5	1.0	25	-1.0	-0.1	-0.6	1.4	35	-1.1	-0.1	-0.6	1.2	31	-1.1	-0.2	-0.3	1.2	35	-0.8	0.1
Unexpected	-0.4	1.3	27	-0.9	0.1	0.1	1.5	35	-0.4	0.6	-0.3	1.2	31	-0.8	0.1	0.1	1.6	35	-0.4	0.7
Bulky	-1.2	1.1	31	-1.6	-0.8	-1.3	1.6	35	-1.8	-0.7	-0.6	0.9	32	-0.9	-0.3	-0.2	1.5	35	-0.7	0.3
Reliable	2.0	0.9	31	1.7	2.3	1.6	1.6	35	1.0	2.1	2.3	0.8	35	2.1	2.6	1.8	1.5	35	1.3	2.3
Versatile	1.5	0.9	33	1.2	1.8	1.7	1.2	35	1.3	2.1	2.2	1.1	35	1.8	2.5	1.9	1.3	35	1.4	2.3
Maintenance-intensive	-2.1	1.0	33	-2.4	-1.7	-1.0	1.8	35	-1.6	-0.4	-2.1	0.8	36	-2.3	-1.8	-0.3	1.8	35	-0.9	0.3

Attributes	Old Dataset																			
	NanoPat										PlastGat									
	CAM					Questionnaire					CAM					Questionnaire				
				CI					*CI*					*CI*					*CI*	
	M	*SD*	*n*	Lower	Upper	*M*	*SD*	*n*	Lower	Upper	*M*	*SD*	*n*	Lower	Upper	*M*	*SD*	*n*	Lower	Upper
Adaptive	1.2	1.0	25	0.8	1.6	1.6	1.3	27	1.1	2.1	1.6	1.0	25	1.2	2.0	1.6	1.3	28	1.1	2.1
Autonomous	1.0	1.1	25	0.5	1.4	1.1	1.3	27	0.6	1.6	1.7	0.9	25	1.3	2.1	2.0	1.1	28	1.6	2.4
Bio-inspired	1.0	1.0	25	0.6	1.4	1.8	1.4	27	1.2	2.3	1.6	1.1	25	1.1	2.0	2.1	0.8	28	1.8	2.4
Dynamic	0.6	1.0	25	0.2	1.0	1.4	1.1	27	0.9	1.8	1.2	0.8	25	0.9	1.5	1.4	1.3	28	0.9	1.9
Energy autonomous	1.8	1.2	25	1.3	2.3	1.7	1.3	27	1.2	2.2	2.5	0.8	25	2.2	2.9	2.3	1.2	28	1.8	2.7
Contains Cadmium	-1.7	1.1	25	-2.2	-1.3	-1.5	1.7	27	-2.2	-0.8	-1.6	1.4	25	-2.1	-1.0	-1.5	1.4	28	-2.1	-1.0
Remote controllable	0.4	1.2	25	-0.1	0.9	0.5	1.6	27	-0.1	1.1	1.8	1.1	25	1.4	2.2	1.6	1.7	28	0.9	2.3
Poisonous	-2.7	0.7	24	-3.0	-2.4	-1.9	1.8	27	-2.6	-1.2	-2.7	0.6	24	-2.9	-2.4	-2.2	1.2	28	-2.6	-1.7
Innovative	1.2	1.0	25	0.8	1.7	1.7	1.2	27	1.2	2.2	1.7	0.9	25	1.3	2.0	2.0	0.9	28	1.6	2.3
Intelligent	1.6	0.9	25	1.2	2.0	1.6	1.3	27	1.1	2.1	1.9	0.8	25	1.6	2.3	1.5	1.5	28	1.0	2.1
Clacking	-1.4	0.9	25	-1.8	-1.1	-0.8	1.8	27	-1.5	-0.1	-1.1	0.9	25	-1.5	-0.8	-1.1	1.3	28	-1.6	-0.6
Complex	-0.4	0.8	25	-0.8	-0.1	0.4	1.4	27	-0.2	1.0	-0.1	0.8	25	-0.5	0.2	0.1	1.0	28	-0.3	0.5
Slow	-1.0	0.7	25	-1.2	-0.7	-0.4	1.3	27	-1.0	0.1	-0.6	0.8	25	-1.0	-0.3	-0.8	1.3	28	-1.3	-0.3
Loud	-2.0	0.9	25	-2.4	-1.6	-1.1	1.7	27	-1.8	-0.5	-1.6	1.1	25	-2.0	-1.2	-1.8	1.1	28	-2.2	-1.3
Capable of learning	1.6	1.0	25	1.2	2.1	1.3	1.4	27	0.8	1.8	2.1	0.9	24	1.7	2.5	1.6	1.3	28	1.1	2.1
Microelectromechanical	0.1	0.5	25	-0.1	0.3	0.2	1.5	27	-0.4	0.8	0.6	0.9	25	0.2	0.9	0.6	1.1	28	0.1	1.0
Molecular	0.1	0.3	25	0.0	0.3	0.4	1.5	27	-0.2	1.0	0.4	0.7	25	0.2	0.7	0.8	1.4	28	0.2	1.3
Contains nanoparticles	-0.2	0.9	25	-0.5	0.2	0.1	1.7	27	-0.5	0.8	0.0	1.6	25	-0.6	0.7	0.5	1.6	28	-0.1	1.1
Cannot be turned on/off	-1.2	1.1	25	-1.6	-0.7	-0.9	1.7	27	-1.5	-0.2	-0.9	0.8	25	-1.2	-0.6	-1.2	1.5	28	-1.8	-0.6
Not compostable	-1.4	1.0	25	-1.8	-1.0	-1.4	1.6	27	-2.1	-0.8	-1.8	0.9	25	-2.2	-1.4	-1.9	1.1	28	-2.3	-1.4
Ecological	2.0	1.0	25	1.6	2.4	1.6	1.7	27	0.9	2.3	2.3	1.0	25	1.9	2.7	2.1	1.2	28	1.7	2.6
Reflective	1.1	0.8	24	0.7	1.4	1.4	1.7	27	0.8	2.1	0.3	1.2	25	-0.2	0.8	0.5	1.4	28	0.0	1.1
Self-luminous	1.0	1.2	25	0.4	1.5	1.5	1.2	27	1.0	2.0	1.0	1.0	25	0.6	1.4	1.0	1.7	28	0.3	1.6
Stiff	-1.1	1.1	25	-1.6	-0.7	-0.7	1.7	27	-1.3	0.0	-0.3	0.6	25	-0.6	-0.1	-0.2	1.1	28	-0.6	0.2
Whirring	-1.4	0.9	25	-1.7	-1.0	-1.2	1.6	27	-1.9	-0.6	-1.2	1.0	25	-1.6	-0.8	-1.0	1.1	28	-1.4	-0.6
Unpleasantly smelling	-2.3	0.9	25	-2.6	-1.9	-1.7	1.7	27	-2.4	-1.0	-1.2	0.8	25	-1.5	-0.9	-1.3	1.3	28	-1.8	-0.8
Unknown	-0.6	0.9	25	-1.0	-0.3	-0.1	1.5	27	-0.7	0.5	-0.5	0.7	25	-0.8	-0.2	-0.6	1.3	28	-1.1	-0.1
Unexpected	-0.5	1.0	25	-0.9	-0.1	-0.1	1.4	27	-0.6	0.5	-0.4	0.8	25	-0.7	-0.1	0.0	1.4	28	-0.5	0.5
Bulky	-1.2	1.1	25	-1.6	-0.7	-0.8	1.7	27	-1.5	-0.1	-0.5	0.6	25	-0.8	-0.3	0.1	0.8	28	-0.2	0.4
Reliable	1.6	0.9	25	1.2	1.9	1.9	1.3	27	1.4	2.4	2.3	0.8	25	2.0	2.6	2.1	1.1	28	1.7	2.6
Versatile	1.8	1.1	25	1.4	2.2	1.9	1.4	27	1.3	2.5	2.1	0.8	25	1.8	2.5	2.1	0.8	28	1.8	2.5
Maintenance-intensive	-1.8	1.3	25	-2.3	-1.2	-1.0	1.6	27	-1.7	-0.4	-1.5	0.9	25	-1.9	-1.2	-0.8	1.7	28	-1.4	-0.1

Note. Color coding above mirrors the same classification scheme used to highlight the BFs of the factor *dataset* in Part 2: Sample 2020 vs. Sample 2021.

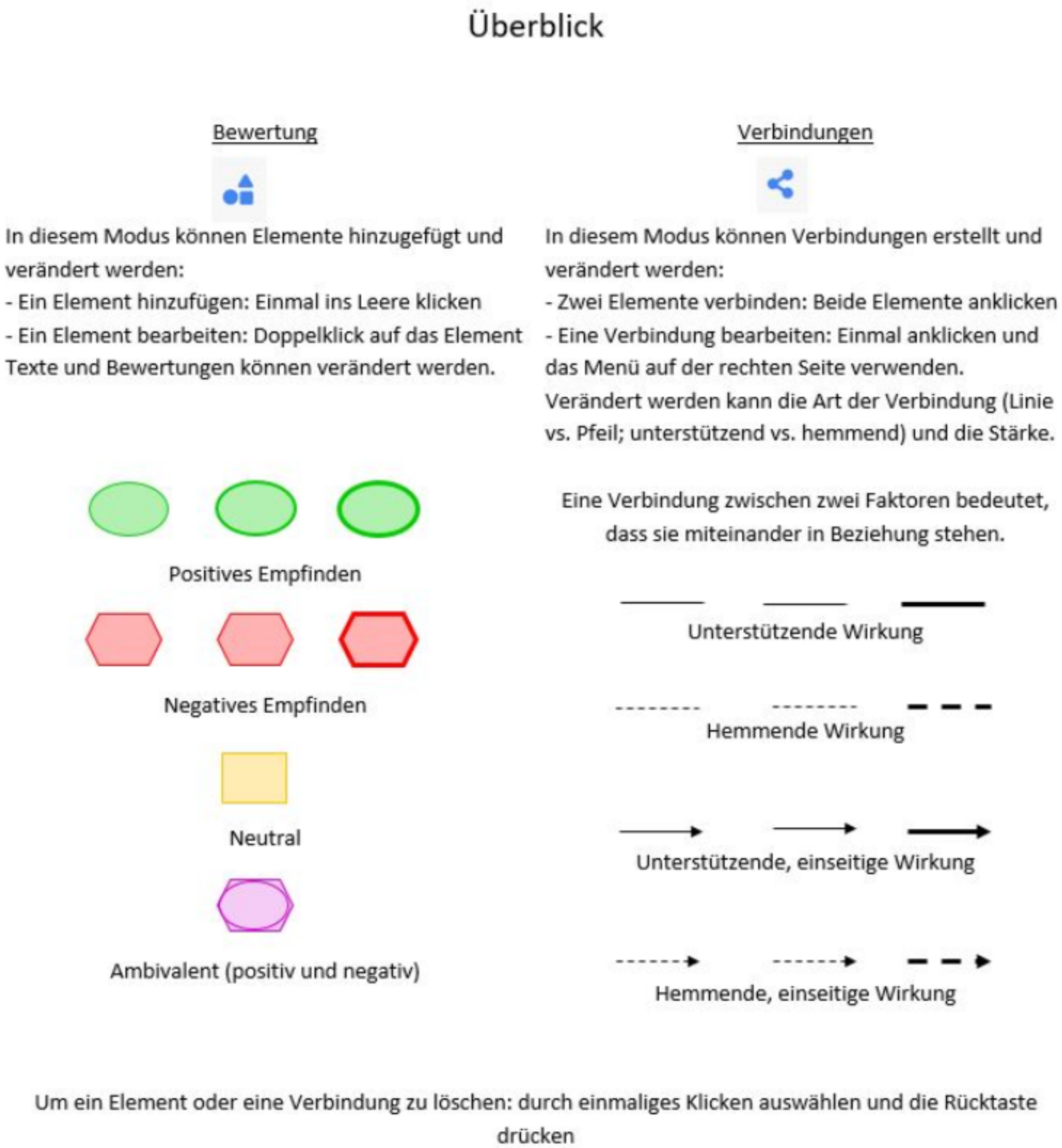
Appendix D

Color Coding System and Interpretation Conventions of the Bayes Factors Derived from Jeffreys (1961)

BF_{10}	Interpretation
>100	Decisive evidence for H_1
30-100	Very strong evidence for H_1
10-30	Strong evidence for H_1
3-10	Substantial evidence for H_1
1-3	Anecdotal evidence for H_1
1	No evidence
1/3-1	Anecdotal evidence for H_0
1/10-1/3	Substantial evidence for H_0
1/30-1/10	Strong evidence for H_0
1/100-1/30	Very strong evidence for H_0
<1/100	Decisive evidence for H_0

Appendix E

Summary of the Rules on How to Draw a CAM in Original German Language



Appendix F

Excerpt of the Questionnaire Used to Assess the 32 Attributes (in Original German)

questback

Im Folgenden möchten wir Ihre Einstellung zu und Ihre Bewertung von Eigenschaften aus dem Nano-Pat-Parka Szenario abfragen.

Zu jeder Eigenschaft bitten wir Sie anzugeben, wie positiv und wie negativ Sie diese Eigenschaft finden. Außerdem fragen wir Sie wie wichtig diese Eigenschaft für Sie ist, das heißt wie stark die jeweilige Eigenschaft Ihre Gesamtbewertung des Nano-Pat-Parkas beeinflusst.

Dafür stellen wir Ihnen zu jeder Eigenschaft drei Fragen:

1. Wie positiv ist diese Eigenschaft für Sie?
(0 = gar nicht positiv; 1 = eher positiv; 2 = positiv; 3 = sehr positiv)

2. Wie negativ ist diese Eigenschaft für Sie?
(0 = gar nicht negativ; 1 = eher negativ; 2 = negativ; 3 = sehr negativ)

3. Wie wichtig ist diese Eigenschaft für Sie?
(0 = gar nicht wichtig; 1 = ein bisschen wichtig; 2 = wichtig; 3 = sehr wichtig)

Wartungsintensiv: Positive Bewertung

0	1	2	3

Wartungsintensiv: Negative Bewertung

Wartungsintensiv: Wichtigkeit

Nanopartikel enthaltend: Positive Bewertung

Nanopartikel enthaltend: Negative Bewertung

Nanopartikel enthaltend: Wichtigkeit

Appendix G

Relative Frequencies of Valent Knots per Participant

ID	Dataset	Scenario	% Rate				Missing
			Positive	Negative	Neutral	Ambivalent	
15	old	NP	40.63	50.00	3.13	6.25	0
20	old	NP	37.50	50.00	0.00	12.50	0
34	old	NP	34.38	46.88	18.75	0.00	0
46	old	NP	43.75	34.38	18.75	3.13	0
50	old	NP	34.38	50.00	6.25	9.38	0
56	old	NP	21.88	43.75	0.00	34.38	0
57	old	NP	40.63	43.75	0.00	15.63	0
67	old	NP	29.03	48.39	12.90	9.68	1
70	old	NP	25.00	28.13	34.38	12.50	0
77	old	NP	40.63	34.38	9.38	15.63	0
78	old	NP	21.88	34.38	43.75	0.00	0
83	old	NP	37.50	31.25	9.38	21.88	0
84	old	NP	37.50	34.38	12.50	15.63	0
96	old	NP	34.38	28.13	28.13	9.38	0
107	old	NP	28.13	37.50	34.38	0.00	0
111	old	NP	46.88	31.25	3.13	18.75	0
115	old	NP	50.00	34.38	15.63	0.00	0
116	old	NP	37.50	31.25	31.25	0.00	0
122	old	NP	18.75	21.88	56.25	3.13	0
125	old	NP	28.13	46.88	12.50	12.50	0
139	old	NP	31.25	34.38	15.63	18.75	0
144	old	NP	50.00	34.38	0.00	15.63	0
149	old	NP	50.00	28.13	12.50	9.38	0
160	old	NP	37.50	31.25	12.50	18.75	0
166	old	NP	18.75	40.63	40.63	0.00	0
10	old	PG	31.25	18.75	37.50	12.50	0
13	old	PG	37.50	25.00	18.75	18.75	0
26	old	PG	50.00	28.13	12.50	9.38	0
28	old	PG	59.38	21.88	12.50	6.25	0
33	old	PG	38.71	32.26	22.58	6.45	1
35	old	PG	43.75	28.13	28.13	0.00	0
36	old	PG	46.88	46.88	6.25	0.00	0
49	old	PG	46.88	43.75	6.25	3.13	0
59	old	PG	31.25	37.50	18.75	12.50	0
63	old	PG	46.88	25.00	6.25	21.88	0
79	old	PG	43.75	46.88	9.38	0.00	0
89	old	PG	46.88	37.50	9.38	6.25	0
92	old	PG	53.13	37.50	9.38	0.00	0

110	old	PG	46.88	40.63	0.00	12.50	0
113	old	PG	46.88	31.25	0.00	21.88	0
117	old	PG	46.88	31.25	6.25	15.63	0
120	old	PG	37.50	40.63	15.63	6.25	0
128	old	PG	43.75	21.88	9.38	25.00	0
132	old	PG	37.50	34.38	12.50	15.63	0
143	old	PG	40.63	37.50	15.63	6.25	0
152	old	PG	25.00	18.75	53.13	3.13	0
168	old	PG	34.38	28.13	37.50	0.00	0
179	old	PG	46.88	37.50	6.25	9.38	0
197	old	PG	40.63	37.50	9.38	12.50	0
10056	old	PG	41.94	32.26	16.13	9.68	1
30	new	NP	56.25	34.38	0.00	9.38	0
33	new	NP	16.67	66.67	5.56	11.11	14
37	new	NP	50.00	34.38	15.63	0.00	0
39	new	NP	46.88	53.13	0.00	0.00	0
45	new	NP	46.88	21.88	31.25	0.00	0
56	new	NP	43.75	50.00	0.00	6.25	0
65	new	NP	14.29	14.29	57.14	14.29	4
95	new	NP	37.93	41.38	0.00	20.69	3
100	new	NP	38.71	41.94	19.35	0.00	1
107	new	NP	53.13	37.50	3.13	6.25	0
109	new	NP	43.75	37.50	0.00	18.75	0
136	new	NP	28.13	40.63	21.88	9.38	0
137	new	NP	15.63	25.00	53.13	6.25	0
147	new	NP	28.13	28.13	43.75	0.00	0
156	new	NP	43.75	31.25	25.00	0.00	0
159	new	NP	51.61	35.48	3.23	9.68	1
166	new	NP	15.63	40.63	43.75	0.00	0
180	new	NP	29.41	58.82	0.00	11.76	15
186	new	NP	38.46	46.15	11.54	3.85	6
188	new	NP	41.94	48.39	0.00	9.68	1
193	new	NP	37.50	43.75	0.00	18.75	0
197	new	NP	31.25	40.63	28.13	0.00	0
200	new	NP	37.50	37.50	25.00	0.00	0
202	new	NP	41.18	47.06	11.76	0.00	15
208	new	NP	37.50	37.50	15.63	9.38	0
211	new	NP	40.74	48.15	11.11	0.00	5
214	new	NP	6.25	18.75	75.00	0.00	0
222	new	NP	46.88	40.63	12.50	0.00	0
227	new	NP	47.83	47.83	0.00	4.35	9
236	new	NP	46.15	42.31	11.54	0.00	6
238	new	NP	41.38	20.69	37.93	0.00	3

245	new	NP	6.25	12.50	75.00	6.25	0
249	new	NP	53.13	37.50	9.38	0.00	0
255	new	NP	50.00	37.50	0.00	12.50	16
32	new	PG	53.33	33.33	13.33	0.00	2
46	new	PG	46.88	25.00	28.13	0.00	0
55	new	PG	15.63	15.63	62.50	6.25	0
70	new	PG	40.63	34.38	12.50	12.50	0
80	new	PG	31.25	25.00	31.25	12.50	0
85	new	PG	38.89	44.44	5.56	11.11	14
93	new	PG	50.00	50.00	0.00	0.00	0
102	new	PG	15.63	21.88	59.38	3.13	0
110	new	PG	43.75	34.38	15.63	6.25	0
128	new	PG	46.88	34.38	15.63	3.13	0
133	new	PG	21.88	25.00	50.00	3.13	0
135	new	PG	21.88	37.50	25.00	15.63	0
150	new	PG	58.06	22.58	0.00	19.35	1
155	new	PG	40.63	50.00	9.38	0.00	0
162	new	PG	40.63	40.63	0.00	18.75	0
168	new	PG	43.75	28.13	18.75	9.38	0
177	new	PG	48.39	41.94	3.23	6.45	1
179	new	PG	34.38	25.00	21.88	18.75	0
187	new	PG	43.75	28.13	28.13	0.00	0
189	new	PG	36.00	24.00	32.00	8.00	7
190	new	PG	35.00	40.00	25.00	0.00	12
192	new	PG	42.31	30.77	26.92	0.00	6
199	new	PG	44.00	40.00	8.00	8.00	7
204	new	PG	43.75	46.88	0.00	9.38	0
212	new	PG	48.39	41.94	9.68	0.00	1
215	new	PG	42.31	57.69	0.00	0.00	6
217	new	PG	40.00	44.00	0.00	16.00	7
219	new	PG	46.15	34.62	11.54	7.69	6
220	new	PG	43.75	53.13	0.00	3.13	0
223	new	PG	46.88	34.38	6.25	12.50	0
232	new	PG	43.75	43.75	0.00	12.50	0
235	new	PG	38.71	35.48	25.81	0.00	1
237	new	PG	31.25	21.88	46.88	0.00	0
246	new	PG	46.88	31.25	0.00	21.88	0
247	new	PG	40.63	40.63	0.00	18.75	0
250	new	PG	56.25	43.75	0.00	0.00	0
251	new	PG	41.38	31.03	10.34	17.24	3
Grand mean overall			38.92	36.05	17.03	8.00	1.45
Grand mean new			38.99	36.79	17.60	6.62	2.44
Grand mean old			38.82	35.01	16.22	9.95	0.06

Appendix H

Relative Frequencies of Valent Knots per Attribute

Attributes	% Positive	% Negative	% Neutral	% Ambivalent	Missing
Adaptive	85.71	0.84	8.40	5.04	2
Autonomous	79.13	0.87	12.17	7.83	6
Bio-inspired	79.49	0.85	17.09	2.56	4
Dynamic	70.18	1.75	24.56	3.51	7
Energy autonomous	85.59	0.85	11.02	2.54	3
Contains Cadmium	2.54	86.44	7.63	3.39	3
Remote controllable	68.64	4.24	12.71	14.41	3
Poisonous	0.86	93.97	5.17	0.00	5
Innovative	89.92	0.00	5.88	4.20	2
Intelligent	87.18	0.00	10.26	2.56	4
Clacking	0.00	81.74	15.65	2.61	6
Complex	5.13	33.33	27.35	34.19	4
Slow	0.88	68.42	22.81	7.89	7
Loud	0.00	90.60	6.84	2.56	4
Capable of learning	87.29	0.00	8.47	4.24	3
Microelectromechanical	27.68	3.57	49.11	19.64	9
Molecular	22.73	7.27	56.36	13.64	11
Containing nanoparticles	17.24	28.45	33.62	20.69	5
Can not be turned on/off	0.85	72.03	10.17	16.95	3
Not compostable	0.00	90.83	5.83	3.33	1
Ecological	89.74	0.85	6.84	2.56	4
Reflective	58.41	7.96	18.58	15.04	8
Self-luminous	67.24	4.31	19.83	8.62	5
Stiff	4.59	55.96	26.61	12.84	12
Whirring	0.86	81.90	15.52	1.72	5
Unpleasantly smelling	0.85	94.02	3.42	1.71	4
Unknown	0.94	36.79	35.85	26.42	15
Unexpected	10.19	37.96	39.81	12.04	13
Bulky	2.65	62.83	30.09	4.42	8
Reliable	96.55	0.00	3.45	0.00	5
Versatile	90.68	0.00	9.32	0.00	3
Maintenance-intensive	0.84	91.60	4.20	3.36	2