

An Exploratory Study on Notational Characteristics of Visual Notations Used in Decision Management

Sam Leewis

Optimizing Knowledge-Intensive Business Processes
Zuyd University of Applied Sciences
Sittard, The Netherlands
sam.leewis@zuyd.nl

Koen Smit, Matthijs Berkhout, Ruben Post

Digital Smart Services
HU University of Applied Sciences Utrecht
Utrecht, The Netherlands
koen.smit@hu.nl, matthijs.berkhout@hu.nl,
ruben.post@hu.nl

Martijn Zoet

Optimizing Knowledge-Intensive Business Processes
Zuyd University of Applied Sciences
Sittard, The Netherlands
martijn.zoet@zuyd.nl

Abstract— The visual representation of Information System (IS) artefacts is an important aspect in the practical application of visual representations. However, important and known visual representation principles are often undervalued, which could lead to decreased effectiveness in using a visual representation. Decision Management (DM) is one field of study in which stakeholders must be able to utilize visual notations to model business decisions and underlying business logic, which are executed by machines, thus are IS artefacts. Although many DM notations currently exist, little research actually evaluates visual representation principles to identify the visual notations most suitable for stakeholders. In this paper, the Physics of Notations framework of Moody is operationalized and utilized to evaluate five different DM visual notations. The results show several points of improvement with regards to these visual notations. Furthermore, the results could show the authors of DM visual notations that well-known visual representation principles need to be adequately taken into account when defining or modifying DM visual notations.

Keywords—Decision Management; Visual Notations; Evaluation; Physics of Notations (PoN)

I. INTRODUCTION

Decisions are amongst the most important assets of an organization [1], and therefore should be managed adequately. A decision is defined as: “A conclusion that a business arrives at through business logic and which the business is interested in managing” [2]. Furthermore, business logic can be defined as “a collection of business rules, business decision tables, or executable analytic models to make individual business decisions” [3]. Examples of decisions are: 1) determine what illness a patient has, 2) determine the loan default risk factor for a specific customer, or 3) determine the maximum credit rating of an organization. If an organization can’t consistently make and execute the right decision(s), large risks are taken that can eventually lead to high costs,

reputation damage, or even bankruptcy. Following the previous example, imagine what will happen when a doctor makes the wrong decision continuously or a customer with a high-risk classification gets a low-risk classification.

One important aspect of Decision Management (DM) is modelling decisions and business logic using a visual representation. Such visual representations are often referred to as notations or modeling standards. An example of a decision modelling notation is the Decision Modeling and Notation (DMN) proposed by the Object Management Group [2] or The Decision Model, defined by von Halle and Goldberg [4].

While empowering the semantic modeling capabilities of notations is desirable, notations also need to be cognitively effective [5]. Cognitive effectiveness, in the context of visual notations, refers to “the speed, ease and accuracy with which a representation can be processed by the human mind” [6]. Generally speaking, important and known visual representation principles are often undervalued in the design of visual notations, which could lead to decreased cognitive effectiveness [7], [8]. Furthermore, these notations are usually not designed with all stakeholders in mind, from someone who never modelled on the one hand (Decision modelling novice) to a Decision modelling expert on the other hand [6], and have no design rationale nor a scientific basis for the choices in the structure of the visual representation [5]. Decision modelling novices do have different requirements in comparison to users who are considered a DM expert. An expert will need more advanced functionalities in comparison to a novice, however, a novice should be able to learn the notation quickly to get started.

This paper examines whether these problems exist in the notations specifically designed for the DM domain, as, to the knowledge of the authors, no earlier studies exist that focus on evaluating multiple DM notations. To do so, a

proper framework to evaluate known visual representation principles needs to be selected.

Several frameworks to evaluate visual notations exist, for example, the Cognitive Dimensions framework [9], the ontological analysis framework [10], and the Guidelines of Modelling (GoM) framework [11]. The most complete and referenced framework on the assessment of visual notations is the Physics of Notations (PoN) theory [6]. This theory is partly based on the Cognitive Dimensions framework, which was the predominant theoretical paradigm in visual notations research [12]. The framework is developed and devoted to design, evaluate, and compare visual notations and is based on theory and empirical evidence obtained from different disciplines, such as perceptual psychology, cognitive psychology, cartography, graphic design, human-computer interfacing, linguistics, and communication theory. Furthermore, one advantage of the PoN framework is that it also offers clear evaluation procedures and metrics so that researchers can easily operationalize them to be evaluated in practice. The PoN framework has been applied by many researchers to evaluate visual notations [13][14]. Since we selected a framework to evaluate DM visual notations with, the following research question is stated: *“How do the selected DM visual notations score with regards to the PoN framework?”*

The rest of the paper is structured as follows. First, the theory underlying visual notations and PoN are elaborated upon in the background and related work. This is followed by the research method utilized to conduct the research presented in this paper. Then, the data collection and analysis processes are explained. Next, in the results section, the PoN scores for the selected visual notations are presented. Lastly, the paper concludes with a discussion, conclusions, and directions for future research.

II. BACKGROUND AND RELATED WORK

DM notations can best be categorized by their complexity and linguistic power. Complexity refers to the ease of understanding the DM notation and linguistic power refers to the amount of results it can produce, indicating its richness. Five different types of DM notations have been defined: 1) labels, textual markers, 2) graphical aids, symbols representing semantic constructs, 3) structured languages, semantic representations of logic, 4) constrained natural languages, ontology defined by base terms and grammar, and 5) pure natural languages, unbound syntax, see Figure 1.

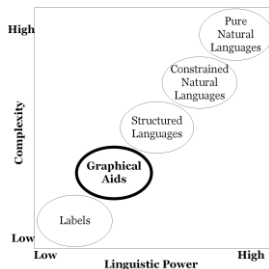


Figure 1. DM notation categorization [15]

The PoN framework is aimed towards visually represented DM notations. Therefore, this study evaluated DM visual notations of the graphical aids type.

The selected elements are drawn from the PoN framework [6]. This framework attempts to evaluate DM notations based on their visual representation, as these are often undervalued principles. It offers nine different principles by which the visual representation of a DM notation is measured against. The principles are as follows [6]:

Semiotic Clarity refers to every symbol having a one-to-one correspondence to their referent concept. If not, one or more of the following four anomalies can occur: 1) symbol redundancy occurs when multiple symbols can be used to represent the same concept, 2) symbol overload occurs when different concepts can be represented by the same symbol, 3) symbol excess occurs when symbols do not correspond to any concept, and 4) symbol deficit occurs when there are concepts that do not correspond with any symbols.

Perceptual Discriminability refers to the ability to differentiate symbols based on their graphical appearance. This can be improved by increasing the number of graphical attributes a symbol represents. For example, adding color, additional shapes, or text to a notation can improve the ability to differentiate between symbols.

Semantic transparency refers to the extent to which the meaning of a symbol can be inferred from its appearance. For example, a rectangle representing a decision has a scarce semantic transparency, while an icon of a calculator representing a formula has high semantic transparency.

Complexity Management refers to the ability of a visual notation to represent information without overloading the human brain. The complexity our brains can handle can be improved by the usage of different concepts. For example, modularization can be used to reduce the complexity of a large system by dividing it into smaller parts or making use of subsystems. Additionally, hierarchy can be incorporated into the notation by representing information on different levels of details.

Cognitive Integration refers to the extent to which a notation enables multiple diagrams to represent a system without overloading the human brain. This can be supported by two concepts, conceptual integration and perceptual integration. Conceptual integration can be achieved by providing a summary diagram as a whole or parts of the diagram or by contextualization, a technique where contextual information on each diagram is showing its relation to elements on other diagrams. Perceptual integration is achieved by providing navigational tools in the notation. Commonly used navigational tools are, for example, lines to provide direction of the flow or a map in which the entire diagram is shown if only a part of the diagram is to be shown on the screen.

Visual Expressiveness is defined as the number of visual variables used in a notation. If a notation has a high number of visual variables, the perceptual discriminability increases, making the notation easier to use. Visual variables are size, brightness, color, texture, shape, orientation, and text.

Dual Coding refers to the use of both visual and textual attributes in a notation. For example, the semantic transparency can be increased by adding a keyword of the semantic concept to the visual representation of the symbol, consequently achieving dual coding.

Graphic Economy refers to the number of graphical symbols used in a notation. The human brain can discriminate around six categories simultaneously, defining the limit of graphical symbols a notation should contain. There are three concepts by which excessive graphic complexity can be reduced: 1) reduce semantic complexity, 2) introduce symbol deficit, and 3) increase visual expressiveness.

Cognitive Fit refers to the Cognitive fit theory, which states that different methods of representation of information are suitable for different tasks and different audiences. This can be respected by creating multiple visual filters for, for example, expert-novice differences or representational mediums.

III. RESEARCH METHOD

The goal of this research is to evaluate several DM visual notations with regards to the PoN framework [6]. When selecting an appropriate research method, one should take into account the maturity of the research domain [16]. Research with regards to visual notations to express business decisions and business logic is scarce [11]. Therefore, a qualitative research approach is selected as our research method.

To evaluate DM visual notations, a structured technique must be selected. We utilize a technique to do so from the body of knowledge regarding visual notations, as it is rather mature, compared to the body of knowledge on DM. Based on the PoN framework, the researchers constructed a template which covers the nine principles of visual notations indicated in [6] (the template itself is available upon request and omitted due to space limitations). Each of the nine principles consists of specific elements characterizing each principle, e.g., the principle ‘*semiotic clarity*’ has four elements of which one represents ‘*symbol overload*’. Every element is represented by a question whether the element is available in the visual notation, and if present, to what extent.

Instead of using a quantitative approach, it is more appropriate to use a mix of quantitative collection and analysis with qualitative thematic coding, as our template also aims to collect motivations of researchers evaluating the visual notations. The coding of the evaluations for the selected visual notations consists of three rounds of thematic coding according to the process of open coding, axial

coding, and selective coding described in [17]. During the coding rounds, four researchers coded the five graphical aids-type notations separately from each other. The results of the coding rounds were compared and their meaning discussed among the four researchers. The process of data collection and analysis is described in more detail in the following section.

IV. DATA COLLECTION AND ANALYSIS

Before the data collection and analysis started, the research team needed to decide which visual notations to evaluate. For this study, the amount of visual notations to evaluate was five. The DM visual notations are selected based on the following criteria: 1) the notation should be applied in practice by multiple organizations, 2) the documentation for the notation should be accessible to be able to evaluate it in detail, and 3) the notation should be a DM graphical aid type. The selected visual notations for evaluation are: *Beinformed* [18], *Berkeley Bridge* [19], *Decision Model and Notation (DMN)* [2], *The Decision Model (TDM)* [4], and *Visual Rules* [20].

The data collection for this study occurred over a period of two months, between March 2018 and April 2018. The data collection is conducted by four researchers representing different levels of expertise on visual notations. Two researchers representing the expert group (researcher 1 and 2) and two researchers representing the novice group (researcher 3 and 4). Separating the coders increases the inter-reliability in the coding [21] and internal validity of the research [22]. Researcher 1 is a lecturer and postdoc researcher with seven years of practical and research experience in the field of DM; Researcher 2 is a PhD-candidate with five years of practical and research experience in the field of DM; Researcher 3 is a Master student with four years of practical and research experience in the field of DM; Researcher 4 is a Bachelor student with two years of research experience in the field of DM. All researchers have experience with visual notations, and completed at least two or more projects in which DM models had to be produced to be utilized in practice. It took the research team a week to gather all data required to evaluate the visual notations. The data consisted of webpages, client case documents, learning documents, meta-models, demo applications, and video repositories with tutorials.

A template is created and utilized by the researchers to cover the nine principles of Moody [6]. Every principle has its own characteristics and thereby every principle in the template has different elements with each their related questions. For each element, a five-point Likert-scale ranging from 1) very poor; 2) poor; 3) neutral; 4) good; 5) very good. Additionally, the value 6) Not Applicable (NA) could be chosen. If NA was chosen it needed to be further specified why. Therefore, the dataset represents a total of four filled-in templates for each of the five visual notations selected.

The data analysis comprised three rounds of thematic coding based on the data analysis techniques described by Strauss & Corbin [17]. The first round of coding identifies the symbols and constructs of each notation, e.g., the different node-types as part of the BeInformed visual notation or the transition-types as part of DMN.

TABLE 1. EXAMPLE CODING NOTATION.

		Visual notation: BeInformed			
		Coders			
		Expert		Novice	
		R1	R2	R3	R4
Perceptual Discriminability	Redundant coding	4	4	4	4
	Perceptual popout	3	4	3	2
	Textual differentiation			2	3
	Iconic differentiation	2	1	3	4

The second round of coding refines and differentiates concepts that are already available and code them into categories [23]. The axial coding round consisted of the indication of the values (using a five-point Likert-scale) for each visual notation together with the principles of Moody [6], as shown in Table 1.

The first and second coding rounds were based on knowledge derived from sources described earlier, however, the coders did not follow courses or applied the visual notation in practice for this specific research.

The third and last round of coding represents the identification of functional categories [23]. The selective coding round included the identification of any consistencies or inconsistencies (using the color grey) within the notations or difference in expertise (Expert/Novice), as shown in Table 1.

The five-point Likert-scale is used to enable calculation of averages used for the comparison of notations, and to create a standard quantification mechanism for the coders to use during the coding of the notations. If doing any quantitative analysis, the Likert-scale is the most accepted and used scale for this purpose [24].

V. RESULTS

In this section, the results from the data collection and analysis phase are shown and further discussed. The results include the differences in values, based on percentages or a five-point Likert-scale, when the coder is of a different expert level (Expert/Novice). Table 2 shows the average of all the analysed visual notations against the nine principles mentioned by Moody [6]. Further on in this section, the results of each PoN principle are discussed in detail.

- **Semiotic clarity**

The ideal notation does not have any Excess, Deficit, Redundant, or Overload in symbols. Therefore, any occurrence in this is seen as a negative (as shown in Table 2). The BeInformed and Visual Rules notation have excess, and/or redundant symbols. The researchers identified

18,75% of the BeInformed symbols as Excess and Redundant. The Visual Rules notation was identified with a 7,69% Excess in symbols.

- **Perceptual discriminability**

A visually strong notation which discriminates itself by the use of text, icons, and visual spacing, in order to stimulate faster identification of the different symbols. Therefore, a higher value is an indication that the notation has a high perceptual discriminability. The BeInformed notation with a 3,06 has the highest perceptual discriminability of the analyzed notations, compared to the DMN notation with a 1,50 (lowest).

- **Semantic transparency**

Semantic transparency covers if the visual appearance of the symbols suggests their meaning. A higher value in this principle is an indication that the notation seems to have semantic transparent symbols. The Berkeley Bridge notation has the highest semantic transparency with a 4,4. This seems the result of the low number of symbols, which is two. The BeInformed and Visual Rules notation seems to have the same result but by their high number of symbols, these notations have the lowest semantic transparency (BeInformed 2,88, and Visual Rules 2,71).

- **Complexity management**

The complexity management principle covers the ability to scale the notation. A higher value in this principle is an indication that the notation is useful on a larger scale by utilizing modularization and hierarchical structuring. The BeInformed notation has the highest value (4,17) in complexity management and seems better when dealing with larger scale projects. The TDM notation seems to be impacted by the low number of symbols in their notation to score the lowest (2,17) in complexity management.

- **Visual expressiveness**

The visual expressiveness principle covers the use of visual variables (colour, 3d symbols, and textual encoding). A higher value indicates that the notations are visually expressive. The TDM notation has a total score of 4,5 and thereby seems to be the highest scoring notation in visual expressiveness, compared to the Berkeley Bridge notation with a 1,5 (lowest).

- **Graphical Economy**

The graphical economy principle covers the number of symbols a human brain is able to discriminate between, this number is estimated to be limited to six. A value above six would be a negative impact on the graphical economy of the notation, which is the case for BeInformed (16), Visual Rules (13), and DMN (9).

- **Dual Coding**

The dual coding principle covers the complement of graphics with text, which is more effective than using each of them on their own. A higher value in this principle indicates that the notation uses dual coding as the most optimal notation. The BeInformed (4.25) and Visual Rules

(4.00) notations are the only notations, out of the analyzed five notations, where dual coding was identified.

TABLE 2. CODING RESULTS

	<i>BeInformed</i>	<i>Visual Rules</i>	<i>DMN</i>	<i>TDM</i>	<i>Berkeley Bridge</i>	
Average Total	2,87	2,97	2,38	2,89	2,53	
Cognitive Integration	2,88	3,83	3,00	2,67	1,92	
Cognitive Fit	2,75	2,25	4,13	4,50	3,88	
Dual Coding	4,25	4,00	N.A.	N.A.	N.A.	
Graphical Economy	*16	*13	*9	4	2	
Visual Expressiveness	3,13	4,00	2,25	4,50	1,50	
Complexity Management	4,17	3,33	3,83	2,17	3,50	
Semantic Transparency	2,88	2,71	2,92	3,56	4,40	
Perceptual Discriminability	3,06	2,69	1,50	2,83	2,53	
Semiotic Clarity	Excess	18%	7%	N.A.	N.A.	N.A.
	Redundancy	18%	N.A.	N.A.	N.A.	N.A.

- **Cognitive fit**

The cognitive fit principle covers the theory that different representations of information are suitable for different audiences. The Visual Rules notation scored the lowest with a 2,25, compared to that of TDM, which scored the highest with a 4,50.

- **Cognitive integration**

The cognitive integration principle covers the range of mechanisms available for dealing with multiple diagrams thereby, helping the reader assemble information from separate diagrams. A higher value indicates that the notation has the mechanisms available to help the reader assemble information when multiple diagrams are shown. The Visual Rules notation has the highest value (3,83) in cognitive integration, compared to the Berkeley Bridge notation (1,92) which does not have the mechanisms to support the reader when dealing with separate diagrams (lowest).

- **Difference Expert/Novice**

Taking into account that having experience in the use of a visual notation, in this case, a modelling language, influences the attitude towards several of the Moody principles. For example, a notation could be more complex for a novice but not for an expert. Therefore, a difference is made between the results of the expert researchers and novice researchers.

TABLE 3. RESULTS DIFFERENCE EXPERT/NOVICE

	Expertise:	Average Total Expert/Novice	Average Total
BeInformed	Expert	2,79	2,87
	Novice	2,95	
Visual Rules	Expert	2,99	2,97
	Novice	2,96	
DMN	Expert	2,25	2,38
	Novice	2,51	
TDM	Expert	2,92	2,89
	Novice	2,86	
Berkeley Bridge	Expert	2,39	2,53
	Novice	2,67	

VI. CONCLUSION, DISCUSSION AND FUTURE RESEARCH

In this paper, a study is conducted in which five DM visual notations, namely: Visual Rules, Berkeley Bridge, Decision Model and Notation, The Decision Model, and BeInformed, were evaluated using the PoN framework [1]. From our analysis, Visual Rules scores best according to the average total of all PoN framework principles. From a theoretical perspective, our study and its results give meaning to the operationalization of the PoN framework. Furthermore, it will enable further exploration of the application of the PoN principles, as well as other DM visual notations not included in this study. Moody [1, p.772] describes the theoretical interactions between the described principles. Our results show that these interactions are, to a large extend, verified. From a practical perspective, the results presented in this paper contribute towards a better awareness for taking into account validated visual notation principles and guidelines. Our results could be utilized by organizations to either evaluate for themselves which visual notation is most adequate or to utilize a visual notation based on our results.

This study has multiple limitations. The first limitation concerns the research team that carried out the evaluation of the visual notations using the PoN framework. This study included evaluations of four researchers, two novice level researchers and two expert level researchers on the DM topic. Therefore, one could argue that the results and conclusions are potentially biased by a low amount of data points for the evaluation of the visual notations included. However, most studies conducted with a focus on evaluating one or multiple visual notations are often centered on the evaluation of the visual notation using one or two researchers. Future research should focus on evaluating visual notations utilizing larger sample sizes that will add to the generalizability of the results and conclusions about the evaluated visual notations. The second limitation concerns the method and framework utilized to evaluate the visual notations, the PoN framework and its operationalization by creating and utilizing a template with the goal to structure data collection and analysis. Utilizing the PoN framework is an explicit choice, however, limits the results because the PoN framework represents a specific lens. Future research could, therefore, focus on applying other frameworks and

theories that focus on uncovering and describing essential notational principles, e.g., Guidelines of Modeling (GoM) [11]. Furthermore, the operationalization of the PoN framework described in [6] is left open for interpretation and perception of the researchers applying it, a good example is the lack of weighting of the nine PoN principles. Therefore, our template is another limitation. This phenomenon becomes clear in the work of [5], which shows that the operationalization of the PoN framework by different research teams often do not always seem to take into account all principles described. To our knowledge, our operationalization included, one-on-one, all principles described in the work of [5]. Future research, however, should focus on how these principles are best measured in practice, i.e., whether Likert scales or other less quantitative measurements are adequate or not. The last limitation concerns the visual notations selected. Although we choose two well-known visual notations, as well as three visual notations applied in the DM practice a lot, the selection of visual notations could coincidentally have resulted in a bias and affect the generalizability of our results. We argue that this risk is more or less mitigated as most studies conducted that utilize the PoN framework focus on only one visual notation, see also [5], while this study reports upon the evaluation of five visual notations. Future research could also focus on evaluating additional DM visual notations.

REFERENCES

- [1] M. W. Blenko, M. C. Mankins, and P. Rogers, "The Decision-Driven Organization," *Harv. Bus. Rev.*, no. June, p. 10, 2010.
- [2] Object Management Group, "Decision Model and Notation," 2016.
- [3] Object Management Group, "ArchiMate® 3.0 Specification," 2016.
- [4] B. Von Halle and L. Goldberg, *The Decision Model: A Business Logic Framework Linking Business and Technology*. CRC Press, 2009.
- [5] D. Van Der Linden and I. Hadar, "A Systematic Literature Review of Applications of the Physics of Notation," *IEEE Trans. Softw. Eng.*, pp. 1–1, 2018.
- [6] D. L. Moody, "The 'Physics' of Notations: Towards a Scientific Basis for Constructing Visual Notations in Software Engineering," *IEEE Trans. Softw. Eng.*, vol. 35, no. 5, pp. 756–778, 2009.
- [7] H. a. Reijers and J. Mendling, "A Study Into the Factors That Influence the Understandability of Business Process Models," *IEEE Trans. Syst. Man. Cybern.*, vol. 41, no. 3, pp. 449–462, 2011.
- [8] D. L. Moody, P. Heymans, and R. Matulevičius, "Visual syntax does matter: Improving the cognitive effectiveness of the i* visual notation," *Requir. Eng.*, vol. 15, no. 2, pp. 141–175, 2010.
- [9] A. Blackwell and T. Green, *Notational systems—the cognitive dimensions of notations framework*, HCI Models. Morgan Kaufmann, 2003.
- [10] M. Rosemann, P. Green, and M. Indulska, "A reference methodology for conducting ontological analyses," in *Proceedings of the International Conference on Conceptual Modeling*, 2004, pp. 110–121.
- [11] R. Schuette and T. Roththowe, "The guidelines of modeling—an approach to enhance the quality in information models," in *Proceedings of the Conceptual Modeling—ER '98*, 1998, pp. 240–254.
- [12] F. Saleh and M. El-Attar, "A scientific evaluation of the misuse case diagrams visual syntax," *Inf. Softw. Technol.*, vol. 66, pp. 73–96, 2015.
- [13] N. Genon, P. Heymans, and D. Amyot, "Analysing the Cognitive Effectiveness of the BPMN 2.0 Visual Notation," 2011.
- [14] D. Moody and J. van Hillegersberg, *Evaluating the visual syntax of UML: an analysis of the cognitive effectiveness of the UML family of diagrams*, LNCS vol. Springer, 2009.
- [15] Gartner, "Taking the Mystery Out of Business Rule Representation," 2013. [Online]. Available: <https://www.gartner.com/doc/2371915/taking-mystery-business-rule-representation>. [Accessed: 01-Feb-2019].
- [16] R. D. Galliers and F. F. Land, "Choosing appropriate information systems research methodologies," *Commun. ACM*, vol. 30, no. 11, pp. 901–902, 1987.
- [17] A. Strauss and J. Corbin, *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory*, 3rd ed., vol. 3. Thousand Oaks, CA: SAGE Publications Ltd., 2015.
- [18] BeInformed, "Be Informed Business Process Platform," 2017. [Online]. Available: <https://www.beinformed.com/>. [Accessed: 02-Jan-2019].
- [19] Berkeley Bridge, "Berkeley Bridge Platform," 2018. [Online]. Available: <https://www.berkeleybridge.com>. [Accessed: 15-May-2018].
- [20] Bosch, "Business Rules Management using Visual Rules," 2018. [Online]. Available: <https://www.bosch-si.com/bpm-and-brm/visual-rules/business-rules-management.html>. [Accessed: 02-Jan-2019].
- [21] H. E. Tinsley and D. J. Weiss, "Interrater Reliability and Agreement," in *Handbook of Applied Multivariate Statistics and Mathematical Modeling*, San Diego, CA: Academic Press, 2000, pp. 95–124.
- [22] H. T. Reis and C. M. Judd, Eds., *Handbook of Research Methods in Social and Personality Psychology*, 2nd ed. Cambridge: Cambridge University Press, 2014.
- [23] A. Böhm, B. Glaser, and A. Strauss, "Theoretical Coding: Text Analysis in Grounded Theory," *A Companion to Qual. Res.*, pp. 270–275, 2004.
- [24] I. E. Allen and C. A. Seaman, "Likert scales and data analyses," *Qual. Prog.*, vol. 40, pp. 64–65, 2007.