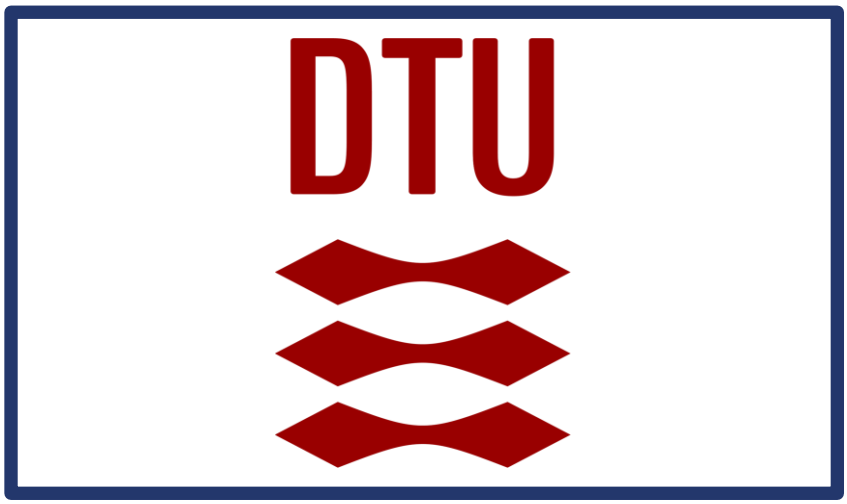
Team Results Document

DeTectUs



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SensUs

1. Abstract: Summary for the SensUs website

Parkinson's disease treatment relies on maintaining appropriate levodopa levels, yet dosing is currently adjusted using limited clinical observations and patient self-reporting, often resulting in unpredictable "off" periods and suboptimal symptom control. Our project combines practical biosensor development with theoretical innovation to advance the future of Parkinson's disease management. We developed an enzyme-based electrochemical biosensor for the continuous monitoring of levodopa in interstitial fluid, based on the immobilization of tyrosinase in a chitosan matrix and glutaraldehyde cross-linking.

Our work extended beyond the laboratory by integrating patient perspectives into the design process. Through interviews with people living with Parkinson's disease and their caregivers, we identified key unmet needs, including timely warnings before wearing-off episodes, reduced dependence on medication reminders, and meaningful long-term data to support clinical decision-making. Building on these insights, we designed a conceptual wearable slap-bracelet that combines reverse iontophoresis for needle-free sampling, continuous levodopa sensing, physiological monitoring, and AI-assisted prediction of wearing-off episodes. Together, these complementary developments demonstrate how continuous biosensing can evolve beyond measuring a biomarker to support personalised, proactive Parkinson's disease management.

2. AP award: Biosensor developed for the Eindhoven Testing Event

2.1. Molecular recognition

Our biosensor uses tyrosinase, a copper-containing oxidase, as the molecular recognition element. In the presence of oxygen, tyrosinase catalyses the oxidation of levodopa (L-DOPA), a catechol compound, to dopaquinone (Cembalo et al., 2023). The resulting quinone is electrochemically active and can subsequently be detected at the carbon screen-printed electrode (SPE) utilised, enabling the quantification of levodopa concentration.

To enable continuous sensing, tyrosinase is immobilised onto the carbon SPE using a porous chitosan matrix. A chitosan film is first electrodeposited onto the electrode surface, after which tyrosinase is drop casted into the polymer network (Zhang & Ji, 2010). Glutaraldehyde (GA) is then added as a cross-linking agent, reacting with amino groups present in both chitosan and tyrosinase to form covalent linkages that stabilise the enzyme within the matrix while preserving accessibility of levodopa to the active sites (Bounegru & Apetrei, 2023). A schematic representation of the working electrode surface is in *Figure 1*.

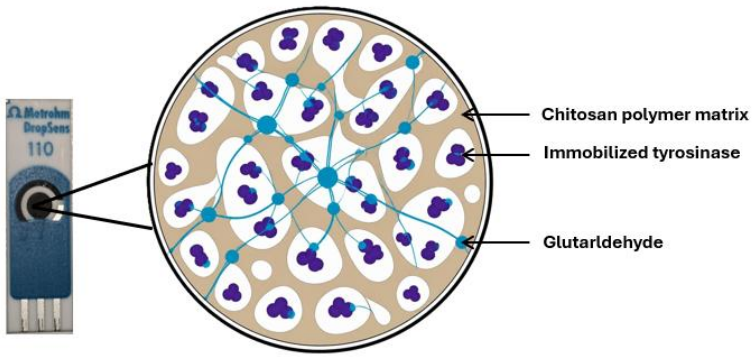


Figure 1 - Illustration of chitosan-tyrosinase-glutaraldehyde matrix on a carbon SPE's working electrode's surface.

2.2. Physical transduction

The sensing principle of our biosensor is based on chronoamperometric electrochemical detection. Tyrosinase catalyses the oxidation of L-DOPA to dopaquinone, generating electroactive species that produce an oxidation current at the working electrode. The resulting current is proportional to the L-DOPA concentration (Cembalo et al., 2023).

Furthermore, the low operating potential chosen for the chronoamperometry minimises interference from other compounds naturally present in ISF.

Disposable carbon SPEs were selected for the detection because they are inexpensive, highly reproducible and suitable for future point-of-care applications. We used *Metrohm's* 110 carbon SPE, featuring a carbon working electrode with a working surface diameter of 0.40 cm, a carbon auxiliary electrode and a silver reference electrode.

2.3. Cartridge technology

The microfluidic design consists primarily of an easily accessible 100 µL sample reservoir which feeds into a sensing chamber containing the working electrode. The cartridge is fabricated with inlet and outlet microchannels whose dimensions allow samples to pass to and from the sensing chamber characterized by laminar flow, ensuring there is minimal mixing of samples during continuous measurement. Samples are pumped through the system via syringe pump which is connected via PTFE tubing to the cartridge outlet. This ensures that consecutive ISF samples can simply be carefully poured into the reservoir without interrupting pumping or measurement.

2.4. Reader instrument and user interaction

The reader instrument consists of a PalmSens potentiostat coupled with MultiTrace 4.5 software, which controls the individual measurement channels and records the current generated by the biosensor. The measured current is subsequently processed using a custom Python script that converts the measured response into a levodopa concentration based on previously established calibration curves.

The sensing cartridge contains the disposable screen-printed electrode which is sealed via silicone O-ring and bolts into the sensing chamber of the microfluidic system, ensuring simple access in case of need for electrode replacement. To perform a measurement, the user inserts the cartridge into the reader, introduces the sample into the designated reservoir, initiates the syringe pump connected to the cartridge outlet, and initiates the analysis through the software interface. The reader acquires and processes the electrochemical data, after which the calculated levodopa concentration is displayed to the user.

3. IN award: Biosensor innovation

We present three interconnected innovations enabling proactive and continuous monitoring for a wearable Parkinson's disease management system. Innovations 1 and 2 target wearability, while innovation 3, combined with temperature correction and signal processing, addresses reliability. The design was guided by both technical performance and feedback from people living with Parkinson's disease, collected in collaboration with the Translational Potential team, with patient comfort and wellbeing as key priorities.

3.1. Wearable sensor

The wearable system consists of two co-located components on the same arm: a multimodal slap-bracelet at the wrist and a levodopa biosensor patch on the mid-forearm, together acquiring the physiological and biochemical signals needed for off-state and dyskinesia prediction.

3.1.1. Technological novelty of wearable sensor

Innovation 1 — Reverse Iontophoresis Levodopa Patch

Continuous levodopa monitoring requires repeated access to interstitial fluid (ISF). Microneedle insertion, the current state of the art (Goud et al., 2019), limits long-term continuous wear. We propose reverse iontophoresis (RI) as a needle-free alternative, using a low DC current (0.1–0.3 mA, below the ~0.3 mA/cm² irritation threshold) through Ag/AgCl electrodes on intact skin to extract ISF via electroosmosis. The negatively charged skin matrix attracts Na^+ ions, which transport water and dissolved solutes towards the cathode (Zheng et al., 2023). Co-extracted interferents such as ascorbic acid, uric acid, and tyrosine are addressed using an enzyme-selectivity layer. RI is established for glucose, lactate, and lithium sensing (Zhu et al., 2025; Giri et al., 2017), and is extended here to levodopa.

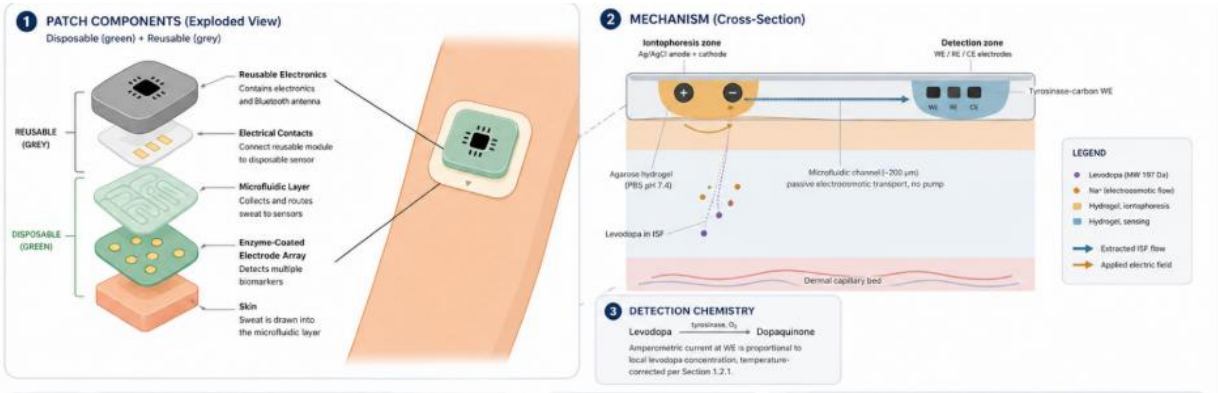


Figure 2 - Schematic of the wearable levodopa biosensor patch, illustrating its layered architecture, reverse iontophoresis-based ISF extraction and electrochemical sensing.

The patch (*Figure 2*) integrates an Ag/AgCl iontophoresis zone within agarose hydrogel (PBS pH 7.4), a passive PDMS microfluidic channel (~200 µm) for pump-free ISF transport, and a tyrosinase-based detection zone (Analytical Team). Tegaderm film and medical adhesive enable 1–2 weeks of wear, while reusable electronics handle temperature correction and wireless communication with the bracelet.

Innovation 2 — Multimodal Slap-Bracelet with fPCB

PD alternates between on-states, as medication wears off, affecting multiple physiological systems. We integrate tremor, heart rate (HR), and skin temperature to predict wearing-off episodes (Arasteh et al., 2023; Victorino et al., 2022). Tremor, a primary PD symptom (Pahwa et al., 2009; Ramesh et al., 2022), is measured via an MPU-6050 IMU (triaxial accelerometer + gyroscope) (Vescio et al., 2021). Autonomic dysfunction manifests as elevated HR during wearing-off (Suzuki et al., 2024; Pursiainen et al., 2007; Kamo et al., 2024) and is tracked with MAX30102 optical sensor (Maxim Integrated, 2018). Reduced peripheral skin temperature marks the off-state (Parry et al., 2019; Pressnell et al., 2025) and partially recovers as levodopa takes effect (Ludwig et al., 2007) and it is measured via a Grove NTC thermistor (GPIO34 analog).

All electronics are integrated on a flexible PCB laminated to the inner surface of the slap-bracelet, where printed traces eliminate intermittent contact failures of discrete wiring (*Figure 3*). An ESP32 microcontroller provides the processing core, WiFi/BLE radio, and ADC for the system. The slap-bracelet form factor enables application with a single wrist tap, addressing three PD-specific constraints: (i) reduced fine motor control, requires self-application without clasps or buttons; (ii) spring-steel substrate curves conformally to the wrist for reliable optical/thermal sensing; (iii) a flat profile allows continuous wear during sleep, when overnight levodopa metabolism directly predicts morning motor state.

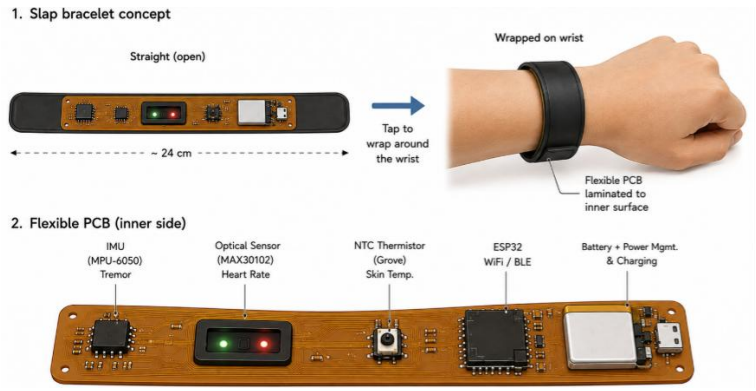


Figure 3 - Conceptual design of the proposed multimodal slap bracelet showing the straight and self-wrapping form factor and the layout of the flexible PCB with integrated sensors.

3.1.2. Technical feasibility of wearable sensor

Reverse Iontophoresis Patch- Feasibility Evidence

RI-driven ISF extraction using electroosmotic flow is validated in FDA-cleared devices such as GlucoWatch (Tierney et al., 2001) for glucose monitoring, and a recent lactate-sensing extraction system (Zhang et al., 2025). Levodopa (MW 197 Da) is close in molecular weight to glucose (MW 180 Da) (PubChem, n.d.-a, n.d.-b), supporting comparable extraction, although levodopa extraction efficiency remains to be experimentally validated. Skin safety is addressed by maintaining current density below reported irritation thresholds and using intermittent iontophoresis cycles (Zhu et al., 2023).

Slap-Bracelet — Feasibility Evidence

The MPU-6050, MAX30102, and Grove NTC sensors were integrated on an ESP32 breadboard prototype and successfully streamed simultaneously at 50 Hz without I2C address conflicts. A real-time dashboard demonstrated integration of tremor, HR, and temperature signals into the prediction pipeline. The levodopa signal remains simulated, so full validation requires integration of real patch data and migration to the final flexible PCB, steps that are considered low-risk due to the established sensor-processing chain.

3.2. Reliability of sensor output

Reliable sensor output is essential for accurate OFF-state prediction, but physiological sensors are prone to drift (e.g., temperature effects on the enzymatic levodopa sensor) and motion artifacts. The system addresses this through sensor-level correction, on-device processing, and multimodal AI fusion to separate real physiological changes from sensor noise.

3.2.1. Technological novelty of reliability concept

Temperature Correction of Levodopa Signal

Tyrosinase's oxidation of L-DOPA is temperature-sensitive, with enzyme activity increasing across the physiological range (Young et al., 2020). Without correction, temperature changes could appear as false levodopa variations. To address this, the reusable electronics of the levodopa patch include a compact temperature sensor (NTC thermistor, SMD, sub-mm footprint) and MCU-based correction applied each measurement cycle using a calibration equation:

$$I_{corrected} = I_{measured} / [1 + \alpha (T - T_{cal})]$$

where T_cal is the reference temperature and α the empirically determined temperature coefficient.

Signal Processing in the ESP32 Microcontroller of the Multimodal Slap-Bracelet

The ESP32 converts raw sensor outputs into clinically relevant features before transmission. Tremor spectral power is extracted from a DFT of a 50-sample accelerometer buffer within the 4–6 Hz Parkinsonian tremor band (Dirkx et al., 2022; Lee et al., 2016). Heart rate is estimated from MAX30102 IR peak detection with a 300 ms minimum inter-beat interval filter to reduce motion artefacts (Renevey et al., 2018; Han et al., 2022). Skin temperature trend is calculated from the rate of change over a 10-minute rolling window to capture dynamic thermoregulatory changes while reducing baseline variability (Coon et al., 2018).

AI Prediction Model — Multimodal Fusion

The Multimodal Fusion model stems from the fact that each signal alone can be affected by other factors. By using all four signals together allows for a more reliable indication of an off state.

A recurrent neural network (RNN) is used. More specifically, we would use a gated recurrent unit (GRU), a simplified variant of the standard LSTM architecture that requires less computational power and performs well on smaller datasets. GRUs learn from training data how much information to retain or discard at each time step, making them well suited to detecting patterns in the signals analyzed here. The final implementation targets a 30-minute prediction horizon, sufficient for levodopa absorption (20–60 min) before an off episode would otherwise occur (Doi et al., 2012).

Before entering the model, the four signals will be brought to a common sampling rate (Schmidt et al., 2018; Hagos et al., 2026), normalized using a sliding window based on the patient's recent data (Bhatt et al., 2022), and split into overlapping time windows. A late fusion approach will be used. Each signal has its own GRU branch, which produces a probability that an off-state is approaching. The four probabilities are then averaged to give the final prediction. Keeping the signals separate makes the model easier to understand and allows it to continue working if one sensor is unavailable (Schouten et al., 2024). The model can also be adapted to each patient by keeping the GRU layers fixed and updating the final prediction layer using their individual data (Keane et al., 2026).

Finally, ablation studies would be of great interest to test how much each signal and model component contributes. This can show whether some sensors or computational requirements can be reduced without significantly affecting performance.

3.2.2. Technical feasibility of reliability concept

The proposed reliability methods are technically feasible using low-power embedded hardware. The levodopa patch temperature correction can be implemented using an NTC thermistor and MCU-based calibration, allowing real-time compensation with minimal computational demand. The ESP32 can process the slap-bracelet features, including tremor, heart rate, and skin-temperature trends, due to their low processing requirements. Individual sensor outputs were observed through a simulated dashboard integration (Figure 4), demonstrating signal combination feasibility, while the AI prediction approach remains a conceptual framework requiring future patient-specific calibration.

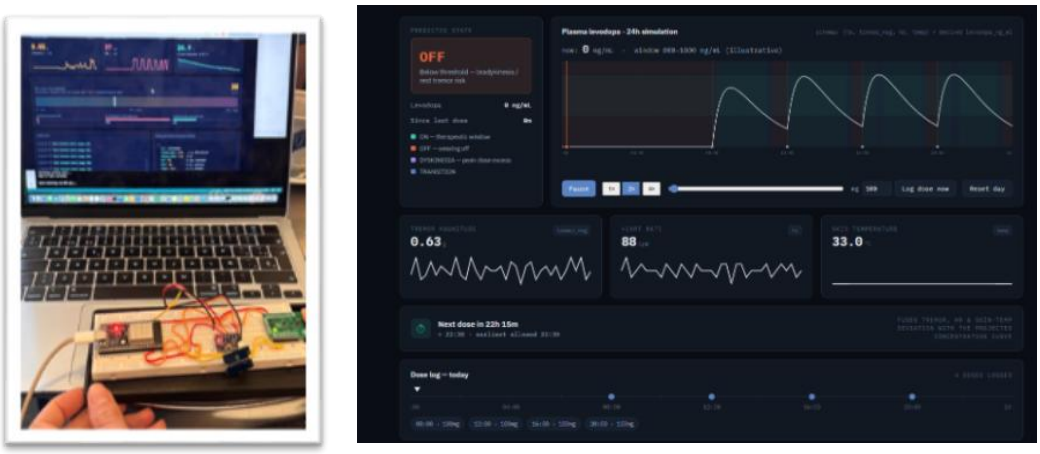


Figure 4 - Prototype test. In the left, dashboard running live via USB with the ESP32 breadboard (MPU-6050, MAX30102, Grove temperature sensor). In the right, dashboard combining tremor, HR, and temperature with simulated levodopa concentration to predict state

3.3. Original contributions

Statement by the team

Our team conceptualized the use of reverse iontophoresis for needle-free levodopa extraction from ISF, a two-component bracelet-and-patch architecture with a reusable/disposable cartridge and pogo-pin connector, a slap-bracelet form factor tailored to people with Parkinson's disease and reduced dexterity, and multimodal AI fusion of levodopa and physiological signals for predictive alerts. We also decided to exclude electrodermal activity (EDA) from the sensor suite after identifying the risk of interference from the iontophoresis current, and proposed patient-specific calibration based on the findings of Arasteh et al. (2023).

Two design elements were adjusted following supervisor feedback: the intermittent iontophoresis protocol (informed by GlucoWatch literature), and the addition of local temperature correction in the levodopa patch.

The ESP32 breadboard prototype integrated the MPU-6050, MAX30102, and Grove temperature sensor. Bench testing confirmed sensor communication using an I2C scanner, FFT-based tremor extraction, heart-rate computation, and real-time visualization through a web dashboard implementing simulated ON, transition, and OFF states.

3.4. Bonus criteria Innovation

Beyond the core innovations described in Sections 3.1 and 3.2, our project identified an additional technical insight with broader innovation potential.

The Pharmacokinetic Gap: Why 30 Minutes Matters

The clinical value of our prediction model depends entirely on the prediction horizon relative to levodopa absorption kinetics. Oral levodopa (immediate release) takes 20–60 minutes to achieve peak plasma concentration (Doi et al., 2012), with significant inter-patient and inter-dose variability driven by gastric emptying rate and competition with dietary amino acids for intestinal absorption. This means a patient receiving an alert at the onset of conscious wearing-off, when levodopa has already declined below the therapeutic threshold, cannot be rescued by an oral dose in time. Effective intervention requires a prediction horizon of at least 30 minutes before conscious awareness.

Our RNN target architecture would need to be specifically designed with a 30-minute output window, trained to recognize the characteristic slope and convergence pattern of the four physiological channels in the 30–90 minutes preceding off-state onset.

4. TP award: Translation potential

4.1 Customer Interviews

To ground our problem definition in real patient needs, rather than in the sensing technology alone, we recruited participants representing three key perspectives along the Parkinson's care journey: patients, caregivers, and a clinical professional. This section describes how these stakeholders were identified, how the interviews were designed and conducted, and what they revealed about where a continuous levodopa sensing wearable could genuinely change day to day life.

4.1.1 Stakeholders and workshop format

We deliberately recruited across the two ends of the Parkinson's disease (PD) severity spectrum, and across both the patient and the caregiver perspective, because a device that satisfies a highly autonomous patient may fail a low-mobility, dependent one, and vice versa. A single "average" patient profile would have hidden this tension entirely.

- **Patients at different disease stages and profiles:** Gerd, diagnosed ten years ago, with severe mobility impairment and heavy caregiver dependence; Anne-Marie, diagnosed ten years ago, a physicist with high autonomy who actively self-manages her dosing; and Margrete, diagnosed around five years ago and mid-stage, interviewed together with a clinical professional.
- **Caregivers / loved ones:** Lene (Gerd's wife and primary caregiver) and Haakon (Anne-Marie's husband), representing the caregiving burden (Macchi et al., 2020), medication reminding, and daily assistance that a monitoring device could offload or support.
- **A clinical professional perspective,** captured alongside Margrete's interview, representing the healthcare system's constraints (limited consultation time, once-yearly neurologist check-ins) that any wearable must work within.

Each group was chosen not simply for diversity, but because each sit at a different point where a wearable's design decisions have consequences: the patient wears it, the caregiver relies on its alerts, and the clinician must be able to act on what it reports within a fixed and short appointment. Selecting stakeholders this way meant that, rather than pitching our sensor concept directly, we could ask what an ideal wearable biosensor for Parkinson's would need to get right for each of them, keeping the validation study anchored in lived experience rather than in what the technology happens to be able to measure.

4.1.2 Interview approach and execution

We conducted three semi-structured interviews (~45–60 minutes each), held individually with each patient and, where applicable, their caregiver present. Interviews followed a guide covering: (1) disease history and current treatment regimen; (2) daily challenges with medication management and interaction with the healthcare system; (3) reactions to and expectations of a continuous levodopa-sensing wearable, including wearability, alerts, and data handling; and (4) unmet needs and desired features. Sessions were documented via written notes rather than audio/video recording, so the material is a paraphrased summary rather than a verbatim transcript. Participants were free to skip any question, and no clinical data beyond what was volunteered was recorded.

4.1.3 The patient journey and its pain points

Across all three interviews, a strikingly consistent pattern emerged despite very different disease stages and personalities. All three participants dose frequently and unforgivingly, every 2–3 hours for Gerd, every 3 hours with time-varying doses for Anne-Marie, and around six times daily for Margrete. All three rely on reminders of some kind, and all still miss doses regardless. All only see a neurologist yearly, for roughly 20 minutes (Sundhed.dk, 2025) where dosing decisions are made from a short physical exam and whatever the patient can recall, not from any objective record of how the year went.

We grouped the findings into three pain points, summarized below together with what each implies for the design of the wearable and the study that will validate it.

Pain point	What we heard	Implication
Dosing burden and off-periods	Missed doses despite alarms and caregivers; off-periods arrive suddenly. For Gerd, staying on schedule is Lene's responsibility, not his own.	A dosing reminder paired with a predictive off-period warning, the warning returns a layer of independence to the patient and relieves the caregiver.
The annual visit gap	Once-yearly, ~20-minute consultations; no objective record of the months in between.	A pre-processed year-long summary that fits inside the existing 20 minutes, rather than raw data for the clinician to read.

Autonomy, trust and data control	Margrete keeps handwritten notes and wants to know what is measured and how accurate it is; Anne-Marie self-titrates; Gerd depends on Lene. Patients want control over who sees the data.	The concept must work across the full autonomy spectrum and remain usable during motor fluctuations and dyskinesia. The wearable therefore needs an ergonomic, easy-to-apply design in addition to explainability and user-controlled data sharing.

Taken together, these findings reframed our problem definition: the opportunity is not simply to detect levodopa levels, but to detect them in a way that restores patient independence, compresses a year of lived experience into a clinician's 20 minutes, and is trusted enough to be worn across the full autonomy spectrum, from Gerd's dependence on Lene to Anne-Marie's self-titration. Equally importantly, they showed that the physical design of the wearable must take ergonomical wearability as a design requirement. Explainability and data-sharing control accordingly became design requirements and study variables in their own right; not secondary features layered on top of accurate sensing.

The full six-stage journey table, including diagnosis and day-to-day living, along with a timeline describing it, is given in Appendix.

4.2 Design of validation study

4.2.1 Selection of the Problem

Levodopa has a narrow therapeutic window and a short half-life, so its effect depends on timing more than on dose alone. Interviews consistently highlighted frequent dosing, missed medication, and unpredictable off periods. Yet the decisions that set that schedule are made in a ~20-minute appointment once a year, from a short neurological exam and the patient's recollection of recent weeks.

The problem we target is therefore the **monitoring gap between when levodopa decisions are made and when the data to inform them exists**. There is no objective record of levodopa levels or motor state at either decision point, the daily dose or the annual titration, leaving both patients and clinicians to work from memory and inference.

This is well scoped for a sensor-based solution since both decisions depend on the same underlying quantity. Continuous levodopa concentration, paired with motion and autonomic signals, is what would let a patient anticipate an off period and a clinician see a year rather than a snapshot. The interview findings guided the prototype design: outputs must be readily interpretable, the wearable must remain comfortable and easy to apply despite motor complications through waterproof, ergonomic hardware, and the system must support both independent and caregiver-supported medication management.

4.2.2 Conceptual Design and Use Case

The proposed solution is a two-component wearable system designed for Parkinson's disease management. The system collects physiological and pharmacological data that are integrated and processed by an AI model. The model is trained on patient-specific on-, off-, and near off-state parameters, enabling prediction of off-state episodes and generation of longitudinal reports for stakeholders. The solution aims to make Parkinson's disease more manageable, reduce uncertainty in daily life, and support personalized care.

Patients wear the system daily and replace the patch every 1–2 weeks. The app provides predictive alerts alongside reminders for medication, patch replacement, and battery status. Caregivers benefit from reduced monitoring responsibility, while clinicians gain continuous objective data to support treatment decisions.

4.2.3 Validation Study Design

Because the sensing chemical and prediction algorithms are not yet operational, the app is researcher-controlled rather than driven by real time data (a Wizard-of-Oz method) (Dahlbäck et al., 1993), so participants react to the interaction and the information itself instead of sensor accuracy.

For the validation study, a mock-up that combines a straightforward clickable companion app prototype, a patch that represents Component 2, and a 3D-printed wristband that matches the form of Component 1 will be used. The app mock-up has four components in line with the journey findings mentioned above: a predictive off-period alert, a dosing-reminder screen, a basic explainability view that shows the trend behind an alert, and a data-sharing screen that allows the participant to instantly select who can see what. To represent the annual consultation, a one-page report summarizes a hypothetical patient's levodopa curve, symptom pattern, and predicted off periods across a year.

Patient and caregiver study – 8–12 people with Parkinson's on levodopa therapy who experience motor fluctuations deliberately spanning caregiver-supported and self-

managing patients; caregivers join where they are currently involved in dosing. Each session opens with a short baseline conversation mirroring the workshop questions (how dosing and off periods are managed today, by whom, and what the annual check-up looks like), then introduces the bracelet, patch, and four app screens without pitching the concept, before walking through an ordinary day and the next annual appointment.

Task-based scenarios cover: a predictive alert scenario; a reminder scenario testing whether it's trusted enough to replace today's method; an explainability scenario where the participant explains in their own words why an alert fired; and a data sharing scenario walking through who gets access. The session closes on what would build enough trust to rely on the device day to day.

Healthcare professional study: 4–6 movement-disorder neurologists and/or PD nurses review a yearlong summary for a fictitious patient as if preparing for that patient's real appointment and are asked whether it would change what they discuss or decide, if it is realistic to absorb in ~20 minutes, and how they'd handle a disagreement between the read-out and their own judgement (Lee & See, 2004). Metrics are chosen for the journey findings that fit within the annual visit timing:

Category	Metric	Tool / measurement
Daily integration & burden	Fit of reminder/alert into routine; who feels “in charge” of dosing, self, device, or caregiver	Debrief question + before/after questionnaire
Trust & explainability	Can explain why an alert fired; confidence in the device vs. own/physician judgement. (Amann et al., 2020)	Comprehension check + 5-point Likert
Usability & wearability	Perceived usability of the app; comfort and practicality for daily wear	SUS + 5-point Likert with open comment
Data control	Satisfaction with granularity of sharing controls; preference vs. current routine	Task walkthrough + forced-choice question

Clinical usefulness (HCP)	Whether the summary changes what's discussed/decided, and fits inside a ~20-minute visit	5-point Likert + qualitative follow-up

Success criteria: the concept is considered validated if a majority of patients/caregivers report reduced day to day burden, if a majority of caregiver supported dyads report responsibility shifting back toward the patient without loss of confidence, and if a majority of clinicians rate the year long summary as more useful than today's appointment (draft targets: ≥70% of patients correctly explain an alert; ≥70% report reduced burden; ≥80% of clinicians rate the summary useful or very useful).

Limitations and next steps: the sample is small and convenience based, not powered for significance; the mock up has no working sensor or prediction; and a single session cannot capture how trust or burden evolve over time. This motivates a staged follow up, bench validation of the patch, an in lab and a take home pilot on real medication timing, and eventually a clinical trial against standard once yearly care.

4.3 Bonus criteria – Translation Potential: a platform business model

Although this project is developed and validated for continuous levodopa monitoring in Parkinson's disease, its underlying architecture is designed as a scalable sensing platform. The reusable wristband serves as a common hardware chassis, while the disposable skin patch functions as an interchangeable sensing cartridge in which only the electrochemical recognition layer (e.g., enzyme or antibody) and its calibration model are biomarker specific. This enables new clinical indications to be addressed by changing the sensing chemistry while reusing the same hardware, software, manufacturing platform, and digital health ecosystem. Likewise, the software remains reusable requiring only biomarker-specific sensing and prediction models. This platform approach reduces development effort while providing a consistent user experience across multiple clinical applications.

Vertical	Cartridge & signal adaptation	Clinical value
Epilepsy	Swap enzyme/antibody layer to an anti epileptic drug (e.g. valproate); reuse tremor/HRV channels for sub clinical myoclonus and preictal autonomic shifts.	Medication reminders, prediction of OFF periods, dyskinesia monitoring through sensor fusion, and long-term treatment optimisation.

Therapeutic drug monitoring	Reuse the wristband's physiological sensors (HR, HRV, motion, temperature), with an optional biomarker-specific cartridge if required.	Continuous monitoring to detect early physiological changes, identify worsening heart function or rhythm abnormalities, and support timely clinical intervention before hospitalisation.
Diabetes	Swap enzyme layer to glucose oxidase (preceded via GlucoWatch); fuse with activity/HRV for hypo-/hyperglycaemia alerts.	Continuous glucose trends combined with activity data to provide predictive hypo-/hyperglycaemia alerts and support insulin management.

Revenue, manufacturing and go-to-market

The platform naturally supports a recurring revenue model. The reusable wristband is sold or leased as the primary hardware, while disposable sensing cartridges provide ongoing revenue through replacement. Additional value is created through subscription-based clinical software, including predictive analytics, clinician dashboards, and secure cloud services. As the same hardware platform is manufactured across multiple indications, production volumes increase while unit costs decrease, with future research and development focused primarily on new sensing chemistries rather than redesigning the wearable itself. Commercialisation would follow a staged approach, beginning with Parkinson's disease, where the clinical need and validation strategy are established in this project. Subsequent indications would build upon the same hardware platform by introducing new sensing cartridges and biomarker specific algorithms, allowing future expansion without fundamentally changing the user experience or system architecture.

5. Team and support

5.1. Contributions of the team members

- Margarida Ornelas served as Team Captain, coordinating the overall project strategy and execution. Co-lead analytical research in ideation, experimental design and wet lab experimentation, mainly focused on the sensing element of the biosensor.

- Amani Sayed shared responsibility for leading this project as team captain, driving project planning, experimental design, and wet lab experimentation, with a primary focus on the biosensors sensing element.

- Yamini Tanuku served as the Analytical team's subteam captain, doing scientific research, experimental design and carrying out experiments in the laboratory, as well as analysing the obtained data.

- Irene Carriazo Badillo served as Innovation subteam captain, coordinating the brainstorming sessions, the ordering of components and the prototype building.

- Verdande Pedersen contributed to the analytical team through discussion, execution of electroanalytical experiments, as well as cartridge design and fabrication.

- Afonso Santos contributed with the AI model conceptualization.

- Peter Kahlke Olesen assisted with the AI model conceptualization.

- Francielle Vieira Gomes was integrated both in Translational Potential and Innovation teams, crossing all relevant information. Participated on the product development and testing, as well as in the patient's workshop and posterior analysis.

- María Caballero Chacón, as part of the innovation team, contributed to concept development and prototype building.

- Costanza Melega, as part of the Innovation team, contributed to concept development and prototype building.

- Mariana Carolina Lopez Pacheco worked within the Translational Potential team, taking part in the patient interviews and their analysis as well as the validation study design.

5.2. People who have given support

- Konstaninos Mengos provided insight into potential cartridge fabrication methods and introduced the team to the laboratory resin printer.

- Daniel-Stefan Cristea provided us with scientific insight and advice on how to proceed in the development of the biosensor as well as aided with ordering and supplying all teams with needed materials.

- Maria Dimaki provided the team with knowledge about microfluidics and necessary components for the development of the biosensor.

- Annette Holek aided the team in all administrative affairs, including budget, lodging and funding requests.

- Winnie Svendsen helped the team with developing a project timeline and coordinating task allocations among team members.

- Maria Lykke Antonsen provided insight and guidance for structured brainstorming and general pitching techniques.

5.3. Sponsors and partners

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6. Final remarks

Participating in the SensUs competition has been an incredibly rewarding and inspiring experience for our team. Throughout this project, we have had the opportunity to apply the knowledge gained during our studies to a real-world biosensor challenge while working in a multidisciplinary and international environment. The project has strengthened our understanding of biosensor development, experimental design, data analysis, and scientific communication, while also teaching us the importance of teamwork, adaptability, and perseverance.

One of the most valuable aspects of this journey has been the opportunity to collaborate with experienced researchers, mentors, and fellow students. Their guidance, feedback, and willingness to share their knowledge have been instrumental in our learning process. We are grateful for the supportive and motivating environment that SensUs creates, bringing together students from different backgrounds who share a passion for science and innovation.

Although we are proud of what we have achieved, this project has also shown us that scientific research is a continuous process. Every answer raises new questions, and every challenge provides an opportunity to improve. We recognize that there is still much to learn, and this experience has motivated us to continue developing our scientific skills and pursue future opportunities in research and innovation.

Finally, we would like to thank everyone who contributed to making this experience possible. Regardless of the competition outcome, participating in SensUs has been an unforgettable experience that has provided us with valuable technical skills, lasting memories, and friendships that we will carry with us throughout our future careers.

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8. Appendix

8.1 Validation of tyrosinase-based L-DOPA detection

The oxidation of L-DOPA catalysed by tyrosinase produces a visual colour change from transparent to brown. The intensity of the resulting colour increases with the L-DOPA concentration, serving as a visual indication of the enzymatic reaction. This colour change results from the formation of melanin-related pigments downstream of L-DOPA oxidation (Fan et al., 2021). Figure 5 illustrates this colour transition for L-DOPA concentrations of 0 µM, 250 µM and 500 µM.



Figure 5 - Visual confirmation of tyrosinase activity in the oxidation of L-DOPA, demonstrated by the characteristic colour change following enzyme addition.

To investigate whether the tyrosinase-catalysed oxidation of L-DOPA could be translated into an electrochemical signal, cyclic voltammetry (CV) measurements were performed in PBS. As shown in Figure 6, the tyrosinase-containing sample exhibited a greater oxidation peak at −0.110 V, whereas the enzyme-free control displayed a smaller, less-defined

electrochemical response. This difference indicates that the observed signal originates from the enzymatic conversion of L-DOPA into electroactive oxidation products.

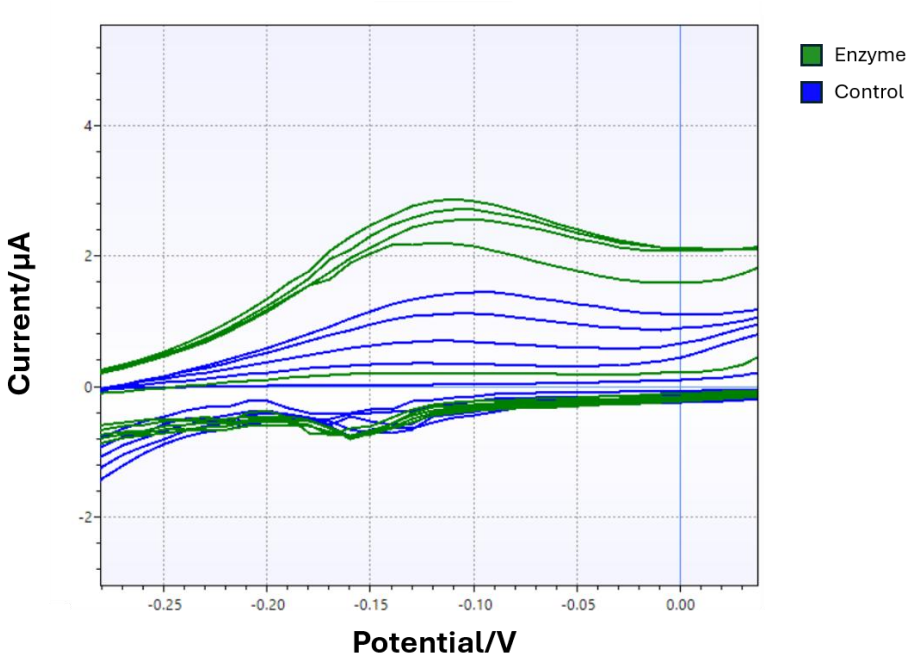


Figure 6 - CV diagram showing greater peak formed for a sample containing tyrosinase.

Based on the oxidation potential identified by CV, chronoamperometric measurements were performed to evaluate the concentration dependence of the electrochemical response. The resulting chronoamperometric graph is shown in Figure 7.

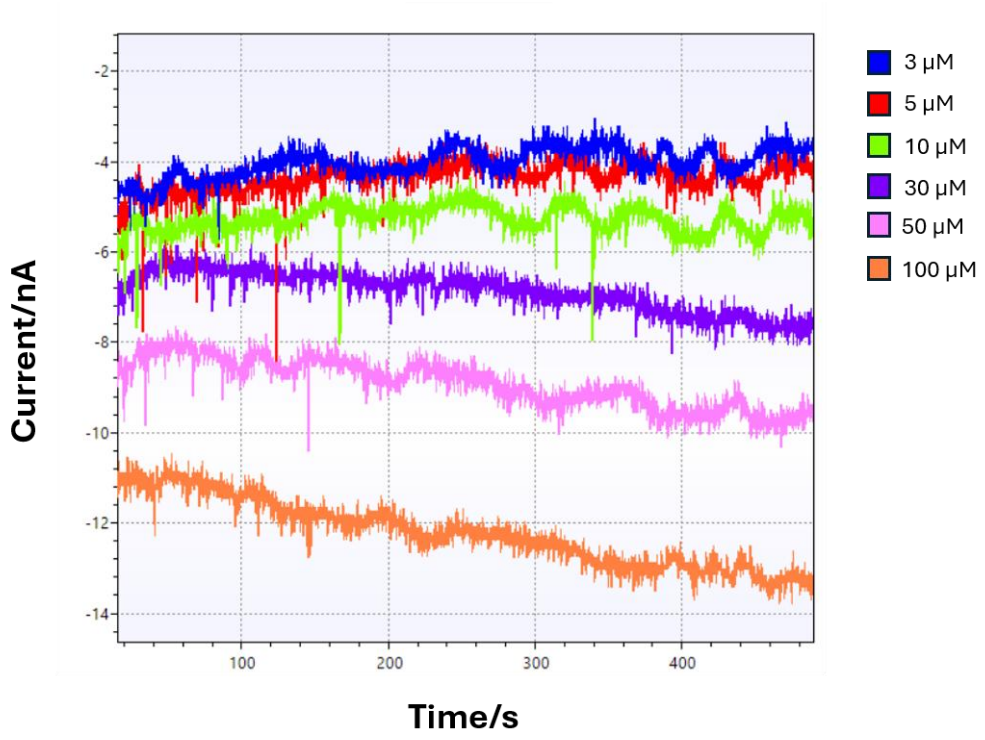


Figure 7 - Chronoamperometric response to increasing L-DOPA concentrations (3–100 µM) in PBS in the presence of tyrosinase. The corresponding enzyme-free controls are not shown for clarity, as they produced significantly lower signal than their counterparts.

An increase in current with increasing L-DOPA concentration was observed in Figure 7, demonstrating a concentration-dependent electrochemical response. This behaviour is consistent with the enzymatic mechanism of the biosensor, where higher concentrations of L-DOPA result in increased substrate availability for tyrosinase-mediated oxidation and subsequent generation of electroactive products.

8.2 Surface characterization

Initially, chitosan was investigated as a biocompatible polymeric matrix for tyrosinase immobilization. However, enzyme loss from the electrode surface during washing indicated poor retention of tyrosinase. To improve the structural stability of the immobilization layer, glutaraldehyde (GA) was incorporated as a crosslinking agent, forming additional interactions between the polymer matrix and enzyme. Electrochemical impedance spectroscopy was then performed to characterise changes in the electrode interface following each modification step. A representative Nyquist plot is displayed in Figure 8.

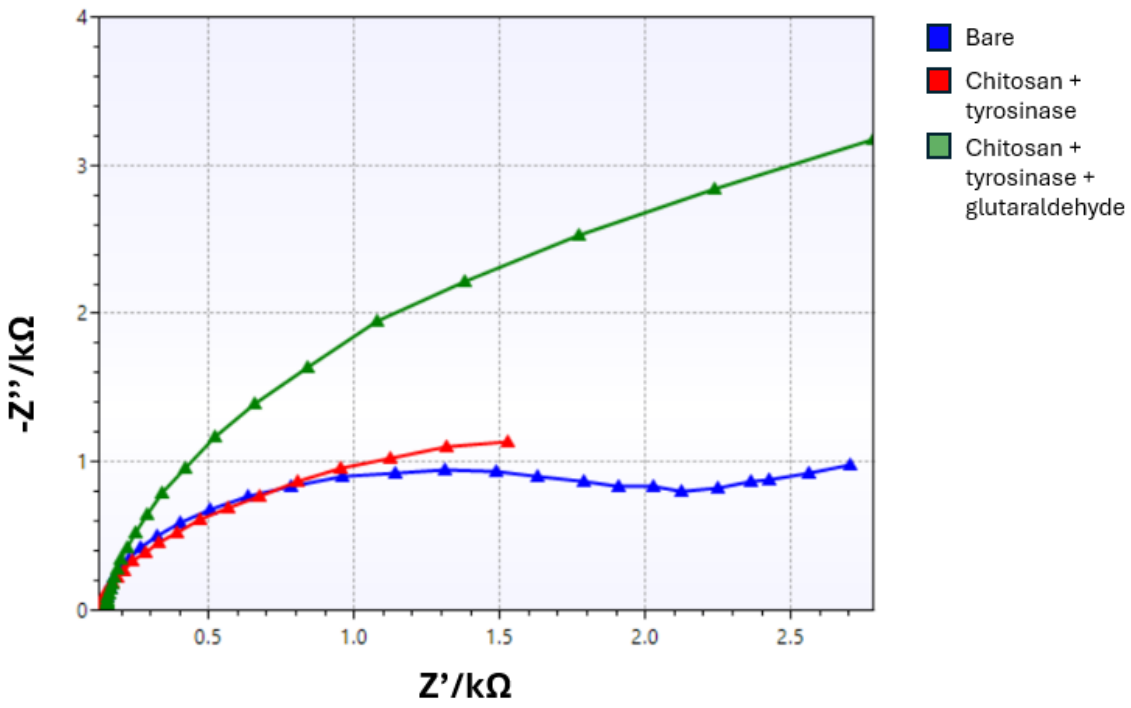


Figure 8 –Electrochemical impedance spectroscopy characterization of the carbon SPE surface after successive modification steps. Nyquist plots compare the bare SPE, chitosan–tyrosinase-modified SPE, and chitosan–tyrosinase–glutaraldehyde-modified SPE.

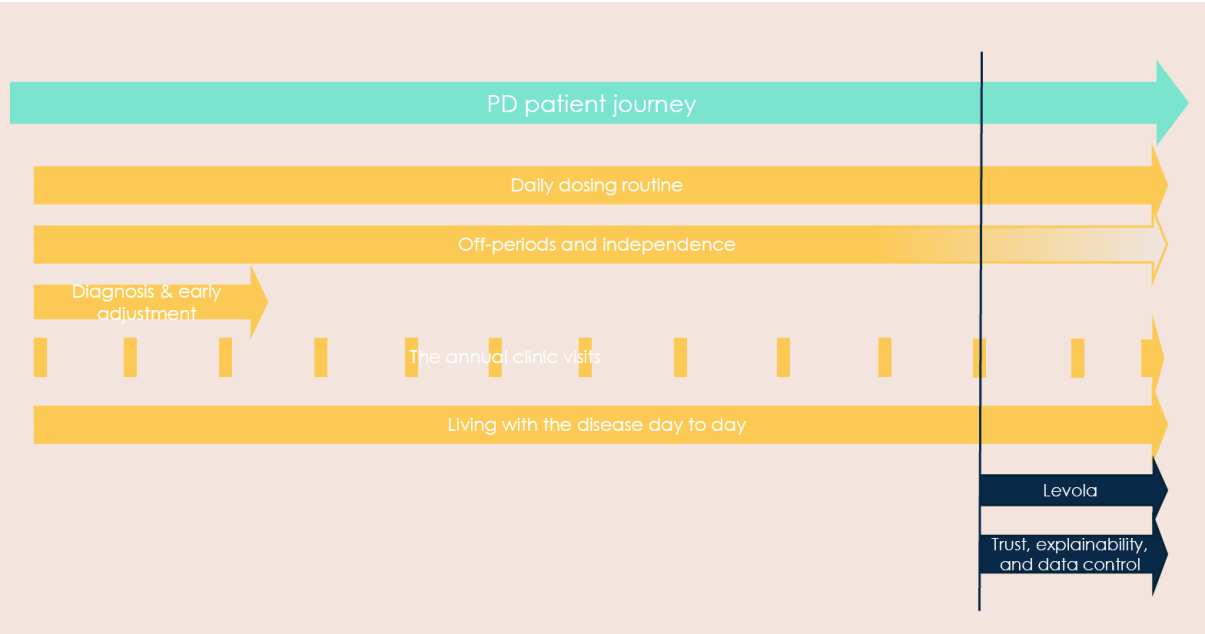
As shown in Figure 8, the modified electrodes exhibited progressively higher impedance compared with the bare carbon SPE. The increase in impedance following the chitosan + tyrosinase deposition and subsequent GA treatment indicates reduced accessibility of the electrode surface to the redox probe, consistent with the formation of an increasingly modified interface. These results support the incorporation of GA as a strategy to enhance the stability of the enzyme-containing layer.

8.3 TP: Validation Study:

Journey stage	What we heard in the workshop	What this implies for the concept
Diagnosis & early adjustment	Diagnosis is often delayed or reached through a specialist rather than a routine check; symptoms are easy to confuse with other conditions (Anne-	A continuous levodopa read-out could help separate a Parkinson's-related symptom from an unrelated one —

	Marie was diagnosed abroad after noticing a speech/communication disconnect; Margrete's team noted symptom overlap with other conditions).	useful both around diagnosis and later, whenever a new symptom appears.
Daily dosing routine	Dosing is frequent and unforgiving: every 2–3 hours for Gerd, every 3 hours with time-varying doses for Anne-Marie, about 6 times a day for Margrete. All three rely on reminders (phone alarms, a caretaker) and still sometimes miss a dose.	One of the most frequently requested features is a dosage reminder, which should be used in conjunction with the predicted off-period warning rather than as an afterthought.
Off-periods & independence	Off-periods bring sudden, hard-to-predict loss of mobility. For Gerd, medication is literally what lets him move (“Motion af Medicin”), and staying on schedule is currently Lene's responsibility rather than his own, making him not fully independent of her.	In addition to providing health information, early notification of an off-period is beneficial since it gives the patient an essential layer of independence and may also provide some relief to the carer.
The annual clinic visit	All three cases converge on the same structural gap - neurologist visits happen roughly once a year, last about 20 minutes, and dosing decisions are made from a short neurological exam covering the most recent experiences instead of how the patient has actually been doing over the previous months.	For physicians, this is the most obvious value proposition. The device provides a representative summary that conveniently spans the months in between visits, processed to fit within the same 20

		minutes, rather than additional data.
Living with the disease day to day	Some patients, like Margrete, build their own intuition for their symptom patterns over time with the help of handwritten documented notes; some, like Anne-Marie, become highly autonomous and already self-adjust dose and frequency, while others, like Gerd, depend heavily on a caregiver for the same decisions.	The idea must be applicable to a wide range of patient autonomy levels. Indeed, for both individuals who actively oversee their own titration and those whose partner does so. Instead of assuming a single profile, the validation research should ideally test with both types of dyads.
Trust, explainability & data control	Margrete specifically wants to know what is being measured, how accurate it is, and how to resolve a disagreement between the device and her physician's judgement. The consensus is that patients want clear control over who can see the data - the patient, the neurologist, the family, or the caregiver.	The fact that the sensing is functional does not imply trust. Rather than focusing only on alerting accuracy, the study and mock-up should examine explainability and data-sharing control as additional characteristics.


PD patient journey
Daily dosing routine
Off-periods and independence
Diagnosis & early adjustment
The annual clinic visits
Living with the disease day to day
Levola
Trust, explainability, and data control