The DX9 Model

A communicative drive model for adaptive AI-based dialog systems

Date: 2025-02-11

Table of Contents

1. Introduction
2. Theoretical starting point
3. Empirical basis and method
4. Drives as an analytic level
5. The dimensional structure of the DX9 model
    - 5.1 D1: Orientation toward authority (S/O/L)
    - 5.2 D2: Regulation principle (R/F/K)
    - 5.3 D3: Energy and expression (I/N/E)
6. The 27 DX9 types as a system variable
7. Comparison with established models
    - 7.1 Big Five (OCEAN/FFM)
    - 7.2 MBTI
    - 7.3 The Enneagram
8. DX9 in relation to language and communication
9. Implications for AI and chatbot design
10. Strengths and limitations of the model
    - 10.1 Strengths
    - 10.2 Limitations
11. Positioning in the research landscape
12. Conclusion
13. References

Appendix A: DX9 typology - type names and descriptions

Appendix B: The DX9 cube (3x3x3) - illustration and reading guide

Appendix C: DX9 type coding for systems/AI (schema + scoring)

- C.1 Coding
- C.2 Recommended data schema (JSON)
- C.3 Scoring principle (online, probabilistic)

1. Introduction

The development of AI-based dialog systems has made the form of communication a central design question. In text-based interactions, user trust and perceived relevance often emerge long before the substantive issue has been fully resolved. Research in human-computer interaction shows that people tend to treat technical systems as social actors and apply social rules to them, even when they know the system lacks human intentions (Reeves & Nass, 1996; Nass & Moon, 2000). In a chatbot setting, this means that forms of address, degree of guidance, structure, affirmation, and tempo quickly become decisive.

DX9 is constructed for a bounded goal: enabling adaptive communication in dialog systems by identifying stable communicative drives and their typical linguistic needs. The model comprises 27 types (3x3x3) and builds on long-term collected survey data and linguistic distinctions in how people express themselves and how they want to be approached. The practical benefit is that an AI can infer (estimate) a probable type from text and then steer language form and dialog policy accordingly.

2. Theoretical starting point

DX9 rests on two theoretical assumptions.

A) Rapid social judgment in the surface of language. Significant parts of human reception happen quickly and partly automatically, before more reflective, conscious reasoning dominates (Bargh & Chartrand, 1999; Kahneman, 2011). Therefore, small differences in language form (e.g., imperatives, politeness, freedom of choice) can have disproportionate effects on acceptance.

B) Dialog with systems is socially interpretable. The Media Equation and subsequent research show that users often respond socially to computers and interfaces (Reeves & Nass, 1996; Nass & Moon, 2000). This implies that chatbot design should be seen as a social-psychological and pragmatic task: the system does not need to be human, but it must avoid communication forms that are experienced as illegitimate given the user's drives.

DX9 therefore aims to provide an operational model for how an AI should phrase itself, rather than a broad theory of who a person is.

3. Empirical basis and method

DX9 is based on approximately 45,000 web surveys collected over roughly 30 years, where recurring linguistic distinctions and preferences have been identified. The material reveals relatively stable patterns in how people formulate needs for (i) autonomy/authority, (ii) regulation (relation-flex-control), and (iii) energy/expression.

The approach is close to research showing that personality and individual variation can leave measurable traces in language (Mairesse, Walker, Mehl, & Moore, 2007), as well as research on linguistic convergence/accommodation in text dialog, where style matching can be observed in large datasets (Danescu-Niculescu-Mizil, Gamon, & Dumais, 2011). For dialog systems, this is crucial: a type can be estimated online without requiring the user to fill in a test.

4. Drives as an analytic level

DX9 emphasizes that the model's primary object is not behaviors or higher cognitive functions, but drives. The distinction is practically important:

- Behavior is observable but often strongly situation-dependent.
- Higher cognition (explicit argumentation, values, strategy) can be consciously regulated and culturally shaped.
- Drives (in DX9's sense) are more basic regulators: needs linked to safety, legitimacy, and how decisions and processes should be held together in dialog.

This aligns with motivational research where basic needs influence the experience of autonomy, relatedness, and competence, which in turn affects motivation and well-being (Ryan & Deci, 2000). DX9 does not claim to replace established motivation theories; it uses the drive level for a more operational purpose: steering language parameters in chatbot dialog.

In chatbot contexts, this provides a strategic advantage: adaptation can be done via text signals in the moment, which can reduce the need for privacy-sensitive user profiles.

5. The dimensional structure of the DX9 model

DX9 consists of three orthogonal dimensions with three modes each.

5.1 D1: Orientation toward authority (S/O/L)

D1 describes what kind of legitimacy and guidance is tolerated and requested.

- S - Self-directed (Självständig): safety via autonomy and one's own decision. Advice should be presented as selectable perspectives.
- O - Independent/Objective (Oberoende): safety via overview, goals, and neutral analysis. Authority is assessed instrumentally.
- L - Loyal/Aligned (Lojal): safety via belonging, stability, and legitimate guidance. Clear frames can reduce uncertainty.

Design implication: D1 governs the degree of directiveness demonstrated and how much the system needs to legitimize its recommendations.

5.2 D2: Regulation principle (R/F/K)

D2 describes how the individual wants dialog and decisions to be held together.

- R - Relation: regulation through social attunement, affirmation, we-language, and consideration.
- F - Flexibility: regulation through options, freedom of choice, and situational adaptation.
- K - Control: regulation through explicit frames, steps, criteria, responsibility, and conditions.

D2 can be linked to pragmatics and politeness theory: how to reduce threats to autonomy (face) through indirectness, options, and mitigation (Brown & Levinson, 1987). In practice, it is about how the system balances social support, degrees of freedom, and structure.

5.3 D3: Energy and expression (I/N/E)

D3 describes the dialog tempo and expression in text.

- I - Introverted: prefers low exposure, precision, time to think.
- N - Neutral: situation-driven, functional, balanced tone.
- E - Extroverted: processes through dialog, higher interactivity, more forward drive.

Language-personality research shows that certain dimensions (extraversion, etc.) often leave measurable traces in text (Mairesse et al., 2007), which makes D3 possible to infer continuously.

6. The 27 DX9 types as a system variable

The combination of D1, D2, and D3 yields a code, e.g., O-F-N. A central point of DX9 is that the code can be directly mapped to system parameters: prompting, response templates, safety strictness, question style, length, and tempo.

For implementation, the type should be handled probabilistically (soft classification), updated over time, and allowed to be local to context (a person may sound more K in a risky task than in small talk). This is consistent with the user-modeling tradition where user models are dynamic (Kobsa, 2007) and with modern overviews of user modeling/profiling (arXiv, 2024).

7. Comparison with established models

7.1 Big Five (OCEAN/FFM)

Big Five is psychometrically strong and broadly established (Costa & McCrae, 1992). In chatbot design, however, a translation problem arises: the trait profile is not itself a dialog policy. DX9 is constructed to provide a short path from type to language parameters.

DX9 strength relative to Big Five: an operational focus on the form of communication and real-time inference from language.

7.2 MBTI

MBTI provides clear categories but is contested in psychometric research. Regardless, a practical issue remains: MBTI is often a test result, not an online signal in ongoing text dialog. DX9 is explicitly intended to be inferred in the dialog and used directly in generation and dialog control, in line with NLP research on text-based personality inference (Mairesse et al., 2007).

7.3 The Enneagram

The Enneagram is motivation-oriented and can feel communicatively intuitive, but it is often narrative and less standardized for algorithmic inference. DX9 avoids extensive narrative and instead uses three concrete regulators that can be connected to linguistic choices.

8. DX9 in relation to language and communication

DX9 can be understood as an operationalization of three communicative control dials in dialog: legitimacy/authority (D1), regulation (D2), and tempo/expression (D3).

This has a clear parallel to Communication Accommodation Theory, where actors converge/diverge in language style depending on social goals and relationships (Giles & Ogay, 2007). Large-scale studies show that accommodation can be measured even in text-based environments (Danescu-Niculescu-Mizil et al., 2011). DX9 provides a more design-oriented vocabulary for making such accommodation systematic.

DX9 can also be linked to grounding theory: how parties establish what is sufficiently understood to move forward (Clark & Brennan, 1991). D2 can be seen as a heuristic here: some users require relational attunement (R), others freedom of choice (F) or explicit structure (K) to experience understanding as safe.

9. Implications for AI and chatbot design

Psychologically and practically, it is well documented that personalization can increase perceived relevance and trust, but that it must be balanced against privacy, control, and creepiness (Komiak & Benbasat, 2006; research on proactive dialog systems: Deng et al., 2025). Within conversational AI there are also reviews on personality/persona/profile in chatbots and personality-adaptive chatbots (Ait Baha et al., 2023; Sutcliffe, 2023).

DX9's design advantage in this landscape:

- Adaptation can be linguistic rather than data-driven (minimizing the need for sensitive profiling).
- The model is parameterizable: it can steer length, structure, directiveness, politeness, affirmation, and tempo.

Example: parameter mapping (principle level)

- R: more affirmation, more relational markers, we-language, softer phrasing.
- F: more options, questions that open choice, clear ability to change direction.
- K: step-by-step, criteria, consequences, summaries, checkpoints.
- S: less normative tone, more you choose.
- L: clearer guidance and stable frames, legitimation via safety/stability.
- I/E: short pauses or reflection questions (I) versus more interactive drive (E).

For proactive systems (that take initiative), this becomes especially important: the same initiative can be experienced as help or intrusion depending on the drive pattern (Deng et al., 2025).

10. Strengths and limitations of the model

10.1 Strengths

- Operational linkage to dialog policy. The model is built to be a control variable in generation and dialog steering.
- Language-proximate inference. Compatible with research showing that individual variation can be read from language (Mairesse et al., 2007).
- Theoretical compatibility. Fits well with HCI findings on social response to systems and with theories of accommodation/grounding (Reeves & Nass, 1996; Nass & Moon, 2000; Giles & Ogay, 2007; Clark & Brennan, 1991).
- Drive focus. Targets motivation/safety regulation rather than observed behavior or higher cognition, which is practical in short dialogs.

10.2 Limitations

- DX9 is not clinical diagnostics and should not be used as such.
- Typing from text is always uncertain and should be probabilistic and updateable (Kobsa, 2007; arXiv, 2024).
- Context can temporarily shift expression (e.g., more K under stress or risk). The system should therefore model both baseline profile and situational state.

11. Positioning in the research landscape

DX9 can be positioned as a communicative drive model at the intersection of behavioral science, pragmatics/sociolinguistics, and human-AI interaction. It complements trait models (Big Five) by having dialog form as the primary unit of analysis and by prioritizing what can be detected and used in real time.

At the same time, it aligns well with the growing research on personality and persona in chatbots and the need for systematic frameworks for adaptive dialog (Ait Baha et al., 2023; Sutcliffe, 2023), as well as broader development toward more proactive and planning conversational AI (Deng et al., 2025).

12. Conclusion

DX9 shifts the focus from describing personality as a general trait to modeling the communicative conditions for dialog to be experienced as safe, legitimate, and effective. In chatbot settings, this is often more actionable than broad typologies: if the form misses the drive level, the system is experienced as wrong even when the content is correct. With a 3x3x3 structure, language-proximate inference, and direct linkage to dialog parameters, DX9 offers a practical framework for adaptive AI dialog systems.

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Appendix A: DX9 typology - type names and descriptions

Each type = D1 (S/O/L) x D2 (R/F/K) x D3 (I/N/E). The descriptions refer to communicative drives and preferences in text-based dialog.

S-R-I - Autonomous reflector: seeks relational harmony without being guided; low exposure; large interpretive space.

S-R-N - Self-directed relationship navigator: relationship matters but on one's own terms; balanced expression; dislikes directives.

S-R-E - Self-directed relationship driver: actively builds relationships without hierarchy; wants dialog, not instructions.

S-F-I - Self-directed experimenter: explores quietly; wants options, not recommendations.

S-F-N - Adaptive individualist: flexible and selective; appreciates open answers and freedom of choice.

S-F-E - Innovative initiator: driven by possibilities; wants inspiring, non-directive language.

S-K-I - Self-directed system critic: accepts structure if rational; factual, low affect.

S-K-N - Principle-based individualist: clear frames but personal decision; neutral, precise communication.

S-K-E - Confrontational autonomous actor: openly challenges control; clear but non-authoritarian language.

O-R-I - Analytical relationship observer: wants to understand relational connections; low exposure, high clarity.

O-R-N - Strategic coordinator: values interplay in the whole; balanced, goal-oriented tone.

O-R-E - Communicative strategist: leads through dialog; appreciates context and purpose.

O-F-I - Reflective optimizer: waits for data; wants choices without pressure.

O-F-N - Classic strategist: seeks the best route; neutral, structured communication.

O-F-E - Change leader: drives improvement; options linked to goals.

O-K-I - Systems analyst: prefers clear models; low affect, high precision.

O-K-N - Structural decision-maker: wants frames and consequences; factual, comparative tone.

O-K-E - Goal and process driver: accepts steering if logical; clear steps toward goals.

L-R-I - Relationship-bound safety seeker: needs affirmation; low exposure; warm tone.

L-R-N - Social stabilizer: seeks belonging; inclusive, calm language.

L-R-E - Group-oriented communicator: engaged by community; clear social signals.

L-F-I - Cautious adapter: dislikes pressure; gentle choices and safe context.

L-F-N - Pragmatic follower: adapts if it feels safe; simple, supportive tone.

L-F-E - Social adaptation agent: absorbs norms through dialog; encouraging guidance.

L-K-I - Rule-based safety custodian: preference for fixed frames; clear instructions, low affect.

L-K-N - Stable implementer: follows proven steps; factual, affirming.

L-K-E - Norm-transmitting authority carrier: communicates/follows norms; clear leadership plus affirmation.

Appendix B: The DX9 cube (3x3x3) - illustration and reading guide

DX9 is visualized as a cube where each axis has three modes. A type is a point in the cube.

- D1 (S/O/L): S -> O -> L
- D2 (R/F/K): R -> F -> K
- D3 (I/N/E): I -> N -> E

Practical reading in a system:

18. Estimate D1 (how recommendations and authority should be packaged).
19. Estimate D2 (how the dialog should be regulated: relation, choice, or structure).
20. Estimate D3 (tempo/expression: reflective, balanced, or dialog-driven).

Figure 1. Illustrative DX9 cube (3x3x3) with dimensions D1, D2, and D3.

Appendix C: DX9 type coding for systems/AI (schema + scoring)

C.1 Coding

DX9 code = D1-D2-D3, e.g., O-F-N.

C.2 Recommended data schema (JSON)


```json
{
  "dx9": {
    "d1": {"label": "S|O|L", "prob": {"S": 0.0, "O": 0.0, "L": 0.0}},
    "d2": {"label": "R|F|K", "prob": {"R": 0.0, "F": 0.0, "K": 0.0}},
    "d3": {"label": "I|N|E", "prob": {"I": 0.0, "N": 0.0, "E": 0.0}},
    "type": {"label": "S-R-I", "confidence": 0.0},
    "evidence": {
      "features": {},
      "last_updated_turn": 0,
      "window_tokens": 0
    }
  }
}
```


C.3 Scoring principle (online, probabilistic)

Use a sliding-window logic (e.g., the last 800-1500 tokens) and update probabilities with a simple logit/score model.

Examples of text features (language signals)

- Imperative frequency ("do", "must", "should").
- Modality/hedges ("maybe", "possibly", "could").
- Question ratio (questions per sentence).
- Structure markers ("step 1/2", lists, checkpoints).
- Relational markers ("thanks", "I understand", "feels", "we", validation).
- Choice markers ("options", "choose", "either/or", "you can").
- Length/tempo (short vs long turns, rapid follow-up).
- Affect/expression (exclamation marks, intensifiers: "very", "super", etc.).

Mapping (principle)

- D2: R increases with relational markers and validation; F increases with choice markers and open questions; K increases with structure markers, imperatives, criteria/requirements.
- D3: I increases with short, thoughtful answers and cautious phrasing; E increases with high interactivity and more expression/affect; N increases when neither I nor E dominates.
- D1 (heuristically hardest; combine several signals): S increases with autonomy statements and dislike of advice; L increases with requests for clear guidance/frames; O increases with requests for analysis/overview.

A simple update rule

21. Compute feature scores per dimension mode.
22. Add scores to an accumulator (with forgetting factor lambda, e.g., 0.85 per turn).
23. Apply softmax to obtain probabilities.
24. Choose label = argmax, but keep probabilities for stability and confidence.