



FM
square

Perception-Based Fuzzy Modelling

Edy Portmann, Gwen Wilke, Luis Terán and Sara D'Onofrio.



$$\mu_A(x) = 1 - \mu_{\bar{A}}(x)$$

$$\mu_A(x) = \frac{x^x}{1+x}$$

$$\mu_A(x) + \mu_{\bar{A}}(x) = \max(\mu_A(x), \mu_{\bar{A}}(x))$$

$$\mu_A \cap B(x) = \min(\mu_A(x), \mu_B(x))$$



$$\mu_A(x) + \mu_B(x) = \max(\mu_B(x), \mu_{\bar{B}}(x))$$

$$\mu_A(x) + \mu_B(x) = \min(\mu_B(x), \mu_{\bar{B}}(x))$$

$$\mu_A \cap B(x) = \min(\mu_A(x), \mu_B(x))$$



Lotfi A. Zadeh

*This booklet is dedicated to Lotfi Zadeh,
the visionary behind the computational theory of perceptions.
By enabling machines to interpret and respond to human sensory data
in ways that mimic human perception, he gives AI a new direction.
This inclusive direction, we are convinced, will soon gain
importance in business, government, and society.*

Message from the founder



To assess facts, we normally apply two-valued methods and draw conclusions of right or wrong. Yet, applying fuzzy methods may lead to more sophisticated approaches to discovering the truth. In addition to 1 (true) and 0 (false), these methods use all values between 0 and 1, fuzzifying classical methods with extreme values of true or false, good or bad, black or white. It also eliminates its problematic dichotomy of all-or-nothing (or either-or) and replaces it with both-and.

The advantage of fuzzy methods is therefore the fact that they can consider qualitative measures in addition to quantitative parameters. To systematically map requirements of decision making with vague or imprecise qualitative factors, classical methods must be extended to include perception-based fuzzy modelling. Lotfi Zadeh's invention makes it possible to model with words and perceptions. At the FMsquare Foundation, we expand conventional with perception-based fuzzy management models, to reduce the gap between machine intelligence and human behavior.

Andreas Meier, Founder



Message from the presidents



The aim of perceptual-based fuzzy modelling is to enhance the quantitative findings of conventional research methodologies, suitable for real creativity and innovation rather than solely optimization. For instance, while surveys can only explore what we already know, the strengths and weaknesses of an innovation can be discovered live through perceptual observation and natural language descriptions.

Lotfi Zadeh, the father of fuzzy logic, coined the phrase ‘computing with words’ to describe a methodology in which the objects of computation are words and propositions drawn from a natural language. Perceptual-based fuzzy modelling describes how one could implement computing with words to make subjective judgments. Perceptual computers use random and linguistic uncertainties in a human way, that can be modelled and observed by a decision-maker.



With perceptual-based fuzzy modelling, we promote a nascent user experience design process to create products and services that provide meaningful and relevant experiences to users. It involves the design of the entire process of acquiring and integrating the product and service, including aspects of perceptual branding, design, usability, and function.

Edy Portmann, President

Gwen Wilke, Vice President

Contents

- 6** User experiences: Designing for the surprising human
- 10** Fuzzy logic and engineering: Adding a human touch
- 14** Modelling the maybes: How flirtation challenges machines
- 18** Learning to hesitate: Why ambiguity is a feature, not a flaw
- 22** Perceptual computing: Probably true, possibly useful
- 26** Concluding remarks by the board of trustees



14



18



6



22



10

We are smart because we are capable of fuzzy thinking.

Designing for the surprising human

Why user experience design needs to let go of tidy models and start embracing the unpredictable, “fuzzy” nature of human judgment.

Don't fit in a box? We neither.

In the world of user experience design, there is an unspoken tension between the neatness we strive for and the messiness we encounter. Every product designer has encountered it: the moment when a beautifully structured interface gets tripped up by real people, doing real things, in ways no spreadsheet could predict. Human beings are, in short, surprising. We're inconsistent, emotional, nonlinear, and often irrational — at least by machine standards.

Unlike binary logic, fuzzy logic lets us express the subtle degrees of truth in human judgment, capturing the nuance and ambiguity that shape our decisions.

This chapter begins with a simple premise: designing for human-centric systems must embrace the inherently unsystematic nature of humans themselves. To do otherwise is to build for a tidy world that simply doesn't exist.

The computational framework that takes this challenge seriously is known as perceptual computing, an approach developed by Jerry Mendel and Dongrui Wu in their book 'Perceptual Computing: Aiding People in Making Subjective Judgments'¹. Perceptual computing doesn't attempt to simplify or



eliminate subjectivity; instead, it works with it. It treats uncertainty as a feature to model.

The problem with perfect logic

Much of computing — and by extension, user experience modelling — is based on a binary view of the world. Inputs are either on or off, valid or invalid, true or false. This crisp logic works well for structured environments and numerical data. However, human experience isn't crisp. It's mushy, interpretive, and deeply dependent on individual context.

“Life is full of subjective judgments,” write Mendel and Wu. “These judgments are personal opinions...influenced by one’s personal views, experience, or background.” They include variables like trust, beauty, aggressiveness, or importance — the kind of things that don’t show up cleanly in a drop-down menu or a bar chart.

Yet, despite this fog of ambiguity, people make decisions all the time. We judge whether a product is intuitive, whether an interaction feels respectful, or whether we’re being over-

¹ Jerry Mendel, Dongrui Wu (2010): Perceptual Computing: Aiding People in Making Subjective Judgments'. <https://www.amazon.com/-/de/dp/0470478764/%22>

Image credit: Design Council

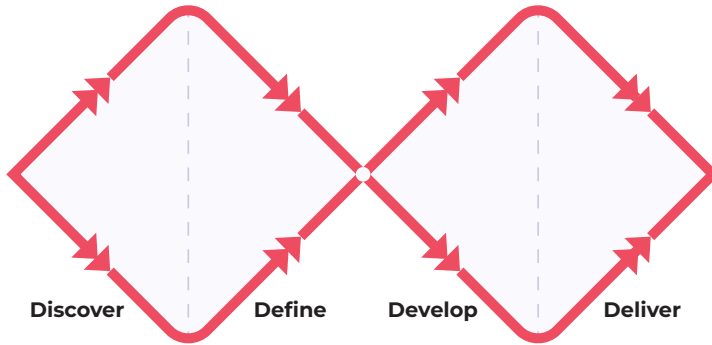


Figure 1: The double diamond is a visual model of the design process, popularized by the Design Council, that outlines four key phases: discover, define, develop, and deliver. It emphasizes both divergent (i.e., exploring a wide range of possibilities) and convergent thinking (narrowing down options and making decisions) throughout the process.

The Double Diamond by the Design Council:
www.designcouncil.org.uk/

whelmed by options. These are not simple yes/no calls. They're the output of perception and intuition shaped by memory, culture, mood, and meaning.

Enter fuzzistics

To capture this kind of rich, impressionistic thinking, Mendel coined the term “fuzzistics” – combining “fuzzy” and “statistics”. It refers to the process of translating the judgments of an individual or group into fuzzy models that preserve ambiguity rather than erase it.

As a complement to standard statistics, fuzzistics doesn't ask users to commit to absolutes. Rather, it invites them to describe their experiences in natural language – phrases like “a bit confusing,” “mostly helpful,” and “kind of dull” – and converts those descriptions into structured representations that can inform design decisions. In this way, fuzzistics acts like a perceptual bridge between the subjective mess of human experience and the tidy models designers require to actually build systems.

This is radically different from conventional user experience metrics. Instead of forcing users to reduce experience to numbers, fuzzistics takes linguistic input seriously and lets the model do the translating.

Modeling subjectivity

This is where perceptual computing takes centre stage. Mendel and Wu define it as a methodology for building problem-specific devices that aid people in making subjective judgments. These devices, which they refer to as perceptual computers, are not general-purpose AI systems. They are tailored models that map uncertain input (often qualitative or linguistic) to output in a way that can be understood and evaluated by the judgment-maker.

Perceptual computing builds on the broader foundations of fuzzy logic – a field pioneered by Lotfi Zadeh and later expanded through the influential work of thinkers like Bart Kosko. In his widely read book ‘Fuzzy Thinking’ and subsequent research, Kosko helped formalize the idea that fuzzy systems – composed of overlapping “rules-as-patches” – could approximate virtually any non-linear process. He demonstrated that fuzzy logic wasn't just philosophically aligned with human reasoning, but mathematically powerful.

Mendel and Wu build on this groundwork, applying fuzzy logic to engineering problems as well as the complex terrain of subjective human judgments. This is especially valuable in user experience design, where perception, not precision, often drives decisions. It's not about what a button does, but how confident or hesitant it feels. It's not

about whether a layout is efficient, but whether it's overwhelming or soothing, and for whom.

A perceptual design mindset

Designing with perception in mind shifts how we frame feedback, usability testing, and system responsiveness. It aligns closely with the ethos of human-centered design, epitomized in 'Seven Tenets of Human-Centred Design' by the U.K.'s Design Council, which urges us to "get past your own great idea," "spend time with real people in real environments," and "follow your users' lead and needs." These are not tasks that lend themselves to crisp inputs. They require interpretive intelligence — the kind that perceptual computing enables.

By modelling subjective responses in a structured way, designers can better tune interfaces

to match how people actually experience them. The goal isn't to reduce surprise but to respect it. To build systems flexible enough to adapt to users as they are, not as we hope they'll be.

In the chapters that follow, we'll examine how fuzzy logic supports this kind of modelling, not only in subjective domains like user experience, but in fields where engineering systems must account for dynamic, uncertain, real-world input. Chapter 2 examines how fuzzy logic has influenced the field of engineering, and Chapter 3 — in what may be our most human application yet — will take a closer look at flirtation. This social signal system defies easy categorisation, but thrives on perceptual cues.

When it comes to modelling human behaviour for the purposes of computing, the only certainty is, paradoxically, uncertainty.

Personal response

How does fuzzy logic preserve ambiguity in human reasoning?

Ambiguity often arises from using different words for similar ideas. Fuzzy logic clusters such words into categories, rather than relying on binary true/false logic. We use structures like residuated lattices to express degrees of truth, capturing subtlety in human judgment.

How can we preserve this richness in statistical models?

Statistics communicate via numbers, while fuzzy logic works in linguistic categories. We can translate between them when needed, allowing richer expression of meaning.

Fuzzy transformations bridge functional analysis and neural networks. They complement neural computation, offering theoretical foundations adaptable to modern demands. Fuzzy logic doesn't compete with neural networks—it translates human-like reasoning into computational models.

Please refer to the QR code on the inside cover of the last page to listen to the full interview podcast.



Biography:

Irina Perfilieva is Professor of Applied Mathematics at the University of Ostrava, Czech Republic. She holds honorary titles from the Amity Institute of Information Technology, India, and the University of Latvia. Her research focuses on fuzzy and mathematical modelling, and she is best known for developing the well-recognized fuzzy transform method used in solving differential and fractional-order equations.

Fuzzy logic and engineering:

Adding a human touch

Engineering has always been about precision, but increasingly, it needs to build systems that think more like people.

A new kind of control

In classical engineering, systems are designed to respond to hard data: pressure values, voltage levels, and flow rates. Measurements are clean, numbers are crisp, and control logic is often binary, meaning – if this, then that. If you've ever adjusted a thermostat or turned on a fan, you've used a fundamental control system: if temperature $>26^{\circ}\text{C}$, turn the fan on; if temperature $<24^{\circ}\text{C}$, turn the fan off. However, if you've ever thought, "It's getting a bit warm in here," you've used a very human system and judgement.

Fundamental engineering control systems deal in clear thresholds. Take, for example, controlling the pressure in a boiler. They work beautifully.

But, what if we're not dealing with a boiler? What if we're instead dealing with human comfort? That's where things get tricky. "Comfort" doesn't start and stop at fixed points. It's a sliding scale. One person's "perfectly pleasant" temperature is another's "insufferably warm." The logic that governs comfort or other human experiences isn't black and white. Rather, it's shades of grey. So, how do we build systems that can operate in that grey zone? The answer is to change the logic and embrace the fuzziness.

Fuzzy logic allows us to design systems that do not simply react to raw measurements, but respond to meaning. Instead of asking, "Is the room hot?" a fuzzy system asks, "How hot is it?" and "How sure are we?" As a result, it uses those degrees of input to make more nuanced, human-like decisions.

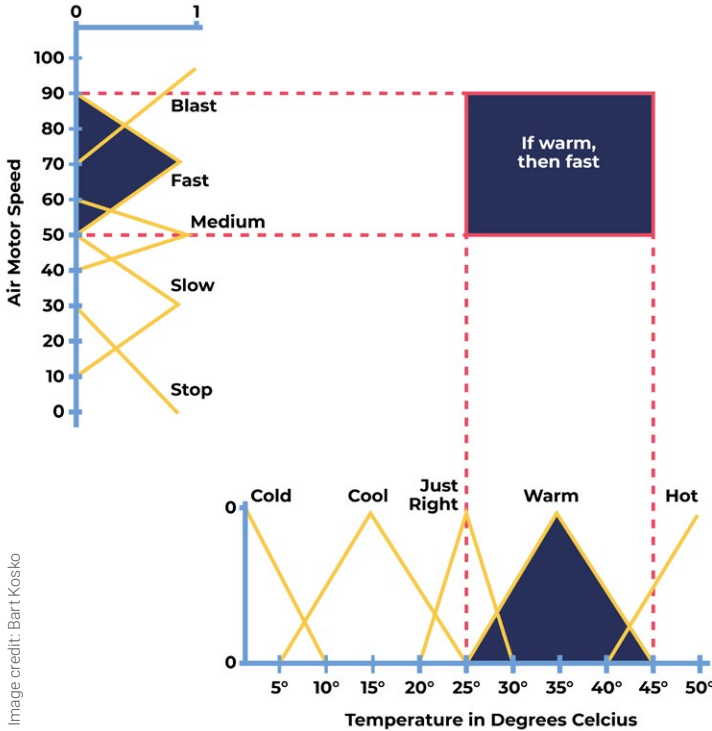


Figure 2. Fuzzy rules look like patches. When we cross a triangle with a second triangle, we get a patch. If our sets are warm and fast, we get the rule: “If the temperature is warm, the motor speed is fast. And this rule is a patch.”

Bart Kosko (1993): Fuzzy Thinking. The New Science of Fuzzy Logic. Hyperion Books. www.amazon.com/Fuzzy-Thinking-New-Science-Logic/dp/078688021X

Image credit: Bart Kosko

This is what makes fuzzy logic so appealing in messy, perception-driven domains. You don't need to model every variable in precise mathematical detail. You need to capture the underlying patterns, and fuzzy patches let you do that. Better still, these patches are explainable. You can look at a fuzzy system and say, “Here's how it behaves when the temperature's rising.” That's something black-box models in AI can't always offer.

Not fuzzy thinking – fuzzy intelligence

There's a misconception that fuzzy logic means vague or imprecise thinking. However, it's in fact the opposite. Fuzzy logic is a disciplined way of reasoning about the nature of human imprecision. It doesn't blur ideas; it structures them.

Think about how people make decisions. We rarely commit to one hard rule. Instead, we weigh

options, consider nuance, and arrive at choices based on multiple, partially accurate propositions. Fuzzy logic captures that process in a way that classical logic simply can't. And funnily enough, logical flexibility turns out to be remarkably efficient. Systems using fuzzy logic have been used to control washing machines, camera focus, train braking systems, and air conditioners, often using a handful of rules and tiny microchips. The logic is lean, transparent, and robust.

It also works well in conditions where traditional models fail—when sensor inputs are noisy, relationships aren't perfectly linear, or “what feels right” is more important than “what calculates precisely.” In other words, it is better to be roughly right than precisely wrong.

This is not only useful in perceptual computing, where systems interpret the world not in

fixed values but in sensations, categories, or descriptions. Fuzzy logic gives engineering a new toolset—one that matches how people describe problems, interpret signals, and make decisions in the face of uncertainty. This toolset opens doors and lets us design machines that don't simply follow instructions but interpret intent. It makes space for systems that engage with human experience, not only physical input.

When design becomes dialogue

In classical engineering, control design is something you impose upon a system. With fuzzy logic, it becomes more conversational – be-

tween experience, expectation, and response. It's not about turning a knob when a threshold is crossed, it's about capturing the sense of "what feels right" and translating that into action.

Fuzzy logic is such a powerful idea because when engineering takes perception seriously, it builds systems that people trust, systems that adapt, and systems that work even when the rules aren't entirely clear.

As we'll explore in the next chapter, fuzzy logic doesn't stop at thermostats and fans. It can help us model something as elusive and socially complex as flirtation. Because if you can model a feeling, you can begin to engineer around it.

Personal response

How are membership functions validated in real-world systems?

Vagueness occurs when properties like "warm" or "tall" aren't precise. Fuzzy sets allow properties to hold to a degree, such as 0.3 or 0.7. Shapes of these sets are derived from the linguistic meaning of the term.

How do you balance explainability with scalability?

Explainability is a strength: linguistic terms are directly modelled. Scalability is harder due to dimensionality. Hierarchies of interpretable submodels provide a global, explainable system.

Why is Fuzzy logic sometimes dismissed as "soft science"?

It's a rigorous mathematical theory using algebra, set theory, logic, functional analysis, and numerical analysis. Modelling imprecision doesn't mean the mathematics is imprecise.

Conclusion:

Fuzzy logic quantifies partial truth, complementing AI systems as complexity grows. It helps maintain explainability and interpretable decision-making.

Please refer to the QR code on the inside cover of the last page to listen to the full interview podcast.



Biography:

Vilém Novák is the founder and former director of the Institute for Research and Applications of Fuzzy Modelling at the University of Ostrava, Czech Republic. A leading figure in fuzzy theory, he has authored five monographs and over 300 papers with more than 7,000 citations. He was honoured at the FLINS 2010 conference in China and named an IFSA Fellow in 2017. He currently serves as Vice-President of IFSA.

Modelling the maybes

How flirtation challenges machines

From winks to whispers, flirtation thrives in ambiguity. Fuzzy logic and perceptual computing help model one of the most slippery aspects of human behaviour.

Flirting with ambiguity

Was that a smile or something more? Human communication is replete with subtleties, but perhaps none more so than flirtation. It dances at the edge of intention — light enough to be denied, clear enough to be interpreted, and vague enough to allow plausible deniability. To a machine trained on crisp logic, it is maddening. However, it presents a welcome challenge for a perceptual system trained on fuzzy reasoning.

In their paper ‘Flirtation, a Very Fuzzy Prospect’², Matthew Martin and Jerry Mendel propose a fuzzy logic framework for modelling flirtatious behaviour. It may sound facetious and superficial, but it is essential to examine flirtation not

as a frivolous act but as a case study in human ambiguity. Flirtation’s power lies precisely in its lack of precision, and that makes it the perfect testbed for fuzzy logic.

Signals in soft focus

Traditional computational approaches operate in absolutes. A transaction is either valid or invalid. A signal is either present or absent. However, flirtation doesn’t adhere to those rules. It suggests rather than states, invites without confirming, and moves in possibilities rather than certainties.

What does it mean when someone leans slightly closer? Or holds eye contact a moment too long? These instances fall into no clear category. Their meaning depends on context, expectation, and interpretation. In classical logic, such ambiguity is a problem. However, in fuzzy logic, it’s the point.



A flirt does not operate with a fixed vocabulary. Instead, the communication is suggestive, drawing from a palette of gestures, tone shifts, physical proximity, and facial expression. None of these cues is definitive. Each exists on a spectrum of meaning.

Fuzzy logic offers the tools to model this spectrum. We can define linguistic variables like “eye contact” or “smile” using fuzzy categories such as “fleeting,” “lingering,” or “intense,” each with degrees of membership. Depending on surrounding cues, a look might be 60% “friendly” and 40% “flirtatious.”

This maps well onto Lotfi Zadeh’s concept of fuzzy sets, where the boundaries between categories are soft and overlapping. In flirtation, there is no strict line between friendliness and flirtation — only gradients. This is where ma-

chines that rely on binary classifiers struggle. By contrast, systems grounded in fuzzy logic can reason through these partial truths.

The dance of mutual perception

It’s important to understand that flirtation is not merely a singular act; it is a social process. Its significance does not emerge in isolation but in the exchanges between individuals. What one person presents as playful, another might interpret as courteous. Consequently, the effectiveness of the signal depends on mutual calibration.

Language is imprecise, and fuzzy logic gives us a flexible framework to model those nuances, helping machines understand human feelings and social cues.

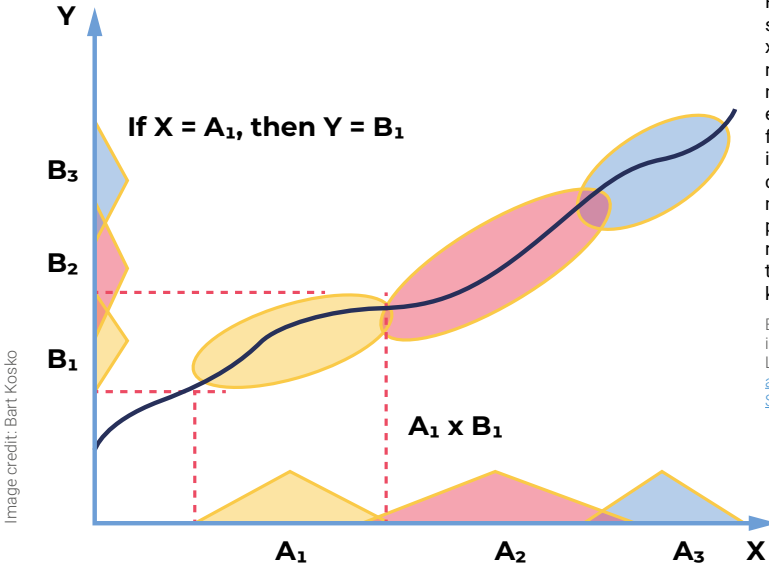


Image credit: Bart Kosko

Figure 3: A perception-inspired system maps inputs x to outputs y , whereby each rule defines a patch. A finite number of fuzzy rule patches can cover the systems function and approximate it to a certain level of perception accuracy. Learning moves and shapes the rule patches. Individual optimal rules cover the bumps or turning points of the (unknown) function.

Bart Kosko (1993): Fuzzy Thinking. The New Science of Fuzzy Logic. Hyperion Books. www.amazon.com/Fuzzy-Thinking-New-Science-Logic/dp/078688021X

This makes flirtation a living example of what Jerry Mendel and Dongrui Wu call perceptual computing: systems that help people make subjective judgments. Flirtation depends on such judgments. And crucially, it operates through feedback. A glance might trigger a smile, which in turn, modifies the meaning of the original glance. The interaction becomes a feedback loop of evolving perception.

This, too, can be modelled. With fuzzy rule systems, we can write rules like:

- If smile is warm and gaze is steady, then interest is likely.
- If distance is close but tone is formal, then ambiguity is high.
- If response is delayed but the smile is returned, then the signal is cautiously positive.

These rules don't yield a binary output. Instead, they produce fuzzy outcomes – “probably interested,” “somewhat receptive,” or “possibly disinterested” – each of which reflects the inherently tentative nature of the domain.

From vibes to variables

To model flirtation computationally, we must first treat it as information. But this isn't data in the classical sense. Instead, it's perception-based, subjective, and imprecise. This is where Zadeh's computational theory of perceptions becomes useful.

The theory proposes that many human judgments – especially those involving impressions, likelihoods, or intent – are best represented not as values but as generalized constraints. These constraints come from natural language: statements like “she's probably into you” or “he seems interested” are not noise but structured perceptual data.

In the computational theory of perceptions, such statements can be translated into a formalism called Generalized Constraint Language. For example:

- “Mary is flirting” → Flirt(Mary) is likely
- “That was just friendly” → Intent(Signal) is ambiguous

These are not measurements, but perceptions. And by using the tools of constraint-centered semantics and precisiated natural language systems can be built to reason with them.

Flirtation, then, becomes a benchmark for designing machines that can navigate the foggy terrain of human intention. It tests whether a system can handle the spectrum of “maybe” as well as the binary “yes” and “no.”

Designing for the maybe

The goal here isn't to teach robots to flirt. It's to teach systems to cope with ambiguity, to inter-

pret intent, and to adapt to the nuanced, non-binary ways humans communicate. Flirtation just happens to be an excellent example.

In perceptual computing, we build systems that don't just count signals. Instead, they interpret them. They don't just follow instructions — they negotiate meaning. As our machines grow more embedded in daily life, their success will depend less on their processing power and more on their perceptual sensitivity. In a way, it's more about meaning than muscle.

Because if a system can handle a maybe, it just might understand a human.

Personal response

How do you model causal relationships in perceptual, non-binary domains?

It's complex. Real-life cues like smiles or gestures vary by context, language, and person. Classical deterministic rules fail; fuzzy logic allows flexible modelling of multi-causality.

How do feedback loops and dynamic interactions fit in?

Parameters must continuously adapt. Fuzzy logic handles imprecision, allowing systems to model evolving behaviours like flirtation, which depend on context, mood, and culture.

What role does language play in fuzzy modelling?

Language is inherently imprecise. Fuzzy sets allow flexible interpretation, accommodating irony, regional variation, and subjective meaning. Classical models fail to capture this variability.

What are the comparative risks of classical vs fuzzy models?

Classical models are rigid and context-bound. Fuzzy logic adapts to real-world imprecision, offering flexible and human-relevant outcomes.

Please refer to the QR code on the inside cover of the last page to listen to the full interview podcast.



Biography:

Cristina Puente Águeda is based at the School of Engineering, Universidad Pontificia Comillas, Department of Telematics and Computer Science. She graduated in Computer Engineering in 2001 and received her PhD in 2010 with European mention, specialising in Natural Language Processing and Soft Computing. She is affiliated with BISC, having spent time at Berkeley with Professor Lotfi Zadeh and in Marseille with Professor Elie Sanchez. In 2021–2022, she founded and leads the research group AEQUITAS, applying AI to study power and equity in the digital age.

Learning to hesitate

Why ambiguity is a feature, not a flaw

*What happens when a machine doesn't just interpret signals but learns when **not** to decide? Flirtation teaches us that intelligence involves timing, feedback, and sensitivity to uncertainty.*

Not just fuzzy—deferential

In the closing pages of 'Flirtation, a Very Fuzzy Prospect: A Flirtation Advisor', Martin and Mendel make a subtle point often lost in discussions about machine intelligence. The flirtation advisor isn't designed to tell you if someone is flirting; it's designed to help you consider whether they might be. The distinction is essential. Rather than resolving uncertainty, the system reflects it back to the user in a structured, interpretable form.


The advisor functions as a sort of perceptual mirror. It interprets cues such as gaze, tone, and proximity, then presents judgments in language that captures their nuance—terms like "possibly flirtatious" or "somewhat ambiguous." These aren't lexical hedges; rather, they're intentional outputs that reflect the experience of genuine social in-

teraction, where impressions accumulate and meaning unfolds gradually in real time.

This makes the system feel less like a calculator and more like a cybernetic conversational partner—one that acknowledges hesitation and creates space for it. That ability to defer, rather than decide, signifies a different kind of intelligence.

Timing is everything

What distinguishes the advisor is its temporal design. The system doesn't operate from isolated signals; it monitors sequences. One smile is merely a gesture. A smile following a lingering gaze, reinforced by a shift in proximity, forms a discernible pattern. The advisor is sensitive to this



A responsible AI doesn't pretend to know everything; it can acknowledge uncertainty and say, 'I don't have enough information to answer'.

unfolding and each input reshapes the context in which future signals are understood.

This quality closely parallels how humans process social situations. Meaning does not always arrive all at once; it develops gradually throughout an interaction. In flirtation in particular, the progression of cues can be as significant as the cues themselves in discerning a pattern.

Within the architecture of perceptual computing, this is significant. Inputs such as voice, gesture, or expression rarely exist independently. Their importance often hinges on what came before and what follows. The advisor models that flow, offering not merely an assessment of “what hap-

pened” but an evolving sense of “what might be happening now, given what just occurred.”

A feedback machine for “maybe”

At the heart of the advisor is a feedback mechanism. This means that each user input changes the actual landscape in which further interactions are interpreted. In social terms, this is second nature. A glance followed by a grin lands differently than a glance followed by silence.

This relational dynamic is captured through fuzzy rule sets. If the smile is warm and the gaze is steady, the system leans toward “interested.” If the tone is formal and the distance is close, it registers increased ambiguity. Every rule contributes, but none operates in isolation. They activate in degrees, generating composite judgments that feel proportionate to the moment.

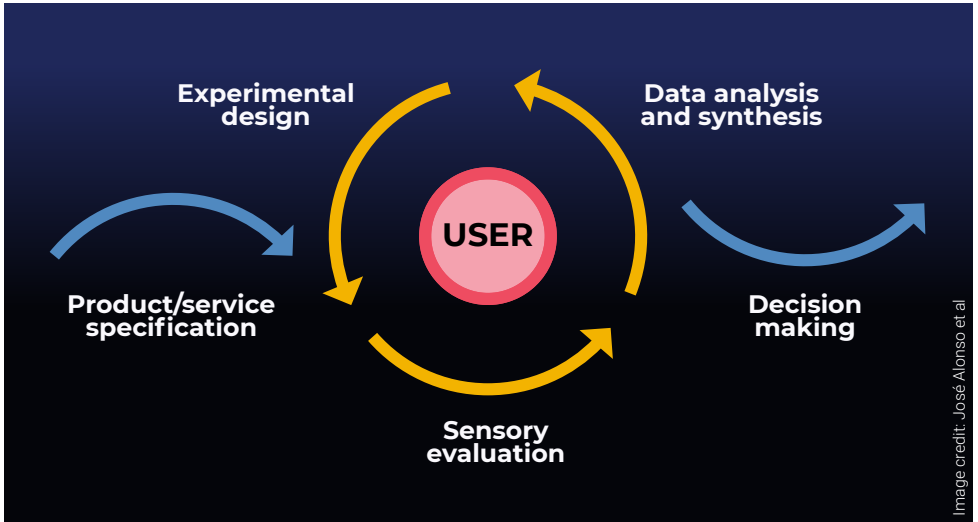


Image credit: José Alonso et al

Figure 4: Perceptions are the foundational input for kansei engineering, which is a person’s subjective impression or feeling derived from an artifact, environment, or situation using all senses and cognitive processes. Kansei engineering is essentially a methodology for capturing subjective human perceptions and translating them into objective design parameters.

What stands out is the transparency of these processes. Users can trace the reasoning behind the system’s suggestions, which fosters trust and introspection—qualities often absent in machine-driven assessments. This isn’t black-box AI. It’s an intelligible tool that promotes reflection.

What flirtation reveals about machine intelligence

Flirtation may seem like a niche area for modeling, but its demands are broadly representative. It engages multiple channels: gesture, tone, timing, and spatial dynamics. It thrives on interpretation, where clear intent is rare and misreadings are always possible. The need for subtlety is not limited to romantic settings. It’s part of customer service, negotiation, education, therapy—any context where impressions shape outcomes.

The advisor’s structure suggests how perceptual systems can perform in such settings. It monitors multiple signals, adjusts dynamically, and avoids premature conclusions. These are valuable traits across sectors. In healthcare, for instance, a pa-

tient’s tone or expression might offer more insight than words. In law enforcement, the hesitation in a response can matter as much as the answer. In other words, social intelligence requires more than detection—it involves interpretation under uncertainty.

Through flirtation, we gain a model for designing systems that are not merely reactive but context-aware—ones that maintain a continual interpretation of events and adjust their outputs accordingly. Machines that assist human decision-making in this manner do not dominate the interaction; they engage and converse. The intelligence is not in the machine, but in the conversation.

A bridge to perception-driven computing

The flirtation advisor provides deeper insight into how machines can process complex, ambiguous experiences. The system does not push towards finality; it remains close to perception, adjusting its assessments as the situation evolves.

This resonates strongly with the wider philosophy behind perceptual computing. These systems are designed not to process precise inputs but to respond to environmental cues like humans do. By interpreting mood, tone, posture, and language as part of an unfolding context, systems begin to take ambiguity seriously.

The advisor isn't merely an example of fuzzy logic in action; it's an early prototype for perceptual machines that provide collaborative judgment. Additionally, its architecture—transparent, incremental, context-sensitive—paves the way for more comprehensive models of perception.

One such model comes from Lotfi Zadeh. In his computational theory of perceptions, Zadeh argues that much of human reasoning involves propositions rooted not in data but in natural language. He proposes that machines should be capable of working with statements like “he seems confident” or “she’s probably not ready”—not by translating them into hard numbers, but by computing with the perceptions they contain.

That is where we go next. If intelligence is to be more than merely speed and certainty, it must be capable of representing and reasoning through the nuanced aspects of human experience.

Personal response

How does hesitant intelligence change human–AI interaction?

AI often relies on statistics, not fuzzy logic, creating unrealistic expectations. Humans defer decisions and recognise uncertainty; machines usually don't. Fuzzy logic helps quantify uncertainty and incorporate human feedback.

How do you integrate human expertise with AI?

Combine expert knowledge with data-driven models, ensuring mathematical soundness. Interactive calibration and context-aware dialogue are essential. Systems must be robust, validated, and transparent.

Avoiding catastrophic forgetting, bias, and misinformation. Fuzzy systems bridge formalized knowledge with uncertainty, supporting explainable, trustworthy AI.

Conclusion:

Fuzzy logic bridges probability and degrees of truth, making AI more robust and explainable. Human–machine interaction benefits from uncertainty-aware reasoning.

Please refer to the QR code on the inside cover of the last page to listen to the full interview podcast.



Biography:

José M. Alonso is a researcher at the Centro Singular de Investigación en Tecnoloxías Intelixentes, University of Santiago de Compostela, and holds MSc and PhD degrees in Telecommunication Engineering from the Technical University of Madrid. He serves on the boards of EUS-FLAT and the ACL Special Interest Group on Natural Language Generation, chairs the IEEE-CIS Task Force on Explainable Fuzzy Systems, and is Associate Editor of the IEEE Computational Intelligence Magazine



Perceptual computing:

Probably true, possibly useful

Why the future of artificial intelligence may depend less on measurement and more on meaning.

From data to doubt

For decades, artificial intelligence has promised to bring human-like cognition to machines. In some respects, it has delivered: machines now see, speak, play games, drive cars, and compose music. However, AI continues to falter in perception—not in visual perception in the narrow sense, but in the broader ability to interpret context, make judgments, and reason with ambiguity—things that humans do effortlessly.

In his paper ‘A New Direction in AI’³, Lotfi Zadeh argued that this shortcoming arises from a mismatch in representation. Traditional computing systems operate on measurements, whereas human minds operate on perceptions.

That distinction is significant. Measurements are crisp, numerical, and precise, while perceptions are fuzzy, linguistic, and often uncertain. Zadeh’s proposal was radical yet straightforward: if we wish for machines to reason more like humans, we must enable them to compute with perceptions.

From crisp sets to fuzzy granules

Zadeh observed that much of human knowledge is granular. That is, we think in clumps or categories: someone is “young,” “middle-aged,” or “old”; the weather is “hot,” “mild,” or “cold.” These are not precise partitions but overlapping regions—what Zadeh called f-granular structures. A person might be 70% young and 30% middle-aged. This form of reasoning does not fit within the strict bounds of predicate logic or statistical models, but it aligns well with fuzzy sets.

In the computational theory of perceptions, granules serve as the building blocks of meaning. They capture how humans cluster information based on similarity, proximity, or function. Importantly, these granules can be articulated in natural language, enabling systems to process statements like “most Swedes are tall” or “it’s unlikely to rain tonight.”

To reason with these kinds of statements, Zadeh introduced the concept of generalized constraints. A proposition like “Dana is young” is restructured as a constraint on a variable: Age (Dana) is young, where young is a fuzzy set. The constraint becomes relational if the proposition is more complex—“Dana is much younger than her husband”. This translation into a formal structure enables machines to reason with perceptual inputs.

The language of uncertainty

Precisiated natural language, introduced in Chapter 3, is central to the computational theory of perceptions. It is a subset of everyday language that can be formalized through translation into what Zadeh calls the generalized constraint language. Precisiated natural language includes propositions such as “usually Robert comes home around six” or “unemployment is low.” These are not facts in the classical sense; rather, they are perceptions. However, they are also meaningful and can be processed computationally with the right tools.

The mechanism for doing this is known as generalized constraint propagation. This technique enables a system to carry forward the uncertainty embedded in perceptual statements, combining and adjusting constraints as necessary. For example, from the inputs “most young men are healthy” and “Robert is a young man,” a percep-

tions-based system might infer “Robert is likely healthy,” where likely is derived from the fuzzy quantifier most. The reasoning here is not black and white. It functions in degrees, reflecting how humans weigh likelihood and context.

Applications without absolutes

The computational theory of perceptions is not limited to abstract theorizing. It offers a framework for practical tasks that defy precise definition. These include:

- Perception-based function modelling describes functions using fuzzy if-then rules, such as “if X is small, then Y is large.”
- Perception-based system modelling, where the states and transitions of a system are themselves fuzzy (e.g., “if the mood is tense and the voice is raised, then escalation is likely”).
- Perception-based time series analysis, where inputs are linguistic categories rather than precise numbers (e.g., “sales were moderate, then dipped slightly, then rose sharply”).
- Perception-based probabilities, where likelihood is expressed as “likely,” “unlikely,” or “very probable” rather than 0.7 or 0.2.

What binds these examples is a rejection of brittle boundaries. Instead of drawing hard lines, the computational theory of perceptions paints soft curves. It trades exactness for expressiveness, allowing systems to navigate domains where facts blur into feelings.

Importantly, Zadeh did not frame the computational theory of perceptions as a replacement for conventional AI, but as a complement. Statistical models, logic systems, and neural networks all have their strengths. But they struggle with meaning. They cannot easily interpret statements like “checkout time is 11 am” when used informally, or understand that “probably”

Sometimes it’s better to be roughly right than precisely wrong—designing systems that embrace approximation can make technology more human-centered and practical.

Image credit: Lotfi Zadeh

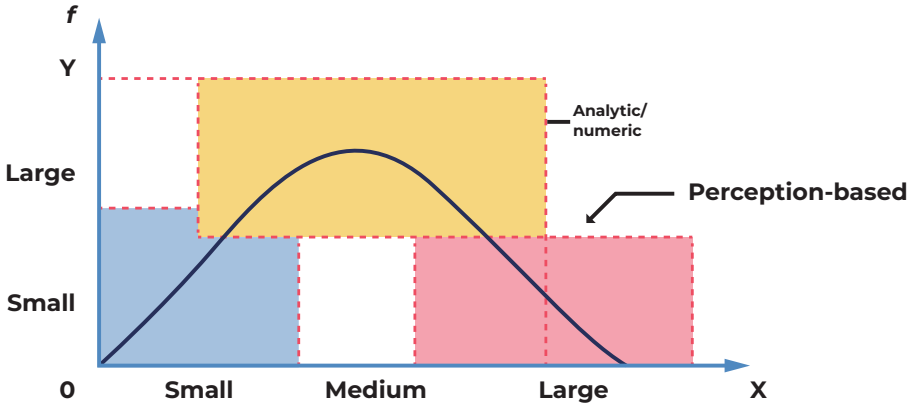


Figure 5: A perception-based function can be represented as a collection of linguistic if-then rules. For example, if X is small, then Y is small, if X is medium, then Y is large, and/or if X is large, then Y is small. The granules in the (X, Y) space are Cartesian products of the granules in the X space and Y space. Thus, in perception-based modelling, the transition and output functions are represented as collections of linguistic if-then rules.

might mean different things depending on who’s speaking. The computational theory of perceptions addresses that gap by treating perception not as noise, but as a signal.

This is not mere semantics. It reflects a deeper insight into how humans reason. When we say someone is “probably bluffing” or “seems nervous,” we’re not stating facts. We’re registering impressions. If we wish for intelligent systems to engage with humans naturally, those impressions must be given computational form.

A fuzzy frontier

Zadeh’s vision remains a frontier in AI—one not defined by faster processors or larger datasets, but by richer meaning-making. The computational theory of perceptions invites us to envisage systems that do not merely process signals but interpret them—rather than simply computing, they contemplate.

In the previous chapters, we’ve explored how fuzzy logic provides a foundation for systems that navigate ambiguity. From user interfaces that model subjective experience to flirtation

engines that reflect social nuance, as well as systems that learn to hesitate, the common thread is perceptual sensitivity.

Zadeh’s computational theory of perceptions provides the conceptual scaffolding for these ideas. It formalizes fuzziness. It builds bridges between language and logic, as well as between perception and process. In doing so, it suggests that the most human form of intelligence may not be the one that knows, but rather the one that understands.

Closing reflection: from precision to perception

Across these five chapters, one theme has quietly persisted: intelligence is not always about getting the right answer. Sometimes, it’s about knowing how to ask the right question—or when not to answer at all.

Fuzzy logic, from its origins in Zadeh’s early work to its extensions in perceptual computing, shows us that approximations can be powerful. Not because they are vague, but because they are appropriate. They match the shape

of human thought. Whether we're designing a thermostat that senses comfort, a system that reads social cues, or an interface that listens to uncertainty, we are entering a space where computation must learn to collaborate with ambiguity.

This booklet has traced a line from the unpredictability of human judgment to the subtle art

of flirtation, through engineering that thinks in curves, and toward a computational theory of perception that doesn't demand clarity but accommodates it if—or when—it arrives.

In short, we've moved from trying to make humans more like machines to asking how machines can become more like humans. The answer, it seems, lies not in crushing uncertainty but in learning to live with it.

Personal response

How do you reconcile imprecision with technical demands for accuracy?

As Carveth Reid said, "It's better to be roughly right than precisely wrong." Complex systems cannot achieve perfect precision; summarizing knowledge often suffices. Human perception filters unnecessary detail, and technology should emulate this.

What about computing with fuzzy granules like "young" or "cold"?

We need perception-based systems. Fuzzy logic models linguistic terms as gradations rather than binaries. This applies to intelligence, ethics, or traffic: machines can assess "how fast" rather than "moving or stopped." Alpha cuts define thresholds instead of insisting on certainty.

What are the real-world advantages over conventional AI?

Humans learn from few examples; traditional AI needs millions. Feedback loops, possibility theory, and fuzzy reasoning better model uncertainty, aligning AI with human understanding rather than brute-force mimicry.

Conclusion:

Fuzzy modelling captures human perception and semantics in a non-binary bandwidth. It informs design of interfaces and systems that respect embodied, perceptual intelligence.

Please refer to the QR code on the inside cover of the last page to listen to the full interview podcast.



Biography:

Edy Portmann is chairman of the Mobiliar Cluster for Resilience and professor at the Department of Informatics of the University of Fribourg. He is heading the resilient systems group at the Human-IST Institute. After an apprenticeship in electrotechnics, he studied business informatics and holds a doctorate in fuzzy logic. He worked for EY, PwC and Swisscom, and was a researcher at the Universities of Berkeley, Bern and Singapore.

Concluding remarks

by the board of trustees



Fuzzy logic challenges the rigid boundaries that have long shaped computation. By moving beyond the binary assumptions of true or false, it offers a way to model the world as humans actually experience it. That is, through gradients, context, and perception – rather than absolutes. As the contributors to this booklet reflect, perception-based fuzzy modelling makes it possible to capture nuances in language and semantics, encouraging more natural, meaningful interactions between people and technology.



For many working in artificial intelligence, uncertainty is something to be minimized or forced into probabilistic categories. Yet, degrees of truth allow systems to reason with ambiguity in a way probability cannot. Fuzzy logic is not an alternative to rigorous thinking, but an extension of it, allowing us to assess qualities and not just quantities. This becomes increasingly important as AI systems grow in scale and complexity.

What emerges from these discussions is a call for a more perceptual, human-aware approach to intelligent systems. In this sense, fuzzy logic is not merely a mathematical tool but a way of widening the frontiers of research and reimagining how technology can better reflect the richness of human thought.

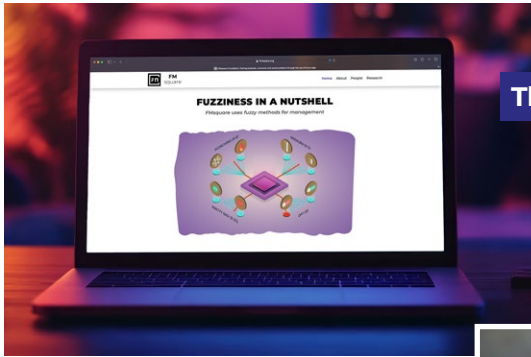
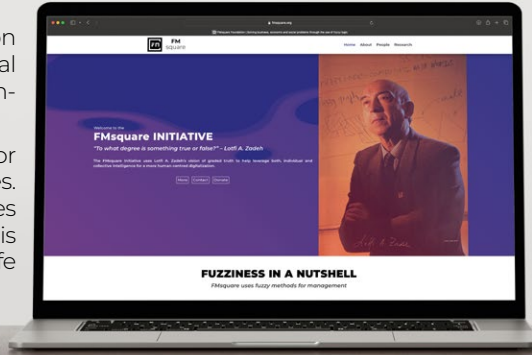
Sara D'Onofrio

Luis Terán

The FMsquare initiative

The FMsquare initiative uses Lotfi Zadeh's vision of graded truth to help leverage both individual and collective intelligence for a more human-centered digitalization.

It promotes fuzzy logic's infinite truth values for business, governmental, and societal challenges. With its holistic approach, fuzzy logic combines biological and artificial intelligence and is inclusive, not exclusive. This mindset supports life in harmony with each other and with nature.

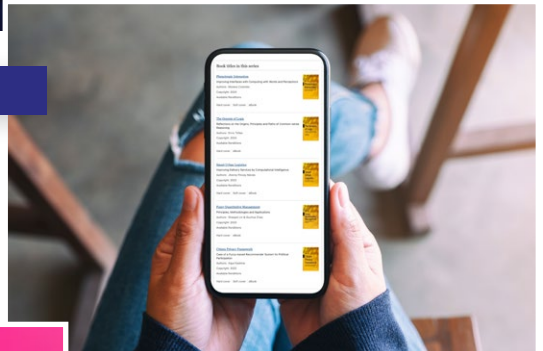


The FMsquare video

See our FMsquare explanatory video, which introduces the foundation and its initiative along with the benefits of fuzzy logic and management methods.

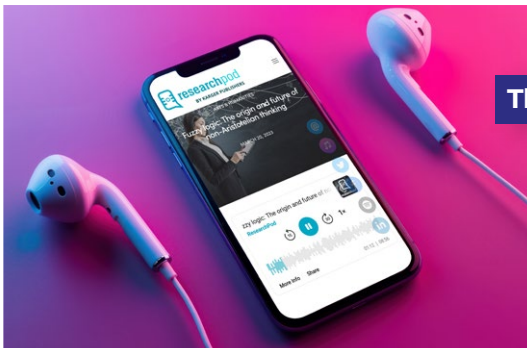
The FMsquare book series

Our international FMsquare book series spotlights the academic research efforts and findings of the initiative through the creation of engaging research books and textbooks on fuzzy management methods.



The FMsquare podcasts

Listen to our exiting FMsquare podcasts where our research is presented and explained in a short and concise manner.



For more information, visit our FMsquare website:





FM
square



E. Portmann, G. Wilke, L. Terán, S. D'Onofrio (2026):
Perception-based fuzzy modelling. The FMsquare Initiative.
DOI: 10.26904/RF2025-8056509312