Developing Instrumentation for Design Thinking Team Performance

Neeraj Sonalkar, Ade Mabogunje, Halsey Hoster, and Bernard Roth

Abstract Multidisciplinary teamwork is a key requirement in the design thinking approach to innovation. Previous research has shown that team coaching is an effective way to improve team performance. However, the tools currently available for effective team coaching are limited to heuristics derived from either experienced design thinking professionals or clinical psychology practitioners. Our research aims to improve this situation by providing design thinking managers, coaches, and instructors a reliable instrument for measuring design team performance. In this chapter, we present the underlying methodology for instrument design. The development of a specific diagnostic instrument, based on a visual notation called the Interaction Dynamics Notation, is explained in terms of both the workflow of data through the instrument and the exploratory studies conducted to design the instrument user interface.

1 Introduction

Organizations are increasingly adopting design thinking as an approach for promoting product, process, and service innovation. In the past decade the term *design thinking* has developed multiple interpretations, including a process for innovation (Brown 2008), an approach towards problem solving (Dorst 2011), a personal creative mindset (Rauth et al. 2010), and an organizational culture oriented towards innovative output (Kolko 2015). Rapid and enthusiastic adoption of design thinking has created an urgent need to deepen our scientific understanding of design thinking for two reasons: first, to prevent shallow interpretations that propagate design thinking as a business fad, and second, to enable organizations to reach peak performance in their design thinking practice. In this chapter, we present research

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to develop an instrument that deepens our understanding of design teams. We developed and refined this instrument with the intention to improve teams' design thinking performance.

2 Why Instrument Design Thinking Teams?

Instrumentation is defined as the development and use of devices that reliably measure a phenomenon of interest. Instruments provide methods to both sense and represent a phenomenon within a measurement scheme; these methods go beyond the limitation of language usage and the subjectivity of individual observers (Baird 2004). Reliable, repeatable, and measurable understanding of a phenomenon is central to the development of scientific knowledge, and subsequently to our ability to engineer and improve the phenomenon.

Considering design thinking broadly as an approach to problem solving that has been adapted from *how designers think and act*, research in design thinking is rooted in the long history of design theory and methodology research in various design disciplines like architecture, engineering design, and product design (Johansson-Sköldberg et al. 2013). However, much of this research is descriptive in nature and lacks instrumentation that could both improve rigor and render the research accessible to practitioners. In this chapter, we present the early stages in the development of one such instrument for design thinking team interactions.

As design thinking matures, we could imagine instruments that measure concept generation, prototyping, or framing that can give teams an understanding of their design activity that goes beyond the limitations of human sensing and allows for the development of high performance design thinking teams that can innovate faster, more reliably, and more efficiently.

3 How to Develop an Instrument for Design Thinking Teams?

Developing a measuring instrument involves sensing the phenomenon of interest and then comparing it with a standard measurement scheme to give an output in units of the agreed standard. The problem with developing an instrument for design thinking is twofold:

1. Design thinking is a complex socio-technical activity that is largely dependent on human interaction and language, which makes sensing the phenomenon inherently subjective.
2. There are no agreed upon standards for specific parameters of design thinking.

Developing an instrument for design thinking involves both designing a sensing device and developing a measuring standard for the phenomenon being measured. The development of a measuring standard would require numerous studies of the design thinking parameter being measured over a number of different contexts to map out a spectrum of variation and determine benchmarks that could be consistent across the different instances. This substantial research effort would benefit from first developing a sensing device that could represent the design parameter being studied in a manner that facilitates analysis. Thus, the first step towards developing a measuring instrument for design thinking is to develop a sensing device. In this chapter, we present the development of such a sensing device for measuring the development of concepts, decisions, or frames through interpersonal interactions in a design team.

4 Interaction Dynamics Notation as a Design Instrument

The Interaction Dynamics Notation (IDN) is a visual notation that models interpersonal interactions in the context of a design activity, such as concept generation, framing of user need, or design reviews (Sonalkar et al. 2013). The relevant parameters that we want to analyze being developed through such design interactions can be highlighted in the IDN output.

The theoretical foundations of IDN are based on cognitive semiotics and theatrical improvisation. The domain of cognitive semiotics employs a notation called as the Force Dynamics Notation (Talmy 1988) that visualizes the meaning conveyed by phrases such as “she let him down” (Brandt 2004, page 42). The Force Dynamics Notation visualizes the meaning in a phrase as a narrative plot, where actors experience forces like “letting down” that affect their narrative journey. Interactive Dynamics Notation, or IDN, adapts this notation for design interactions. In its current implementation, IDN captures the meaning conveyed in a speaker turn—verbal or non-verbal—in terms of the force it has on the subsequent response. For example, we say designer A asked a question, not because of the intonation in her tone, or her inferred intention, but because a team member B responded to A as if answering a question. If no one responds to A, her turn is not coded as a question.

IDN consists of 12 symbols. The original IDN set of symbols, published earlier, has evolved over time through new experiments and further research. They now include ignored and ambiguity. Deviation and interruption are no longer in the symbol set. The current set of IDN symbols are outlined in Table 1.

Consider an instrument based on the Interaction Dynamics Notation. Let’s call it an IDN instrument. The IDN instrument takes a conversation from video data and converts it into a visual representation of a sequence of symbols. Further, relevant design parameters are highlighted in the representation to analyze design relevant constructs emerging through conversation. For example, in concept generation activity, the responses can be highlighted to map out how concepts are co-created through interpersonal interactions. Figure 1 shows the operations that constitute the

Table 1 The symbols that comprise the interaction dynamics notation

Move A A "move" indicates that a speaker has made an expression that moves the interaction forward in a given direction.	Question ? A A question indicates an expression that elicits a move.	Silence Silence is a state in the conversation when none of the participants speak as they are engaged in other individual level activities.	Block C Block indicates an obstruction to the content of the previous move.
Support for move B Support-for-move indicates that the speaker agrees with and supports the previous move.	Support for block C Support indicates an acceptance of a block by another person.	Overcoming B C Overcoming a block indicates that though a block was placed in front of a move, a speaker was able to overcome the block and persist on course of the original move.	Deflection A B When a speaker blocks a previous speaker's move, that speaker or another can deflect the block with a move that presents an alternative direction for the interaction.
Yes and C A move is considered to be a "Yes and" to the previous move if it accepts the content of the previous move and adds on to it.	Humor A,B Humor indicates instances of shared laughter in teams.	Ignored A Ignored implies that speaker A's utterance was actively ignored by others on the team.	Ambiguous X Ambiguous denotes a researcher's inability to assign a symbol to that speaker utterance due to improper audio/video or indistinguishable speech.

IDN instrument. The instrument takes video data as input and, as output, gives the sequences and times of occurrence (or event time) of the 12 IDN symbolized interaction responses. The instrument achieves this conversion by first identifying speaker turns in video data. Then multiple analysts code the speaker identified video data with IDN *individually*. Their individual outputs are checked for data reliability and inter-analyst agreement. If found to be reliable and containing a relatively high level of agreement between analysts, the analyst output is considered as the instrument output. If the analysts' output is not found to be reliable, analysts collectively code the video as a team to identify and resolve disagreements.

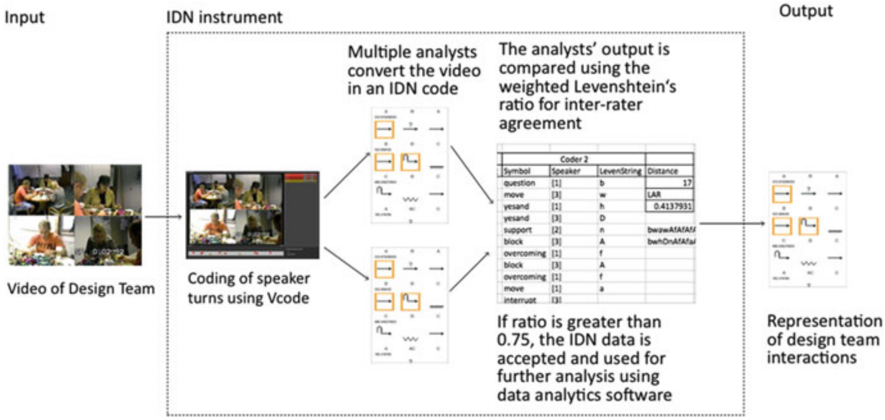

Fig. 1 The operations that constitute the IDN instrument

5 Stages of Development for the IDN Design Instrument

Transforming IDN from a visual notation to an instrument involved developing a reliable and efficient process for converting video of team interactions into an abstract representation of interaction patterns. As of today, assigning IDN symbols to speaker turns in a design team video cannot be accomplished computationally because of the variability of human conversation and the need to analyze participant responses in relation to each other. The coding of video into IDN symbols requires human judgment. Hence, a reliable and efficient human analyst is essential in the development of a process to convert design team video into IDN representation. The following processes were developed to hire and train undergraduate students into reliable and efficient IDN analysts.

5.1 Hiring and Training Analysts

5.1.1 Hiring of IDN Analysts

The guiding questions for developing a hiring process for people to become IDN analysts were:

1. Does a person need to have specific aptitude to be an IDN analyst?
2. How might we test the aptitude of candidates for IDN analyst positions?

We took the Emotion Coding Lab[1] established by Janine Giese-Davis at the Stanford Psychiatry Department as a role model. The Emotion coding lab trained

[1] http://stressandhealth.stanford.edu/people/giese-davis.html

students to code video data with specific coding schemes; students categorized the moment-to-moment emotion responses of the participants in the video. The lab screened applicants through an interview process involving video observation. Applicants who could detect emotions of people in their lay description of events occurring in the video were hired as coders, and applicants who tended to focus on words and did not notice emotions were not hired for coding emotions. Considering the coding of the Interaction Dynamics Notation, we identified the following aptitude parameters as prerequisites for becoming an IDN analyst:

1. Motivation to study innovation and design thinking
2. Curiosity to understand teamwork
3. Ability to concentrate on video data for long intervals of time
4. Ability to detect resistance to ideas expressed in the video. IDN codifies this resistance as a block.
5. Ability to identify "building on" of ideas. IDN codifies this as yes-and.
6. Sensitivity to non-verbal gestures and movements.

These parameters were tested in an interview process, which included asking candidates to describe what they noticed in specific video clips by highlighting interactions with blocks, yes-and, and non-verbal gesturing. The candidates who could correctly identify these interactions, and who showed motivation to study teamwork and design thinking, were selected for IDN analyst positions.

5.1.2 Training of IDN Analysts

The candidates who joined as IDN analysts participated in an 8-h training program followed by 2 weeks of individual practice on video clips of varying levels of complexity. Interspersed in the training were consensus coding sessions where the entire group, including the research team, coded a video together. Table 2 describes the activities conducted and the rationale for including them in the training program.

After their training, the analysts were given video data to code with IDN. They submitted the coded video files and IDN outputs files back to the research team, which were compared with the codes from different analysts to ensure data reliability.

5.2 Improving Reliability of Coding

Since the conversion of video in an IDN representation required human analysts to code the video, there was a need to design ways to ensure that inter-coder reliability so that the instrument output does not vary from one analyst to another. The following reliability measures were developed over multiple iterations of using and refining the IDN instrument.

Table 2 IDN Training program elements

Activity	Description	Rationale
Experiencing interactions	Participants engage in improve games such as sound ball, "I am a tree," "Yes Let's," and word-at-a-time story. Participants also practice concept generation with response constraints such as saying no, yes-but and yes-and.	These activities enable IDN trainees to have an experiential understanding of the concepts that we use in IDN.
Using interaction metaphors to describe design conversation	Participants are exposed to the role of metaphors in concept formation. They are asked to draw a metaphor for design conversations that they have participated in the past, and then share with the group.	Following Lakoff and Johnson (2008), metaphors are key to how we form concepts. Asking IDN trainees to engage in developing their own metaphors for conversations helps them conceptualize from their own experience. This activity in turn sensitizes them to how IDN was developed as a notational scheme.
Introduction to IDN	Participants learn how and why the Interaction Dynamics Notation was developed and what the different symbols of IDN are. They are also introduced to the IDN Tool.	This session is a formal introduction to IDN as a visual notation.
Consensus coding	IDN trainees and instructors code video clips together using the Interaction Dynamics Notation.	Consensus coding helps trainees learn how to assign IDN symbols in a social setting that facilitates peer learning.
Individual practice	IDN trainees code video with the IDN Tool and then check their work against the IDN output previously coded by the instructor. The video clips are of varying levels of difficulty. The trainees do not advance to next level until their earlier level output matches the benchmark.	Individual practice helps trainees in building expertise.
Professional vision session	Once the trainees have practiced IDN for 2–3 weeks, they discuss what makes them effective as IDN analysts. They share what they look for in video data, how they deal with maintaining attention on video, and describe their biases and difficulties as IDN analysts.	Describing how they code video as IDN analysts makes them aware of what goes into being a professional IDN analyst. The professional vision, which encapsulates how analyst should behave, is shared amongst the group of analysts.

5.2.1 Developing a Data Reliability Metric

We approached the task of finding a suitable inter-observer agreement metric as a design problem, starting with the design requirements. We identified the following requirements:

1. The metric needs to calculate agreement at the sequence level instead of at each individual position level.
2. The metric needs to be based on known statistical measures with proven usage.
3. The metric needs to be easy to use.

With these requirements in mind, we evaluated the inter-observer agreement metrics commonly used in psychology and education research that routinely uses human coders. Researchers currently use a number of different inter-observer agreement metrics to compare the data of human analysts. These range from simple percentage agreement to more sophisticated metrics such as Cohen's Kappa (Cohen 1960; Hubert 1977), which takes into account chance agreement. However, on detailed evaluation, these metrics did not meet the criteria of calculating agreement at the sequence level instead of at individual position level. For example, metrics like Cohen's Kappa measure agreement at the level of each individual position, as explained as follows.

If we have a pair of sequences "abcdeabcdeabcde" and "bcdeabcdeabcdea," Cohen's Kappa will give perfect disagreement since it will detect that each place in the first sequence does not match with the corresponding place in the second sequence. However, if we analyze the pair at a sequence level, we see that sequence 2 is an offset of sequence 1 by just the letter "a," which has been moved from the beginning of the sequence to the end of it. Since IDN notation needs to be compared at a sequence level and not at the level of each position in the sequence, we needed a different metric.

On conducting further literature review to study domains that deal with sequence level comparisons, two disciplines emerged as promising: computational linguistics, which involves alphabetic string comparisons such as spell checkers, and bioinformatics, which matches genetic sequences. Both fields used a basic algorithm to calculate the Levenshtein's Distance or Edit Distance between two sequences: the number of insertions, deletions or substitutions required to convert one sequence into another (Yujian and Bo 2007). For example, it takes 2 substitutions and 1 deletion to convert the sequence SITTING into KITTEN (substitute K for S, E for I, and delete G). Hence, the Levenshtein's distance between SITTING and KITTEN is 3. We found that Levenshtein's distance meets our criteria for measuring inter-observer agreement for IDN. Since IDN is a string of symbols, it can be easily converted into an alphanumeric form and then two sequences can be compared using the standard Levenshtein's distance algorithm. To further normalize the metric, we developed the Levenshtein's Agreement Ratio (LAR) which is defined as (length of longest sequence—Levenshtein's distance between them)/ length of the longest sequence. The LAR value for the above example of SITTING and KITTEN is 0.57. The value of LAR varies between 1 for perfect agreement to 0 for perfect disagreement. After evaluating the acceptable values for various other metrics, a minimum LAR value of 0.7 was considered acceptable for IDN data.

A custom defined function was created in Microsoft Excel to calculate LAR for IDN sequences. However, on further testing with actual IDN data coded by analysts, we realized that a weighted Levenshtein's distance (Ziółko et al. 2010) could be used since some symbol mismatches do not have much impact on further analysis. For example, missing an interruption symbol is of lower consequence than missing a block. Hence, a weighted Levenshtein's Agreement Ratio (wLAR) was developed by considering a lower penalty for disagreements regarding missing interruption, substituting block with overcoming, block with block-support, deflection with overcoming, yes-and with yes-and-question and support with yes-and. The same acceptable value of at least 0.7 was retained for wLAR.

5.2.2 Refining IDN Symbol Set and Rules

The wLAR range for acceptable IDN data was between 0.7 and 1. However, the analysts frequently produced IDN output that measured between 0.4 and 0.6. On examination of the IDN sequences that varied beyond the acceptable range, we observed that analysts often disagreed in assigning speaker turns, and in coding of specific symbols such as 'support' and 'deviation'. Hence, we re-evaluated the rules of the IDN symbol set to better model design team interactions, and improve the reliability inherent in the rules of the symbols. The rules of some of the symbols such as 'support' were modified to remove elements that influenced disagreements. The symbol 'interruption' was eliminated, as it did not have an as much impact on the final model as expected. We added symbols 'ignored' and 'ambiguous' to model conversations more accurately. This refinement of the IDN symbol set and rules helped increase the wLAR value to 0.7–0.75.

6 Developing Requirements for IDN Instrument User Interface

Our objective in developing the IDN instrument was not just to measure design thinking team interactions, but also to influence their interactions to improve performance. The IDN instrument thus required a user interface that could provide designers with readouts that are relevant and useful to their team performance. In this section, we describe three studies performed with the IDN instrument to understand what kind of instrument feedback design teams find useful and relevant. The studies were designed to vary on three different dimensions: in-situ versus in-lab recording, delayed versus real-time feedback, and human-mediated versus direct feedback.

6.1 Study 1: Lab-Based Human Mediated Delayed Feedback

This study was conducted in collaboration with a graduate level course on creativity and innovation at the Hasso Plattner Institute for Design (d. School) at Stanford University. The instructors had given a 3-week project to seven student teams. The researchers worked with these seven teams to record a video of their on-going design conversations in a lab setting, and then gave them an IDN report of their team interactions within a period of 5 days. We recorded a 30-min video segment of team activity, and analyzed 15 min of the video segment using IDN instrument. From each team's IDN data, a few significant response types were identified and codified in a report format. Figure 2 shows the IDN feedback report of one of the teams, which were handed out to each team in a class session. The researchers explained their analysis for about 10 min and enacted a few interactions. Thereafter, teams had 10 min to discuss the reports with their team members. The reports contained some observations and guiding questions for discussing these observations within the team. The class session ended with an open Q&A session with the researchers. As per their class practice, the students submitted written reflections on the feedback session, which the instructors shared with the research team.

The session reflections showed the impact the feedback session had on some of the students. Below are few of the reflections noted by the students.

<<Team photo with A, B, C identifiers>>

Out of the 30 min interaction session, 15 min of video were analyzed using the Interaction Dynamics Notation.

A. Response Types Occurring in Interaction

	A	B	C	Total
Move	15	17	30	62
Question	3	17	6	26
Support	25	16	18	59
Humor	6	5	6	17
Yes And	3	10	10	23
Block	1	1	2	4
Overcoming	0	0	0	0
Deflection	1	2	0	3

Your team showed a large amount of humor i.e. your team had the maximum instances of laughter among all the teams analyzed. This behavior, along with support, exhibits a high level of group cohesion. Your group also asked a large amount of questions. Asking questions can help lead to more concept generation and more deep reasoning.

The few blocks that were observed in your team were met with deflection, rather than overcoming. Deflection implies accepting a block and suggesting alternative ideas. Overcoming implies rejecting a block and persisting in the original idea. Block-overcoming interactions can seem argumentative and are associated with deep reasoning through argumentation.

Discussion Questions:

How do you encourage your teammates' ideas?
Have you experienced argumentation as a means to deep reasoning in your team interactions?

B. Team Roles based on interaction responses observed

Supporter: Person A

Supporting behavior is key to maintaining group cohesion. In the Interaction Dynamics Notation, supporting behavior is identified through back-channeling behavior, positive acknowledgment, and indications of approval.

Questioner: Person B

Question-asking has been correlated with design performance in prior research studies. We identified the people who exhibited greater question-asking behavior as questioners.

Discussion Question: Do you sense these roles in your team? Who do you believe plays these roles in your team?

C. Balance of Contribution

Persons B and C were more active during the team interaction than person B.

We calculated the aggregate number of IDN responses, excluding humor and support, to arrive at the individual contribution of each team member.

	A	B	C
Contribution	23	47	48

Prior research on collective intelligence has indicated that balanced team contributions in general are correlated with higher performance. However, there is no research specific to design thinking teams on this topic.

Discussion Question: What do you think about the balance of individual contributions in your team? Are you okay with the current contribution levels?

Fig. 2 IDN instrument based feedback report

"... the experiment... gave us a very clear picture of how we work and interact with each other... Among the things that we are considering is transitioning from the "blocking method" to the "deep questioning method" of approaching the problem and see which one works best for us."

"I also was slightly skeptical about the CDR report given that it focused on the quantity of specific contributions from team members, disregarding quality completely."

"I also appreciated the analysis... about our group. The conclusion of its analysis was that I am more a questioner than someone who moves things. So I'm glad to know that and in the future I'll try sometimes to move things on instead of asking deep questions."

Overall, the research team noticed that most students accepted the feedback as a reflection of themselves as individuals, rather than one data point in the dynamic process of teamwork. The nature of the feedback report with an emphasis on individual contribution and numerical analysis versus sequence analysis could have contributed to this effect.

6.2 Study 2: In-Situ Human Mediated Delayed Feedback

Two student teams from ME310, a graduate level course in Engineering Design at Stanford University, were selected for this study. Video of the team's activity was recorded in-situ in the ME310 studio. The teams called the researchers to record their on-going activity when they were engaged in their design project discussions. Researchers analyzed the video using the IDN instrument and conveyed findings from the analysis back to the teams with a 2-week delay. Figure 3 shows screenshots from the video recording of the two delayed feedback teams.

This feedback session was followed by an interview in which the researchers asked about the teams' perception about the feedback. The teams reported the following perceptions about the feedback they received.

1. The teams felt the feedback was as expected, without any surprises. The students had noticed similar tendencies in their team behavior and the feedback validated what they had noticed before.
2. The teams felt the feedback was not useful since the conversation occurred 2 weeks prior to feedback. Most students did not remember the conversation.
3. When asked as to what kind of feedback the teams would consider meaningful, one of the teams mentioned they needed more information about specific methods for concept generation rather than feedback on their interactions.

When giving feedback, the research team noticed the following:

1. It was difficult to give normative feedback since the naturalistic conversations of the team did not pertain to a specific design phase such as concept generation or

Fig. 3 Video stills from the design team sessions recorded in-situ

decision-making. The conversations touched upon a number of aspects including coordinating logistics, generating concepts, and clarifying plans.
2. The researchers were cautious not to bias the team with normative feedback about beneficial or detrimental interaction patterns since the patterns studied earlier might not be applicable to the teams' context.

6.3 Study 3: Direct Real-Time Feedback

This study was conducted with two student teams in ME310, a graduate level course in Engineering Design. Real-time feedback was implemented by having the researchers sit next to the teams being analyzed. The researchers coded the interactions of the teams as they were occurring in an excel sheet on the Google Documents platform that was linked to a graph. This graph changed in real-time as the researchers coded IDN; the team could see the graph on a laptop screen set in front of them. These real-time sessions were video recorded as well, for future analysis. Figure 4 shows the real-time setup and Fig. 5 shows the graphical feedback display visible to the teams.

The real-time display showed a bar graph with three categories: generative behaviors, deep-reasoning behaviors, and team cohesion. We obtained these categories by combining several IDN symbols, as we believed that showing the IDN representation would be complicated for design teams to understand in real-time.

An interview with team, in which the researchers asked about the teams' perception of the feedback, followed the real-time feedback session. The teams reported the following:

1. The team members were aware of the display and they glanced at the display at times, but did not know what to do with the information displayed.
2. On a scale of 1–5, 1 being no difference, 5 being significant difference; the teams rated the display as 1 to 2. It made little to no difference to the on-going conversation.
3. A few team members mentioned they would prefer a personalized display that showed their behavior parameters rather than a team level display of interaction information.

Fig. 4 In-situ real-time feedback display for design teams

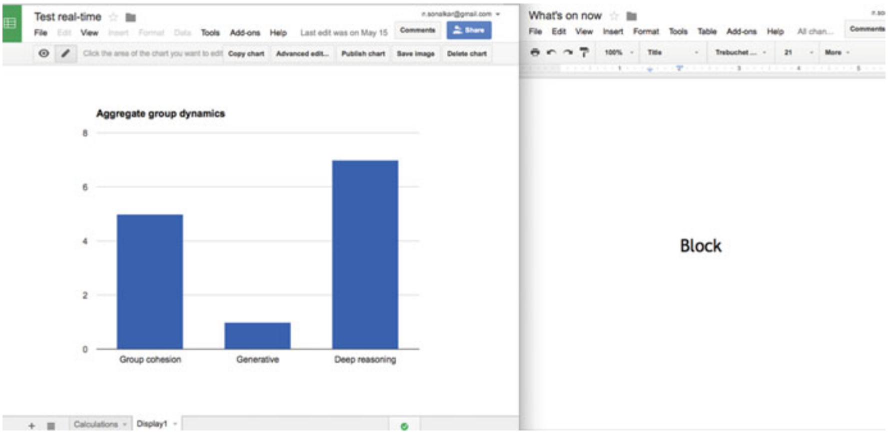

Fig. 5 The display showed a bar graph of three categories and in-the moment coding of IDN in the form of words flashed on the screen

4. One team reported that they had an implicit desire to see all the bar graphs grow equally. They felt unhappy if one of the bars was low.
5. One participant mentioned he would like to see a graphical display that showed both positive and negative progress. He felt if the feedback showed negative progress then it would be more relevant to the team.
6. Most team members felt they needed feedback that was actionable. The current feedback did not come with what they should do when they saw the parameters vary.

The research team when giving feedback noticed the following:

1. The researchers could just barely keep up with the conversation. It was important to be able to hear well, which was difficult since the studio environment was noisy. Hence it is likely that some complex symbols like ‘block-overcoming’ and ‘yes and’ were missed.

2. Due to heavy cognitive effort, the researchers could perform real-time IDN analysis for at the most up to 20 min at a time.

This study indicated that the design teams did not perceive real-time feedback to be useful, largely because they did not consider the feedback to be relevant and actionable. The real-time feedback was cumulative and the teams reported that perhaps negative feedback could be more relevant to them in real-time. Though teams did not perceive the feedback to be particularly useful, the study uncovered potential directions for further inquiry such as personalized feedback and variation in the graphical representations of the feedback.

6.4 IDN Instrument User-Interface Design Requirements

The three studies described in this section point to the following design requirements for developing a user interface for an IDN instrument.

1. Timeliness: The feedback needs to be given in a timely manner so that the team has the opportunity to understand it and act on it. Teams consider delayed feedback to be less useful. The studies indicate that feedback given just after a design session, or up to a 5-day period after the session, may be useful to the design teams.
2. Non-disruptive nature: The feedback should not disrupt the flow of the design team interactions unless the designers themselves or the severity of the situation call for it.
3. Lucidity: The feedback needs to be presented in a manner that designers can understand in a short period of time. The cognitive effort to understand feedback should not disrupt the ongoing design activity.

Besides the requirements for the IDN instrument user interface, the studies also revealed that the design teams receiving feedback need to be prepared beforehand. The design teams need to be given a mental model of how to do design with interaction feedback. The design teams need to have the skills to both understand the feedback and to act on it. Feedback cannot be presented as an afterthought; it should be integrated in the routine processes of design thinking.

7 Next Steps in Design Thinking Instrumentation

In this chapter, we described the on-going development of the IDN instrument for measuring design thinking team interactions. The first step in developing the instrument was to create a sensing system to convert actual team interactions into a representation that can be then compared with a measurement standard. The sensing system was successfully developed and was further used with design teams to generate a set of requirements for developing a user interface. However, while conducting these studies, it became clear that the next most significant step is the development of a measurement standard so that the instrument output given to users can perceived as relevant and useful.

Design thinking is a context dependent activity. Context parameters such as the nature of the problem, its domain, the expertise of team members, and the diversity of the team can potentially play an important role in influencing the team interaction behaviors that count towards innovative product outcomes in a design team. The measurement standard to be developed would need to take these context parameters into account. Therefore, the next step in developing a measurement standard is the characterization of design context and a descriptive model of high performance design team interactions associated with relevant context parameters.

The sensing system, a user interface, and a measurement standard that takes into account design context would together constitute a scientific instrument for design thinking. Instrumenting design thinking teams has the potential to transform design thinking from a purely heuristics driven activity to an activity where scientific knowledge is employed to provide relevant feedback that augments human ability to achieve innovative outcomes reliably and efficiently.

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