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What Are You Up To? Exploring Cat–Owner Interaction Through Behavior Visualization

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Kurzfassung

Diese Arbeit stellt den Prototypen PurrTime vor, der tragbare Sensorik mit Verhaltensvisualisierung kombiniert, um die Katzenhaltung zu unterstützen und kritische Reflexionen über Technologie im Alltag anzustoSSen. PurrTime nutzt einen IMU-Beschleunigungssensor am Schulterblatt der Katze und ein Klassifizierungsmodell, das Verhaltensweisen mit einer Genauigkeit von 86% erkennt. Über eine mobile Anwendung erhalten Nutzende Echtzeit-Updates sowie tägliche Zusammenfassungen, die als Ergänzung zu eigenen Beobachtungen dienen. Die Evaluation erfolgte durch angeleitete Nutzungssitzungen und halbstrukturierte Interviews mit 11 Katzenhaltenden, gefolgt von einer thematischen Analyse zur Extraktion zentraler Belange der Nutzenden.

Die Ergebnisse zeigen, dass aggregierte Daten besonders geschätzt wurden, um sich aus der Ferne über das Tierwohl zu vergewissern. Dabei war Vertrauen in die Vorhersagen nicht einfach gegeben, sondern wurde aktiv ausgehandelt und stark durch die wahrgenommenen Konsequenzen von Fehlprognosen beeinflusst. Während Langzeitdaten Potenziale für tiefere Einblicke in Routinen boten, äuSSerten Teilnehmende auch Sorgen über emotionale Distanzierung und eine Überabhängigkeit von der Technik. Basierend auf diesen Erkenntnissen skizzieren wir Design-Implikationen für Tier-Tracking-Systeme. Diese umfassen Überlegungen zur Reduzierung des Kontrollaufwands, zur Kommunikation von Unsicherheit, zur Gewährleistung von Privatsphäre und emotionaler Kontrolle bei Langzeitaufzeichnungen sowie zur Wahrung des Tierwohls als Grundvoraussetzung.

Abstract

This thesis presents a wearable sensor and behavior visualization prototype system called PurrTime, aiming to explore how everyday cat care can be supported and how technology integrated into daily life can be reflected upon. PurrTime combines an IMU accelerometer worn on the cats left shoulder blade, a behavior classification model with 86% accuracy, and a mobile application that provides real time behavior updates and daily behavior summaries, which can be used together with manual records. We evaluated PurrTime through guided experience sessions and semi structured interviews with 11 cat owners. Thematic analysis was used to extract recurring themes.

The results show that participants valued summary information as a way to quickly check their pets condition and gain reassurance when they were away from home. However, trust in predictions was not taken for granted, but needed to be negotiated, and was shaped by the perceived cost of errors. Participants further imagined that long term records could reveal previously unseen daily routines, prompt small care adjustments, and reshape feelings of closeness, while at the same time raising concerns about overreliance and emotional distancing. Finally, participants expressed ambivalent attitudes toward lifetime archives and digital memorialization, including differing reactions to the idea of virtual reconstruction. Based on these findings, we outline design implications for companion animal tracking systems, including reducing the cost of checking, communicating uncertainty, ensuring privacy and emotional control over long term records, and treating cats comfort as a prerequisite.

Contents

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List of Abbreviations

ACI Animal Computer Interaction. 1–5, 10, 13

ANN Artificial Neural Network. 5

ANOVA Analysis of Variance. 5

AP Access Point. 23

API Application Programming Interface. 14, 25, 26

BLE Bluetooth Low Energy. 23, 24

CNN Convolutional Neural Network. 5

DTO Data Transfer Object. 26

GLM Generalized Linear Model. 5

HCI Human Computer Interaction. 1–6, 8, 10, 13

HTTP Hypertext Transfer Protocol. 20, 23, 26, 29

IMU Inertial Measurement Unit. 1, 3, 5, 6, 17, 22, 24, 47, 48

JSON JavaScript Object Notation. 20, 23

JWT JSON Web Token. 26

LDA Linear Discriminant Analysis. 6

LSTM Long Short Term Memory. 5, 16

MAC Media Access Control. 23, 28

MLP Multilayer Perceptron. 6, 16–18, 20

MTU Maximum Transmission Unit. 23

NTP Network Time Protocol. 22, 24

ODBA Overall Dynamic Body Acceleration. 5

QDA Quadratic Discriminant Analysis. 6

ReLU Rectified Linear Unit. 17

RF Random Forest. 5

SiLU Sigmoid Linear Unit. 17

SOM Self Organizing Map. 5

SVM Support Vector Machine. 6

TCP Transmission Control Protocol. 23

UDP User Datagram Protocol. 14, 22–26

UTC Coordinated Universal Time. 22–24, 26, 27

1. Introduction

Living together with cats requires owners to continuously observe and interpret their behavior. Owners judge their cats comfort and health by observing posture, activity level, and feeding frequency. However, these cues are often subtle and fragmented. When owners are away from home, observation becomes even more limited. Even attentive owners may notice that something has changed, but find it difficult to specify what exactly has changed, how long it has lasted, or whether it fits within the cats normal routine. This creates a recurring tension in the context of pet care: owners want to gain timely awareness of their cats condition, but access to behavioral information is constrained by time, distance, and cats tendency to hide pain [1].

The emergence of wearable sensors and machine learning points to a promising direction [2, 3, 4]. Accelerometers can be used to continuously capture cats activity data, and machine learning classification models can be applied to infer behavior. However, simply listing activity labels does not mean that behavior can be directly understood. In everyday care, limited accuracy and uncertain predictions can shape how owners judge the systems reliability, affecting when they trust the outputs and when they fall back on their own experience [5]. Therefore, for cat owners, the challenge lies not only in sensing and classification, but in how to interpret the data and combine it with their prior experience to better align with their cats living patterns.

To explore these questions, we approached the problem from the perspectives of Human Computer Interaction (HCI) and Animal Computer Interaction (ACI), and developed PurrTime, a behavior visualization prototype based on wearable sensors. PurrTime combines an Inertial Measurement Unit (IMU) accelerometer module worn on the cats left shoulder blade with a behavior classification model and a mobile application. This allows owners to continuously track their cats condition through real time behavior updates and daily summaries, as well as manual daily and expense records. The current model supports four behavior categories: Inactive, Active, Eating, and Grooming.

We evaluated PurrTime through guided experience sessions and semi structured interviews with cat owners. Our goal was not only to verify model performance and accuracy, but to understand how people interpret visualized data in specific contexts, how trust in the system is established, and how they imagine potential behavior changes and ethical concerns around digital beings in long term use.

Based on this aim, the thesis addresses the following research questions:

1. **RQ1: How do behavior visualizations support daily care?**
   a) **RQ1.1: What gaps do owners see in current pet monitoring tools?**
   b) **RQ1.2: How do owners use behavior summaries for reassurance and care adjustments?**

2. **RQ2: To what extent do owners trust and rely on the behavior visualization system?**
   a) **RQ2.1: What role does owners intuition play in the use of the technology?**
   b) **RQ2.2: How do owners react to erroneous information provided by the application?**
3. **RQ3: How do long-term behavioral records influence the human-cat relationship throughout the animals life and beyond?**
   a) **RQ3.1: How does finding hidden routines affect closeness and understanding?**
   b) **RQ3.2: What are owners attitudes towards preserving or recreating their cats life digitally?**

The core contributions of this thesis are threefold. First, it presents a functioning prototype system, including the sensor setup, machine learning parameters, and software side architecture. Second, it collects users views and insights through interviews on the relatively novel direction of combining hardware and visualization in the context of pet care. Finally, it summarizes a set of design implications applicable to companion animal behavior tracking systems.

The remainder of the thesis is organized as follows. Chapter 2 reviews related work across HCI, ACI, wearable sensing for animal behavior recognition, visualization for sensemaking, interpretive challenges in understanding animal behavior, and trust calibration in everyday systems for appropriate long term reliance. Chapter 3 describes the study design, participants, data collection, and analysis approach. Chapter 4 details the design and implementation of the PurrTime system. Chapter 5 presents the qualitative findings. Chapter 6 discusses how these findings answer the research questions and outlines design implications, limitations, and future work. Finally, Chapter 7 concludes the thesis.

2. Related Work

This thesis draws from several bodies of research due to its interdisciplinary character. One is HCI, a field that keeps expanding its research range, from work efficiency to daily experience [6], meaning [7] and reflection of interaction with technology [8]. Another is ACI, which treats animals not only as test subjects but also as legitimate users and stakeholders. Their needs, cognition, and welfare are vital in design [9]. The last body of work concerns wearable sensors and machine learning. Prior research has demonstrated the possibility of using Tri-axial accelerometer or IMU based accelerometer to capture and classify animal behaviors. What connects these subjects is a mutual practical question: when technology produces behavioral information, how does that information become understandable and useful in real life care?

Imagine cat owners often make decisions based on incomplete or ambiguous signals. They can feel that some changes have happened in their cats behaviors, but it is hard to explain what actually changed, how long those changes have lasted, or whether those changes are part of their normal behaviors. Wearable sensors can provide continuous data to alleviate the lack of observations, and machine learning can transform original signals into meaningful labels. However, these outputs still need to be interpreted, as a single behavior label cannot provide deep insights, especially when owners need to connect it with cats daily activities, events, or personal knowledge.

This is where HCI and ACI become important. HCI provides insight into how people use data to construct principles of understanding, especially through interaction, comparison, and long term reflection. ACI affords a perspective from animals, where behavior monitoring becomes part of the relationship between human and animal rather than a purely technical problem. Meanwhile, literature from the sensors field is also important, because it defines what behaviors can be detected and under what conditions, which in turn shapes what can be visualized.

First, this chapter briefly outlines the development of HCI, and it then describes the emergence of ACI as a complementary field, providing the foundation of technology as a medium between human and animal interaction. Next, it surveys wearable sensor research on animal behavior recognition, showing both the technical feasibility and a gap in how those data are interpreted by owners. Third, it discusses visualization as a medium for sense making and reflection, including work on narrative and personal dashboards, and how these ideas translate to the pet care context where the tracked subject is the animal rather than the user. Then we review the difficulties and limitations people face when understanding and observing animal behavior, and why interpretive support is needed in this process. Finally, it examines trust between people and systems in everyday life, focusing on how trust is built, broken, and calibrated, and why maintaining an appropriate level of reliance is critical in long term pet behavior monitoring.

2.1. Bridging HumanComputer Interaction and AnimalComputer Interaction

Unlike traditional subjects, HCI as an interdisciplinary subject has undergone several significant shifts and transformations since its inception in the 1980s due to technological developments and changing demands.

To trace these developments, Carlisle [10] first proposed this term in his article because computers are unlike all other tools; they do not have a specific purpose or limitations. In its tool centered phase, HCI aimed to integrate with cognitive psychology and system design in order to enhance task performance and usability in work oriented contexts [11].

With the widespread adoption of computers and their integration into everyday life, interaction increasingly extends beyond the individual user. People use computers as mediating artifacts to coordinate activities, share information, and collaborate with others through technologies such as email and web based systems. However, individual and cognition focused models of interaction are no longer sufficient for explaining how technologies are embedded in everyday work practices and organizational contexts. Suchmans theory of situated action challenged plan based and cognitive accounts of interaction by emphasizing the contingent and improvised nature of human activity [12]. Building on this perspective, Grudin [13] demonstrated how collaborative systems often fail when formalized technical structures conflict with situated work practices and organizational realities.

Subsequent HCI has focused not only on work efficiency and collaboration, but also on human emotions, values, meaning, and the role of technology in everyday life and culture [6, 7, 14]. Users are no longer passive recipients of information, and emotions are no longer treated as mere noise. Instead, technology is interpreted from the user's perspective, connecting its use with the user experience [15]. Researchers began to examine how interaction with technology shapes identities, values, and emotions, not only in relation to other humans but also in relation to non human others such as games, AI, animals, and the environment among others, positioning interaction as a cultural and experiential process.

In this context, Mancini proposed in the manifesto [9] the establishment of ACI as a unique discipline that extends HCI principles to animals, because traditional HCI has placed excessive emphasis on the human and user centered design [16] rather than animals' self cognition, behavior, and need. From user centered design to animal centered design, animals are recognized as legitimate users, stakeholders, and participants.

This shift also means that design goals and evaluation criteria should fully take into account animal welfare, agency, and differences between species, rather than treating animals as mere objects of monitoring. In addition, since animals cannot directly express themselves, studies that rely on behavior and context need to depend on the researchers' cautious interpretation, which also reflects methodological challenges in the ACI field, especially ethical issues involving consent, burden, and potential harm.

Building on this foundation, Hirskyj-Douglas et al. [17] reviewed the field seven years after the original manifesto, outlining how ACI has matured into a research domain with its own methodological and ethical frameworks while remaining closely linked to HCI.

HCI and ACI complement each other in their research focus and methodologies. HCI contributes theoretical frameworks concerning human experience, reflection, and meaning-making, while ACI provides methodologies for engaging with non-human participants and explores ethical considerations in cross-species design. By integrating these approaches, researchers move beyond studying humans or animals in isolation to investigate how contemporary technology, as a medium, can enhance mutual understanding and relationships between them.

2.2. Wearable sensing for animal behavior recognition

With the growing popularity of Artificial Intelligence and the recent advances in machine learning tooling which have significantly lowered the technical barrier for programming [18, 19], the integration of wearable sensing technologies with machine learning approaches such as feature based models and deep neural networks has become a widely adopted and central methodology in animal behavior research [20, 21, 22]. Compared with traditional approaches that rely on manual observation and video annotation to describe behavioral patterns through qualitative or basic quantitative analysis such as Analysis of Variance (ANOVA) or Generalized Linear Model (GLM), sensors provide a continuous and non-invasive means of recording activity data. Accelerometer based systems offer advantages in mobility, data compactness, and animal comfort. Triaxial or IMU accelerometers have been applied across various species:

Smit et al. [2] verified the possibility of using accelerometers to predict cat behavior. In a controlled environment, accelerometers were positioned on the collars and harnesses of twelve cats and a 7-day experiment was conducted. Features such as mean, min, max, sum, Overall Dynamic Body Acceleration (ODBA), and others were extracted from the accelerometer data. In subsequent model training, using four hours of manually annotated video data, the authors compared the accuracy of Random Forest (RF) and Self Organizing Map (SOM) on collar and harness setups. They concluded that SOM achieved higher accuracy than RF, and that the harness setup achieved higher accuracy than the collar setup.

Hussain et al. [3] were the first to implement cat activity detection based on a Long Short Term Memory (LSTM) model, using data from three sensors (accelerometer, gyroscope, and magnetometer) collected from 10 cats over one month. They compared model performance among LSTM, 1D Convolutional Neural Network (CNN), and Artificial Neural Network (ANN) for ten cat behaviors using features such as standard deviation, mean absolute deviation, mean, minimum, maximum, interquartile range, energy measure, skewness, and kurtosis. LSTM achieved the highest accuracy at 95.94%.

Goodall et al. [4] used a homemade collar accelerometer and one hour of labeled data per cat to train a recurrent neural network based on LSTM, successfully predicting 11 domestic cat behaviors, such as low activity, high activity, and resting, with an accuracy of 80.16%.

Kumpulainen et al. [23] used data from 45 medium to large sized dogs to develop a machine learning model and to evaluate the impact of accelerometer placement and gyroscope usage on model performance. Each dog wore an accelerometer positioned both on the collar and on a harness. The performance of four models, Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM), and Classification Tree, was compared. SVM achieved the highest accuracy of 91.4% when using harness data. However, the researchers also noted that individual differences between dogs could lead to variations in model accuracy.

Galan et al. [24] proposed an embedded animal behavior recognition system that enables real time classification directly on a wearable collar device. Using data from an IMU accelerometer, a low power micro-controller was employed to run a Multilayer Perceptron (MLP) model for recognizing three horse gaits, standing, walking, and trotting. After offline training, the model was deployed on the device using a lightweight embedded neural network library, enabling on device inference and reducing wireless data transmission. In practical experiments, using Kalman filtered IMU data, the embedded system achieved an average classification accuracy of 81.01%.

These studies have given valuable technical foundations for machine learning based modeling and have confirmed the feasibility of using accelerometers to identify animal behaviors. However, most previous work has remained at the level of technological validation, focusing on feature extraction, sensor placement, and model performance metrics. Animals are treated primarily as sources of data, while questions about how such data are understood, experienced, or integrated into everyday life by pet owners are rarely explored.

Although this accuracy-oriented perspective has established an important technical basis, it overlooks a vital question: how can recognized behavioral information be transformed into meaningful experiences? This gap between technology and understanding lies precisely at the heart of HCI inquiry.

2.3. Visualization as a medium for sense-making and reflection

In the HCI field, visualization is changing from a way of showing data to a medium that supports meaning construction and reflection. It not only shows data or facts but also reshapes how people understand, perceive, and use information [25]. This shift becomes clearer when visualization is considered as part of an ongoing reasoning process. Sense making is usually described as an iterative process in which people search for and collect information, build initial explanations, and revise those explanations when new evidence occurs [26]. Visualization can simplify information extraction and use visual encoding to support users tasks.

Apart from analysis discovery support, narrative visualization also strengthens meaning making and how design influences interpretation. Segel et al. [27] pointed out that, compared to traditional storytelling that uses written text, narrative visualization uses visual encoding expressiveness and effectiveness to gain attention and uses data to tell a story. Hullman et al. [28] further noted that narrative visualization can use rhetorical design to guide users interpretation in order to affect their attitudes and decisions. Therefore, the effectiveness of visualization has also expanded to include emotional involvement and behavioral influence. Kennedy et al. [29] emphasized that the interaction between users and data has sociocultural parameters, meaning that visualization can act as a tool to facilitate cognitive and behavioral transformation. This aligns with the transformative dimension of reflection discussed by Baumer [30], where technology moves beyond simple data representation to prompt users to challenge their underlying assumptions and reconsider their future choices.

Recent research suggests that the meaning of visualization often emerges when data is connected to lived experiences and situated context [31, 32]. People do not interpret data recklessly, but connect it with personal habits, values, and context.

In the pet care field, these concerns are even sharper because the tracking object is not the user but the animal. This points to the paradigm shift from the Quantified Self to the Quantified Other [33]. People seek visualization methods that can help them transform sensor data into pet welfare, daily activities, or potential problems. As Nelson and Shih [34] demonstrated with CompanionViz, visualization in this field needs to be able to bridge the gap between pets and owners, supporting owners interpretation according to their own understanding in their everyday context.

2.4. Human understanding of animal behavior and the need for interpretive support

Unlike direct communication through language between humans, understanding the behavior of companion animals is complex and relies heavily on experience. Pet owners rely on subtle and obscure signals such as posture, daily routines or small changes during interaction [35]. These challenges are particularly striking in felines, as cats may reduce visible signs of pain as a protective strategy [1]. New pet owners often find it difficult to link these subtle changes to a cats pain and in some cases, they may not notice these changes at all.

Evidence from feline medicine shows that many disease symptoms occur through cat behavior at home rather than as a single snapshot during a consultation. For example, chronic musculoskeletal pain such as osteoarthritis is often associated with observable changes that owners can observe, including gait changes, reduced jumping, and altered activity levels. However, these changes are often misunderstood by cat owners as ageing or personality traits [36]. Clinical assessment of chronic musculoskeletal pain in cats often depends on owners' observations and reports of changes at home. This facilitates the development of structured, owner reported instruments such as the Feline Musculoskeletal Pain Index and related owner completed measures [37, 38]. These tools reflect one important point: even though owners are at the center of daily behavior observation, transforming those observations into reliable interpretation is still not easy and requires structured instruments.

Another complex issue is that pet owners evaluations are not always neutral, but are also affected by expectations, dependencies, and social habits. Research by Bouma et al. [39] shows that cat owners interpret cat behavior with anthropomorphic perceptions, which leads to less accurate interpretation of cat behavior. This does not mean owners are careless; rather, it highlights that daily understanding consists of informal theory and selective attention. In real life, owners might detect one abnormality but ignore other important factors such as weather, visitors, or schedule changes.

These limitations imply that the understanding of animal behavior requires the support of structured interpretation rather than short term or casual observation. Wearable sensors with automatic behavior prediction can reveal some hidden and imperceptible behaviors. However, data driven systems cannot promise understanding on their own, as owners still need to combine these data with daily habits and long term trends. As Li et al. [32] mentioned, the value of a system is not only in data collection but also in supporting users self reflection. In this regard, visualization becomes the interpretation layer, as it affords a time dimension that lets users compare current data with personal baselines, discover changes, and link events to specific contexts.

Importantly, interpretive support does not require the system to reply to why a behavior happens. Instead, it provides a frame that helps users ask better questions and make reasonable observations. In detail, it can comprise clear timelines and daily conclusions, comparisons between different days, and context annotations such as weight, medication, and diet changes. By transforming continuous sensor data into stable and understandable data, it affords owners a basis for cognition and reflection that is difficult to achieve through direct observation.

2.5. Technical Reliability and Trust Calibration

The actual duration and frequency of use of pet wearable monitoring devices depend on owners trust in the underlying algorithms. In the field of HCI, trust is often treated as a multidimensional expectation grounded in users perceptions of a systems predictability and technically competent performance, including reliability [40]. For cat owners, performance metrics of machine learning models such as accuracy, recall, and F1 score shift from being purely numerical statistical indicators to becoming a basis of confidence in everyday pet caring.

Algorithm accuracy and peoples trust in cat wearable systems are not linearly related. Parasuraman et al. [41] point out that even when the performance of an automated system changes, users responses may diverge. When the false alarm rate is high, automation is often disused and users may experience alarm fatigue (the cry wolf effect), that is, they ignore or disable potentially critical notifications. Conversely, when a system is perceived as powerful, owners may rely on it uncritically, reduce their own monitoring, and thus misuse it. In the context of pet care, this may cause already subtle symptoms to be overlooked.

In addition, trust between humans and devices is fragile. Dzindolet et al. [42] found that people often assume machines should be perfect. Therefore, when a machine makes an error, even if its overall accuracy is still higher than that of humans, it often leads to a rapid collapse of trust. This is consistent with the asymmetry principle proposed by Slovic [43], which states that negative events are more likely to be noticed and have a much greater impact on trust than positive events. Trust is built slowly, but a single failure can destroy it instantly, and once lost it is often difficult to recover. This also reflects the trust challenges faced by long term behavior monitoring. Research by Lee et al. [5] emphasizes appropriate reliance and trust calibration, that is, aligning users trust levels with the systems actual capabilities and adjusting them over time through use experience. From this perspective, the role of visualization is not to present an unquestionable result, but to combine the result with understandable context, for example by supporting users in reviewing specific time periods, enabling owners to compare system outputs with their own observations. At the same time, related studies also show that when a system makes errors, providing explanations or helping users understand why the system makes errors can help mitigate trust collapse caused by errors and influence subsequent reliance [42].

3. Methods

Due to the interdisciplinary nature of this research, we adopted methods that combine system development with qualitative user research. Following HCI and ACI traditions, the evaluation does not focus solely on technical performance, but emphasizes users understanding, experience, and emotional responses.

The methods consist of two main components. First, we describe participant recruitment and qualitative data collection through semi structured interviews, focusing on how cat owners interpret and reflect on behavior visualizations. Second, we outline the qualitative analysis used to identify main and recurring themes across participants accounts.

Note. The thesis also involved developing a machine learning based behavior recognition component to generate the visualizations. As this algorithm served primarily as an enabling system component, technical details of the data processing pipeline and model training are reported in Chapter Design and Implementation.

3.1. Participants

From September to December 2025, we recruited 11 participants through friend referrals and personal networks. All participants were required to be cat owners, since the study focused on daily interaction with a system designed for monitoring and visualizing cat behavior. To ensure effective engagement with the prototype system, participants were recruited from a young demographic with experience using smart devices and mobile applications. Participation was voluntary, and informed consent was obtained from all participants (see Appendix A).

We offered both remote and in person study sessions. Details are provided in the following section Study setup and conditions. After completing the study experience, all participants also took part in semi structured interviews to collect qualitative feedback and ensure a sufficient number of interview samples [44]. An overview of the participants and their cats is shown in Table 3.1.

Due to the influence of various factors, not all cats directly experienced the wearable device during the study. In some cases, cat owners currently live in Vienna but their cats are in their hometown (P5, P6, P7, P9, P10), while in others, one cat showed discomfort or unwillingness to wear the device (P8). Consequently, only the cats of participants P1, P3, and P11 wore the device in their homes. For all other participants, engagement with the system focused on demonstrations, visualizations, and discussion rather than direct physical use by the animals.

Table 3.1.: Overview of participants and their cats. Each cat is listed separately.

ID	Gender	Nationality	Age	Cat name	Cat sex	Cat age	Participation
P1	Male	Chinese	28	Tieqiu	M	~1 year	In person
				Tiegun	M	~1 year	
P2	Male	Chinese	27	Pidan	M	3 years	Remote
				Oli	F	9 years	
P3	Female	Chinese	26	Xiaohei	M	<1 year	In person
P4	Female	Chinese	25	Ober	M	3 years	Remote
P5	Female	Austrian	25	Luna	F	13 years	In person
P6	Female	Turkish	30	Duman	M	3 years	In person
				Odin	M	2 years	
				Balim	F	1.5 years	
P7	Male	Ukrainian	18	Paramon	M	9 years	In person
P8	Female	Chinese	35	Wangzai	M	<1 year	In person
P9	Female	Russian	27	Bagheera	F	17 years	In person
P10	Female	German	23	Ali	M	17 years	In person
P11	Male	Chinese	26	Ginger	M	3 years	In person

3.2. Study setup and conditions

All steps were conducted through a guided experience, followed by a semi structured interview. Each participant followed the same experience procedure to ensure a consistent understanding of PurrTimes core functions and implementation logic, aiming to control variables in the subsequent semi structured interviews. We conducted both in person and remote sessions.

In person sessions. In the in person condition, participants were allowed to directly experience the app and hands on interaction with the wearable device, and when conditions permitted, their cats were asked to wear the wearable sensor for trial use. Depending on the level of cat participation, the experience session might focus more on interaction with the wearable device or on the app experience and discussion.

Remote sessions. Remote sessions were conducted via video conferencing. The researcher demonstrated how the wearable device works with the classification model to infer cat behavior by simulating sensor orientations corresponding to specific cat actions, and demonstrated the use of the app. Participants discussed the system based on the demonstrations and their own daily routines. Under this condition, no new sensor data were collected.

3.3. Procedure

Before the hands on walkthrough, a presentation slide deck was used to explain to participants the logic behind the wearable setup and the machine learning model, and why their combination can be used to predict cat behavior. Participants were informed of the overall accuracy of the classification model and the accuracy of each individual behavior. The researcher then guided both in person and remote participants through a series of tasks, ranging from creating an account and a cat profile to pairing the device and exploring the visualizations.

For sessions that included the wearable trial, the wearable was attached to the harness and placed on the cat, and the cat was allowed to move freely under the supervision of the owner and the researcher while the system streamed and updated behavior information. A detailed step by step description of the tasks is provided in Appendix B.

Notes on Variations Across Sessions: Although we ensured that the content of each step was consistent, not all participants experienced a real working scenario in which the wearable device was bound to a cat. When real usage was not possible, we focused on manually simulating cat behaviors by controlling the orientation of the accelerometer to demonstrate real time behavior visualization, so as to maximize participants ability to express opinions regarding understanding, trust, and expected use.

After the experience session ended, the researcher invited participants to freely discuss and answer specific questions based on the experience they had just had.

3.4. Data collection

3.4.1. Human participant data

Qualitative data from human participants were collected through semi structured interviews conducted after participants had experienced the entire system. The interviews were designed to elicit participants reflections on their everyday practices of caring for their cats, their interpretation of the systems visualized behavior data, and their perceptions of trust, emotional impact, and ethical implications.

The interview protocol consisted of five thematic sections:

1. Daily routines and existing habits of interpreting cat behavior
2. Trust and reliance on the system
3. Emotional impact and changes in the humancat relationship
4. Ethical and privacy considerations
5. Long term use and speculative scenarios, including ideas of digital memory and representation of animal life

Interviews were audio recorded with participants consent and subsequently transcribed verbatim. The resulting transcripts constitute the primary qualitative dataset used for analysis in this study. A full version of the interview guide is provided in Appendix B.

3.4.2. Cat related data

Cat related data were collected through the wearable sensing system during short home deployments and saved in the database. We used these data to demonstrate the systems end to end operation and to generate visualization examples, not to draw generalizable conclusions about behavior. As mentioned above, only cats belonging to participants P1, P3, and P11 wore the device. For other participants, no new animal sensing data were collected during the study.

3.5. Data analysis

Interview transcripts were subjected to a thematic analysis to detect commonalities and divergences among the experiences of the participants. Thematic analysis was selected as it offers a systematic, yet flexible way to analyze qualitative data and is appropriate for investigating meanings, interpretations, and experiences [45].

For each theme, we reviewed all interview transcripts and compared participants accounts to identify recurring viewpoints, differences, and tensions, with particular attention to how participants linked the visualizations to their everyday life and their existing knowledge of their cats.

The resulting themes and subthemes form the structure of the qualitative findings presented in Chapter Findings.

3.6. Ethical considerations

This study followed ethical principles in the fields of HCI and ACI. All human participants were informed about the aims, procedures, and scope of the study before participation. Participation was voluntary, and informed consent was obtained from all participants. Participants were informed that they could withdraw from the study at any time without providing a reason and without negative consequences.

Ethical considerations regarding animals were treated as a central component of the research design. In line with ACI literature, animals were regarded as stakeholders rather than passive objects of study, and their comfort and well being were prioritized over data collection goals [9]. Therefore, the direct interaction with the wearable device was not mandatory. If a cat was not present, appeared uncomfortable, or showed unwillingness during the study session, the deployment process was canceled.

The study did not involve invasive procedures or interventions that could cause harm or distress to animals. The wearable device was lightweight and used only in short sessions under supervision. The primary goal of the research was on human interpretation and sense making of animal related information, rather than on modifying or influencing animal behavior.

4. Design and Implementation

This chapter describes how PurrTime was constructed as a wearable based visualization system. Figure 4.1 shows how data flows through the entire system. The wearable sensor sends the extracted features to the NestJS backend server via the User Datagram Protocol (UDP) protocol. NestJS acts as an intermediate hub, forwarding the features to the cloud based behavior classification model to obtain inferred behavior labels, and storing the information in the PostgreSQL database for persistence to support later Application Programming Interface (API) calls. It also provides WebSocket channels to the frontend to enable real time data transmission and updates in the view pages.

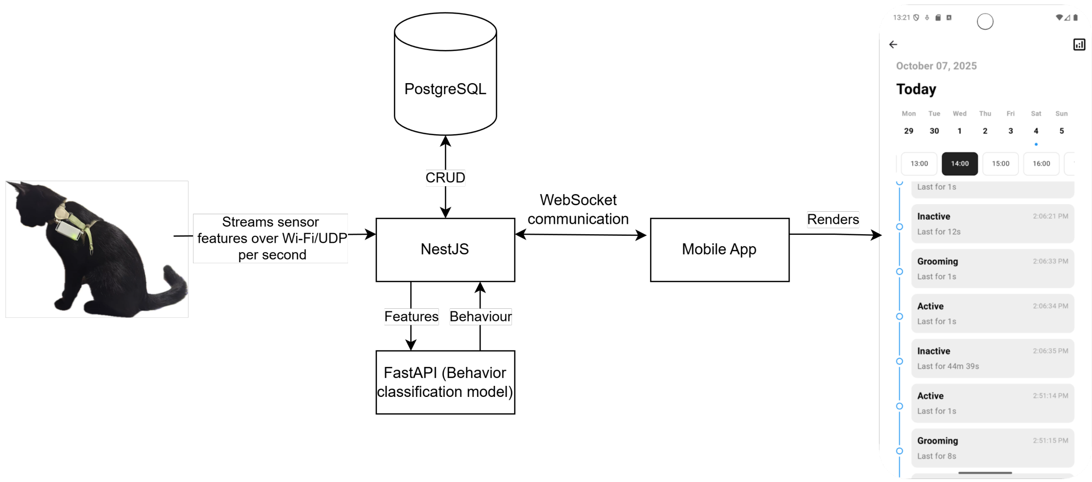


Figure 4.1.: Data flow of PurrTime, ending in the mobile app view of inferred behaviors.

4.1. Model data processing

Since Michelle et al. [2] publicly released the dataset from their earlier project which comprised behavior annotations from twelve cats, each recorded for approximately four hours, we did not need to manually collect new training data. Instead, we ensured that our accelerometer configuration (including sampling rate, orientation, dynamic range, and mounting position) was consistent with the original study to maintain comparability.

The released dataset contained three primary files: (1) `accel_data`, providing per-second triaxial accelerometer readings; (2) `anno_data`, containing timestamped behavior annotations; and (3) `model_meta`, describing the annotated time segments used in modeling. We merged the `accel_data` and `anno_data` files using the shared `catId` and `timestamp` fields to obtain a unified table of synchronized sensor and behavior data. The `model_meta` file was then used to refine this dataset by trimming incorrect or unused time intervals.

Because the harness-mounted accelerometer showed higher overall accuracy compared to collar placement [2], we retained only the harness data for subsequent analysis and model training.

From the 25 initial annotated behaviors, we refined and merged them into four broader categories: Inactive, Grooming, Eating, and Active (see Table 4.1).

Table 4.1.: Mapping of original behaviors to four merged categories.

Category	Merged behaviors
Inactive	Lying, Sitting, Standing
Active	Trotting, Walking, Rubbing, Jumping, Play-fight, Climbing
Eating	Eating
Grooming	Grooming

After merging all annotated data, we obtained a preliminary behavioral dataset for each cat (see Table 4.2). However, the dataset showed a strong class imbalance, with Inactive behaviors accounting for over 82%. To mitigate this issue, we randomly undersampled the Inactive class to 30,000 samples. Furthermore, two cats, JellyB (which had no Grooming samples) and George (which had very few samples), were excluded from the dataset. The final dataset therefore comprised ten cats (C1–C10 in Table 4.3), each contributing balanced and representative samples of the four major behaviors: *Active*, *Eating*, *Grooming*, and *Inactive*.

Table 4.2.: Initial cat behavior counts.

ID	Cat name	Active	Eating	Grooming	Inactive	Total
C1	Neville	350	378	1681	10 035	12 444
C2	Cho	301	670	1057	8569	10 597
C3	MrsNorris	165	524	338	5037	6064
C4	Harry	211	509	1092	9962	11 774
C5	Jube	555	604	940	9086	11 185
C6	Nimbus	376	289	934	10 028	11 627
C7	Hermione	449	642	1629	7567	10 287
C8	Merry	193	1734	1657	8957	12 541
C9	Hagrid	428	263	685	9855	11 231
C10	Scabbers	199	803	1550	8479	11 031
C11	George	431	205	209	3222	4067
C12	JellyB	148	241	0	9494	9883

Table 4.3.: Final cat behavior counts.

ID	Cat name	Active	Eating	Grooming	Inactive	Total
C1	Neville	350	378	1681	2950	5359
C2	Cho	301	670	1057	2580	4608
C3	MrsNorris	165	524	338	1497	2524
C4	Harry	211	509	1092	2955	4767
C5	Jube	555	604	940	2659	4758
C6	Nimbus	376	289	934	3029	4628
C7	Hermione	449	642	1629	2326	5046
C8	Merry	193	1734	1657	2657	6241
C9	Hagrid	428	263	685	2900	4276
C10	Scabbers	199	803	1550	2630	5182

The resulting dataset contained 47,389 samples distributed across four categories as shown in Table 4.4.

Table 4.4.: Final class distribution after under-sampling and cat filtering.

Behavior	Number	Percentage
Inactive	26,183	55.3%
Grooming	11,563	24.4%
Eating	6,416	13.5%
Active	3,227	6.8%
Total	47,389	100%

4.2. Model training

We selected an MLP model as the behavior classifier. While temporal sequence models such as LSTM [3] can yield higher accuracy for sustained, high activity behaviors, especially in sensor time series data, one of our main goals was second level latency so that PurrTime could display the cats current behavior in real time. Temporal sequence models typically require multi second context windows and additional buffering, which increases end to end delay and computational cost. In contrast, the MLP model in our setting has competitive accuracy along with fast inference on one second feature windows and a small footprint, which is suitable for lightweight deployment. Based on the above considerations, we adopted the MLP model for online prediction.

Dataset split From the processed data of 10 cats, we split the dataset into a 6:2:2 ratio for training, validation, and evaluation of the model: six cats (C1 to C6) for training, two for validation (C7 and C8), and two for testing (C9 and C10). Because the Active class was severely underrepresented, we applied oversampling only to the training set to reach 3,000 Active samples, adding 1,042 duplicated samples. Validation and test sets were left unchanged. The final sizes were 27,686 samples for training, 11,287 for validation, and 9,458 for testing.

Features We used per-second, non-overlapping aggregation: the device sampled the IMU accelerometer at 30 Hz and, for each one second interval (30 samples), computed four statistics per axismean, minimum, maximum, and sum, forming a 12-dimensional feature vector:

1. X: Mean, Min, Max, Sum
2. Y: Mean, Min, Max, Sum
3. Z: Mean, Min, Max, Sum

We applied the *StandardScaler.fit_transform* method to the training dataset for normalization and used *StandardScaler.transform* on the validation and test features to ensure that the model learned only from the training data, thereby avoiding potential data leakage.

Model architecture We adopted a three layer lightweight MLP model that maps the 12 dimensional feature vector to four behavior classes:

1. Layer 1: Linear(32) → BatchNorm1d → SiLU → Dropout p=0.3.
2. Layer 2: Linear(16) → BatchNorm1d → SiLU → Dropout p=0.1.
3. Output: Linear(16→4).

The first hidden layer expanded the input to 32 neurons in order to capture non linear interactions between axis specific acceleration features. Batch normalization was used to normalize layer inputs on a per batch basis which could stabilize training and reduce sensitivity to feature scale [46]. We used the Sigmoid Linear Unit (SiLU) activation function [47] because it is smooth and non monotonic, which helped gradients flow in both positive and negative regions. Compared to Rectified Linear Unit (ReLU) [48], SiLU avoided hard thresholding and reduced the risk of inactive neurons, which was particularly beneficial for shallow networks and continuous sensor based features. A dropout rate of 0.3 was used to mitigate overfitting given the moderate dataset size.

The second hidden layer reduced the number of neurons to 16, encouraging the model to learn a more compact internal representation of behavior relevant features. As in the first layer, both Batch normalization and SiLU were used to maintain training stability and non linear expressiveness. A lower dropout rate preserved informative features in later stages of the network.

The output layer produced class logits. A softmax was applied at inference to obtain class probabilities. In subsequent model calls, we could not only obtain behavior labels, but also output confidence scores for each behavior category.

Training objective To ensure the model focuses on the minority and challenging class (*Active*), we adopted Focal Loss as the training objective [49]. Based on the standard cross entropy, Focal Loss adds a factor $(1 - p_t)^\gamma$ which can down weight well classified examples. During training, the model focuses on those challenging and imbalanced samples. This mechanism does not dismiss easy samples at once, but reduces their effect along with prediction confidence which is highly effective in imbalanced classification problems.

Optimizer Model parameters were optimized using the AdamW optimizer, which decouples weight decay from gradient based parameter updates and has been shown to improve generalization in neural networks [50]. A learning rate of 5×10^{-4} and a weight decay of 3×10^{-3} were used. The *AMSGrad* variant was enabled to further stabilize convergence.

4.3. Behavior Classification Model Result

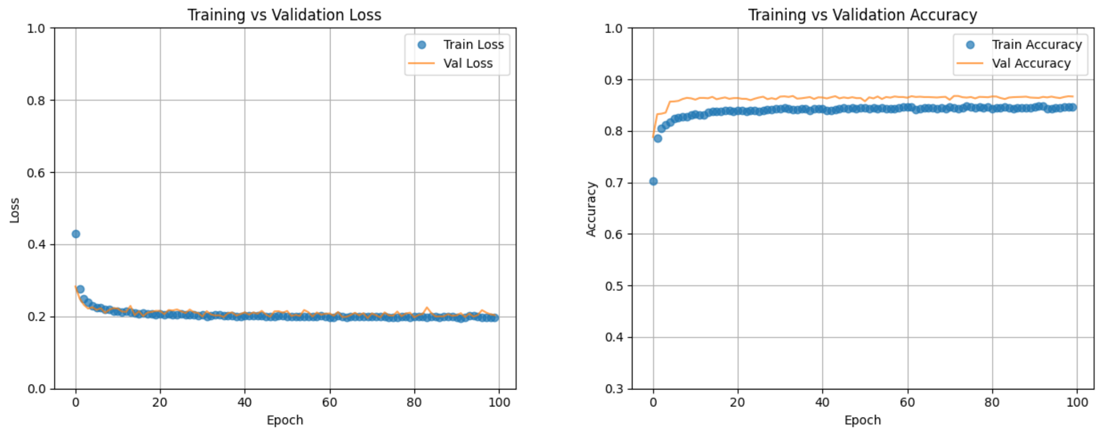
Fig. 4.2a and Fig. 4.2b show the learning curves of the MLP behavior classification model over a 100 epoch training run. The accuracy increased rapidly in the first few epochs and then fluctuated slightly in the range of 0.850.87, while the loss curve also decreased synchronously to around 0.2. These two figures indicate that under the current training setting, the model was neither underfitting nor overfitting, but learned in a stable manner.

We used the confusion matrix Fig. 4.3 to illustrate the model prediction results on the testing dataset, and Table 4.5 to present the F1 score of each behavior. For Inactive, the accuracy was 0.92, the recall was 0.9, and the F1 score was 0.91. For Eating, the accuracy was 0.85, the recall was 0.86, and the F1 score was 0.85. Grooming was often misclassified as Inactive, resulting in an accuracy of 0.75, a recall of 0.78, and an F1 score of 0.77. Active had the smallest number of total samples, and even though Focal Loss was used to increase its weight, its precision was 0.71, recall was 0.75, and F1 score was 0.73. The overall accuracy of the model was 0.86, which represented a relatively high accuracy level among existing non time series classification models.

Table 4.5.: Classification report (test set).

Class	Precision	Recall	F1-score
Active	0.71	0.75	0.73
Eating	0.85	0.86	0.85
Grooming	0.75	0.78	0.77
Inactive	0.92	0.90	0.91
Macro avg	0.81	0.82	0.82
Weighted avg	0.86	0.86	0.86

Overall accuracy: **0.86**.



(a) Training vs. validation loss (b) Training vs. validation accuracy

Figure 4.2.: Learning curves of the MLP.

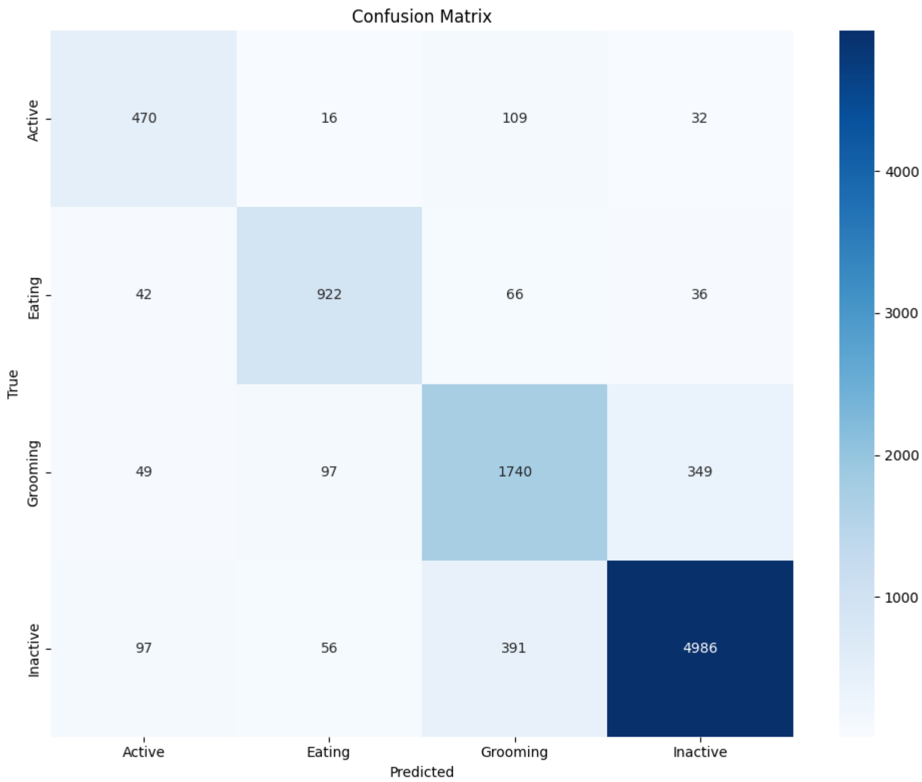


Figure 4.3.: Confusion matrix

4.4. Machine learning inference service

To save memory and reduce energy cost in the firmware, while also keeping model execution and preprocessing consistent across clients, we deploy the MLP model on a cloud service [1]. The cloud server exposes an application programming interface. Once it receives 1-second window features, it returns a predicted behavior label together with a probability distribution.

4.4.1. Model packaging and preprocessing

At startup, the inference service loads three components: a torch script model *model.pt*, a standard scaler *scaler.pkl* and a label encoder *label_encoder.pkl.* Scaler and label encoder are generated during training and saved as separate files. This ensures the same scaler and label encoder are applied during deployment as in training.

The service accepts a 12-value vector of features, with mean, minimum, maximum and sum for each axis of the accelerometer. Prior to inference, the input is reshaped into a single row, normalized with a stored scaler, and converted to a floating point tensor. A softmax function is applied on the model output to obtain class probabilities and the predicted classes are decoded into human understandable labels with a label encoder.

4.4.2. Prediction API

The service exposes a `/predict` endpoint that accepts a JavaScript Object Notation (JSON) payload with a single field, `features`, which is a list of 12 floating point values. If the length of the features does not correspond to the expected dimension, the service responds with a Hypertext Transfer Protocol (HTTP) 400 error. For other unexpected errors, the service returns an HTTP 500 status code, so the backend can tell input errors apart from transient service issues.

Request format.

```
POST /predict
{
  "features":[0.008,-0.484,0.199,0.266,
   0.831,0.668,1.043,24.937,
   -0.5372,-0.629,-0.43,-16.116
  ]
}
```

The response includes the predicted class index, the predicted label, and a probability dictionary over all behavior classes.

[1] `https://purrtime-fastapi.onrender.com/`

Response format.


```
{
  "class_id": 2,
  "class_name": "Grooming",
  "probabilities": {
    "Active": 0.33445319533348083,
    "Eating": 0.006100521422922611,
    "Grooming": 0.4276186227798462,
    "Inactive": 0.23182770609855652
  }
}
```


We measured end to end inference latency over 50 requests on the same network and reported the mean response time (38 ms). Most of this time (37 ms) was spent waiting for the server response. This level of latency is sufficient for our second-based real-time updates.

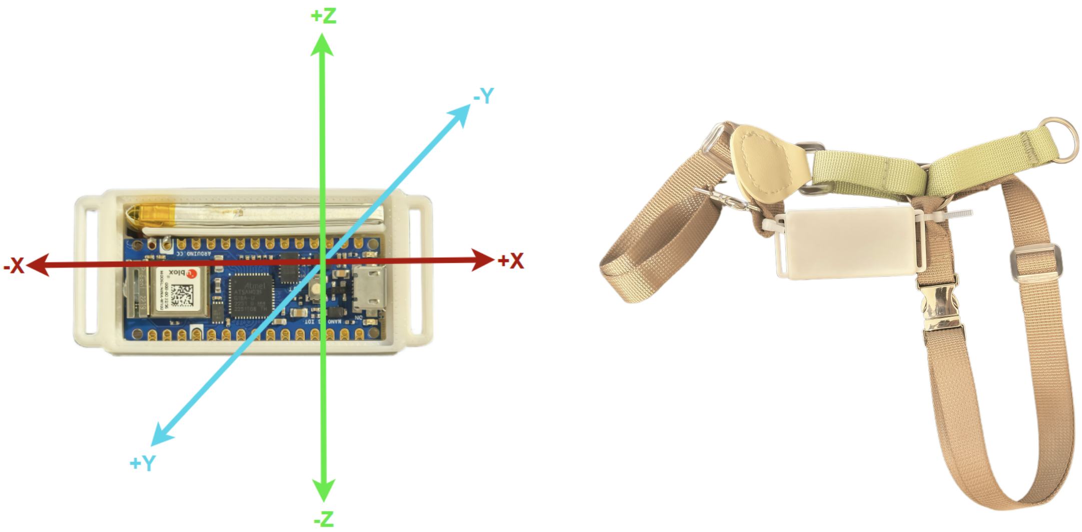
4.5. Wearable device

4.5.1. Hardware overview

Given this wearable form is designed for cats, we followed the Wearer Centered Framework proposed by Paci [51]. We first chose some lightweight and unobtrusive solutions which can interfere with cats daily activities minimally. The Arduino Nano 33 IoT, which is the smallest Arduino IoT prototyping board, was selected as the core microcontroller, featuring a u-blox NINA W102 WiFi BLE module and an on board LSM6DS3 accelerometer [52]. This wearable device consists of four components:

1. the Arduino Nano 33 IoT
2. a TP4056-based power and charging module with a USB Type-C interface
3. a 421243 Li-ion battery
4. a 3D-printed resin enclosure.

We use zip ties to strap it to the harness, and when the cat wears it, the device is mounted on its left shoulder blade. The assembled device measures $7 \times 3 \times 2$ cm and weighs approximately 20 g. Figure 4.4 illustrates the wearable device and its harness mount.



(a) Widget

(b) Widget on harness

Figure 4.4.: Wearable device and harness mount.

4.5.2. Power and charging

The prototype uses a rechargeable Li ion battery connected to a TP4056 charging module. Users can charge their devices without opening the cover using the Type C port on the side. It is important to note here that this prototype is designed for short term deployment and user study rather than a mature product. The battery life of the device is approximately four hours.

4.5.3. Sensor acquisition and feature extraction

Once the device is powered on, the IMU is initialized and the accelerometer range is configured to an $\pm 8g$ through the sensor control register. The accelerometer samples at 30 Hz, which means that in a 1s time window, each axis samples 30 times. The firmware computes simple summary statistics on device to calculate mean, min, max, and sum per second for each axis, in order to provide features for the models inference.

To remain consistent with the coordinate system used in the training dataset, the firmware reverses the X axis and Z axis before computing the aggregated features.

4.5.4. Timestamping and time synchronization

To ensure temporal consistency across sessions and across different devices, the firmware synchronizes its clock using the Network Time Protocol (NTP) [53]. Once it establishes a connection with WiFi, it queries an NTP server over UDP to synchronize its clock, then formats timestamps as Coordinated Universal Time (UTC) ISO 8601 strings before sending packets.

4.5.5. WiFi provisioning and persistent pairing

The device provides a simplified WiFi connection process for non technical users. During the first use, it enters Access Point (AP) mode, and users can find and connect to a WiFi network named *Cat_Device_AP* in the WiFi list on their mobile device. Meanwhile, it launches a lightweight HTTP server for configuration, and users can send home *WiFi_SSID*, *WiFi_Password*, and *Cat_ID* via the PurrTime app. Once it receives the credentials, the firmware switches to station mode, attempts to join the home network, and stores the credentials and identifiers in flash for auto reconnection in future sessions.

During runtime, the firmware keeps monitoring the connection status. When connectivity is lost, it can fall back to AP mode to allow reconfiguration without requiring serial debugging tools.

4.5.6. Device registration and backend communication

After joining the home network, the firmware registers the device with the backend by sending a device identifier which is derived from the WiFi Media Access Control (MAC) address. A registration flag is stored locally and used as a guard; only when the device is connected to WiFi and registered does the accelerometer feature collection method become enabled.

For each one second time window, the firmware creates a JSON packet which contains *Cat_ID*, *UTC timestamp* and *12 extracted features*. Because the device sends packets frequently during operation, UDP is used instead of the standard Transmission Control Protocol (TCP) mode to minimize overhead and latency.

- `catId`: string
- `timestamp`: ISO 8601 UTC timestamp
- `features`: array of 12 floats ordered as
  - `xMean, xMin, xMax, xSum`
  - `yMean, yMin, yMax, ySum`
  - `zMean, zMin, zMax, zSum`

4.5.7. Optional BLE streaming mode

In early experiments, to verify the accuracy of the trained model on data collected by the designed device, we also implemented a logic based on Bluetooth communication. When the Bluetooth mode is enabled, the device broadcasts a custom Bluetooth service. To avoid Maximum Transmission Unit (MTU) related truncation, long messages are split into smaller chunks before notification. This Bluetooth Low Energy (BLE) mode was used as a development and validation support tool, because the Arduino Nano 33 IoT cannot run WiFi and BLE modes at the same time.

4.5.8. Conclusion

Table 4.6 summarizes the key hardware specifications and firmware parameters used in the wearable prototype.

Table 4.6.: Wearable prototype hardware specifications and firmware parameters.

Component / parameter	**Value**
Microcontroller board	Arduino Nano 33 IoT (u-blox NINA-W102 WiFi and BLE module)
Inertial sensor	On-board LSM6DS3 IMU (accelerometer used in this study)
Wearable mount	Harness mount near left shoulder blade
Approx. size and weight	$\sim 7 \times 3 \times 2\,\mathrm{cm}$, $\sim 20\,\mathrm{g}$ (assembled)
Battery and charging	421243 Li ion battery with TP4056 charging module (USB Type C)
Accelerometer range	$\pm 8g$
Sampling rate	30 Hz
Window length	1 s (30 samples per axis per window)
Feature representation	12 summary features (mean, min, max, sum per axis)
Axis alignment	X and Z inverted to match reference dataset convention
Timestamp format	UTC, ISO 8601 string
Time synchronization	NTP sync after WiFi connection
Primary transmission mode	UDP packets from device to backend
Packet payload fields	`catId`, `timestamp`, `features` (12 floats)
Alternative transmission mode	BLE notifications for controlled streaming and debugging

For reproducibility, the wearable firmware and configuration workflow are available in our code repository.[2] The repository includes the Arduino firmware and setup instructions, while sensitive information such as credentials has been removed.

[2] `https://github.com/SUNZHIYUAN0102/PurrTime_Arduino`

4.6. Backend and Database

4.6.1. Backend

The backend [3] is implemented with NestJS [54] and TypeScript. It affords a RESTful API for user and cat management, logging, daily record querying, and aggregation oriented toward visualization. In addition, it supports real time behavior updates via WebSocket and receives device packets through a UDP listener. We chose NestJS because it encourages a modular structure, supports dependency injection, and has a rich ecosystem that can simplify the backend development.

Architecture The backend follows a modular structure, meaning every domain is implemented as an independent module, which can organize and manage its own structure. The benefit of this structure is reduced code coupling and improved reusability. In the current implementation, our main domain contains users, cats, devices, authentication, records, behaviors, charts, and data seeding. Controllers are responsible for external interfaces and request flow, and services are used to encapsulate business logic and data operations. Figure 4.5 illustrates the high level request handling flow in the backend.

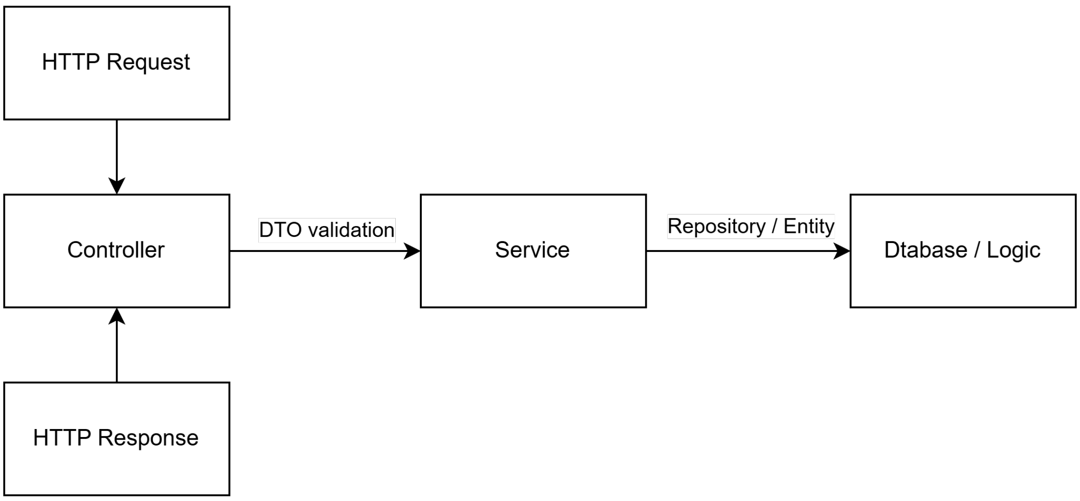


Figure 4.5.: NestJS architecture

Server initialization and global concerns The server is started through `NestFactory.create()` and listens on `process.env.PORT` or the default port 3000. The WebSocket adapter is configured globally at startup for supporting later visualization behavior snapshot sending. Swagger is configured through `DocumentBuilder` and served under the `/api` route for generating OpenAPI documentation and Bearer token authentication, to simplify API testing during development.

[3] `https://github.com/SUNZHIYUAN0102/PurrTimeBackend`

To decouple from database entities, we use Data Transfer Object (DTO) to satisfy class definitions during API queries. By invoking the global `ValidationPipe`, DTO validation is implemented to reduce the probability of format errors entering the server layer, while also simplifying error handling.

Authentication and access control User authentication is implemented using JSON Web Token (JWT). When a user completes registration, the password in the database is stored as hashed text by bcrypt [55] rather than plain text. The server side then signs a token to the user as an identity credential. For subsequent requests, the user is required to carry this token in the HTTP request header to access resources. The same authentication mechanism is also implemented in WebSocket connections to ensure consistency in access control.

UDP support for behavior data The backend receives wearable packets through a UDP listener implemented with Node.jss built in *dgram* module, integrated into our NestJS service. Every UDP data packet contains cat id, sensor features, and timestamp. Once it is received, we use the inner behavior service to call the outer behavior prediction FastAPI deployed on the cloud server to get the result. This keeps the machine learning runtime independent from the main API and allows the inference component to be updated or scaled separately. The system tolerates occasional packet loss at the one second level.

Timezone consistent querying Although the backend is deployed on a server hosted in western Germany, users may be in different time zones. Each request includes a custom *x-timezone* header. We use *Luxon* [56] to convert UTC timestamps to the users local time when computing query ranges.

```
const local = DateTime.fromISO(date, { zone: 'utc' }).setZone(userZone)
```

Real time delivery for the mobile client In order to implement real time behavior updating on the user's phone, the backend provides a WebSocket channel which can be subscribed. Send a subscribe message in the following format to establish a subscription with the backend.

```
type IncomingMessage =
  | { type: 'subscribe'; catId: string; hour?: string; tz?: string }
  | { type: 'unsubscribe'; catId: string }
  | { type: 'snapshot'; catId: string; hour: string; tz?: string }
  | { type: 'ping' };

type OutgoingMessage =
  | { type: 'pong' }
  | { type: 'unauthorized'; reason?: string }
  | { type: 'error'; message: string }
  | { type: 'snapshot'; catId: string; hour: string; data: any[] };
```

The backend uses a Map to associate cats with the sockets that subscribe to them and uses socketView to save the time range of cat behaviors that the current context is focusing on, which is used to determine whether subsequent updates should be pushed.

```
  // subscriptioncatId -> Set<socket>
  private catSubs = new Map<string, Set<WebSocket>>();
  // socket -> {userId, tz}
  private socketCtx = new Map<WebSocket, { userId?: string; tz: string
   }>();
  // socket -> recent view (catId, hour, tz)
  private socketView = new Map<WebSocket, ViewCtx>();
```

Once a cat has new behavior data written, it iterates through all WebSockets that subscribe to this cat to check whether the timestamp of the current behavior data is within their focused time range. If it is, new data will be sent to the client through a snapshot message to achieve real time behavior updates.

```
// Restore the "user focused hour range" to [start, end) under the user's
     timezone
const userHourStart = DateTime.fromISO(viewHourIso, { zone: 'utc' })
  .setZone(tz)
  .startOf('hour');
const userHourEnd = userHourStart.plus({ hours: 1 });

// New sample timestamp
const hit = DateTime.fromJSDate(saved.timestamp, { zone: 'utc' })
  .setZone(tz)
  .toMillis();

if (hit >= userHourStart.toMillis() && hit < userHourEnd.toMillis()) {
  try {
    const data = await this.behavioursService.queryBehavioursByHour(
      catId,
      viewHourIso,
      tz
    );
    const out: OutgoingMessage = {
      type: 'snapshot',
      catId,
      hour: viewHourIso,
      data,
    };
    ws.send(JSON.stringify(out));
  }
}
```

4.6.2. Database

The backend uses PostgreSQL as the primary database and maps entities through TypeORM. We store timestamps in UTC (*timestamptz*) and convert them to the users time zone when computing query ranges, which helps avoid date range mismatches when querying record and behavior data. Figure 4.6 shows the entity relationship diagram of the current database schema.

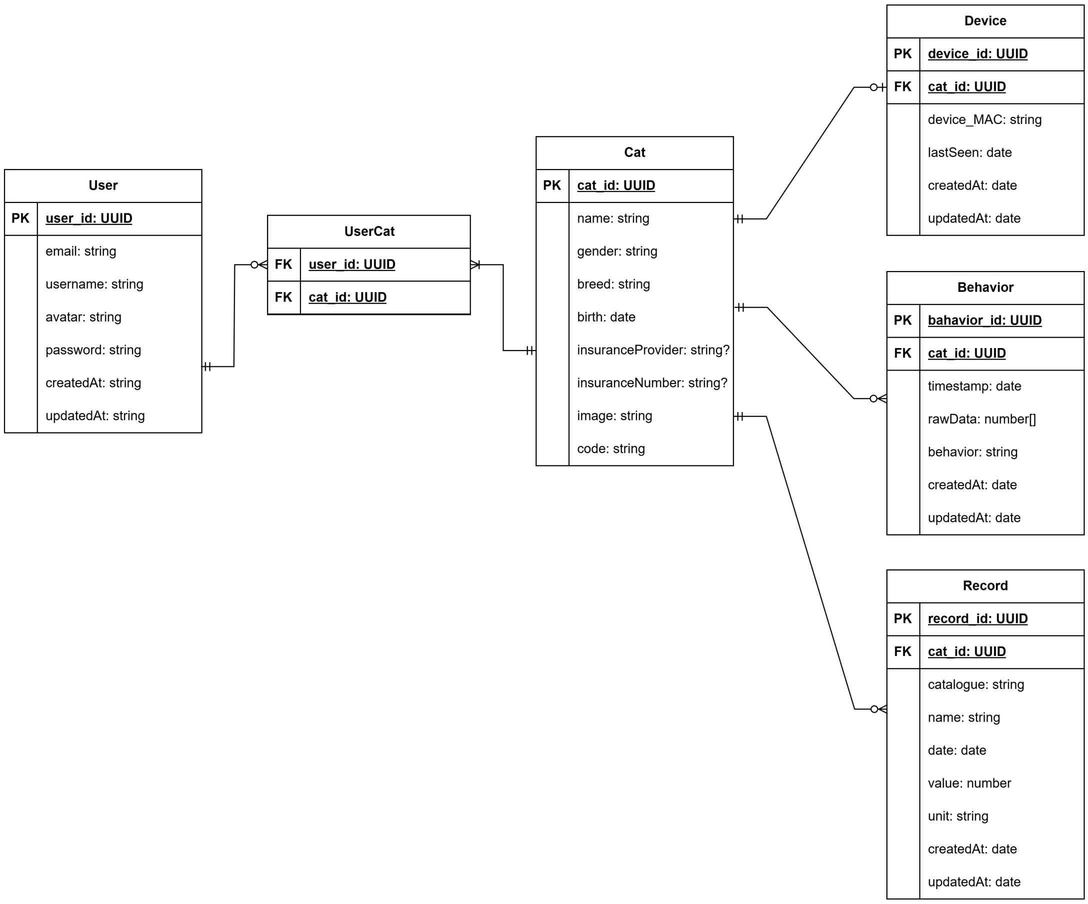


Figure 4.6.: Entity relationship diagram

Core entities User, Cat, Device, Behavior, and Record comprise the core entities. User represents registered users. Cat stands for monitored animals and stores attributes such as name, gender, breed, birth, etc. Once a cat is inserted into the database, a unique identifier code is generated, which enables additional users to join as co owners. Device represents the wearable sensor, tracking both device MAC address and the last seen timestamp. Records store cat daily life data manually recorded by users, and the catalogue attribute is used to distinguish daily events or expense. A complete record also includes a name, a value, a unit, and a timestamp. Behaviors store inferred cat behavior data, including a timestamp, accelerometer data (features), and behavior labels predicted by the model.

Relationships and integrity The relationship between user and cat is many to many, which means one cat can have multiple owners. Every cat can only bind with one device; it simulates the expected deployment method where one wearable is attached to one animal at a time. Records and behaviors belong to exactly one cat through many to one relations. Deleting a cat cascades to delete dependent records and behavior samples, preventing orphaned time series data.

4.7. Frontend implementation

The mobile app of PurrTime[4] is implemented in Flutter [57], a cross platform development framework which can compile for both Android and iOS mobile systems. The frontend is designed to support three main goals:

1. Account and cat profile management
2. Daily care and expense logs recording and charts analysis
3. Behaviors visualization through historical views and real time updates

4.7.1. Technology stack and project structure

This mobile app is built in Flutter, and pages are implemented using a component based approach. Page navigation is implemented using GetX, a lightweight and flexible state management library that also provides functions such as named routes, dependency injection, and reactive state updates. GetStorage is used for persistent data storage, such as the user token. HTTP communication is implemented using the Dio library, and it is wrapped as a functional helper to set global request configuration, to intercept requests and responses, and to handle errors and exceptions. In addition, in order to improve the app's usability and consistency on mobile devices, some libraries such as splash screen, portrait orientation locking, and screen size adaptation are also used.

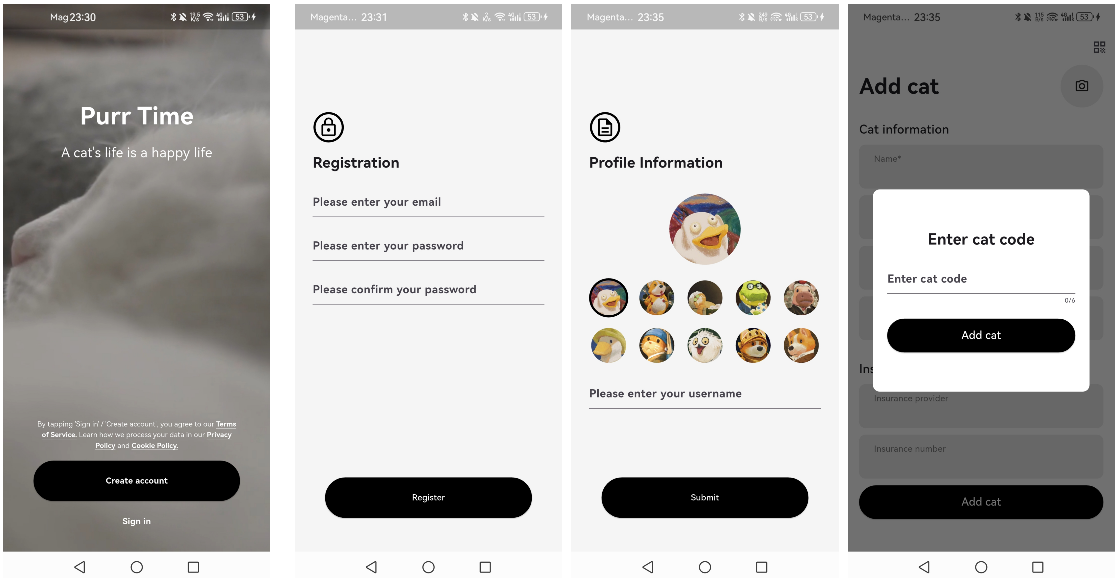
4.7.2. Identification pipeline

To ensure that only users with complete information can use the app, we set a series of information validations, and by setting different routes, we navigate users to the pages where they need to fill in information. It mainly consists of four pages:

1. Welcome page, users can choose sign in or sign up (Fig. 4.7a)
2. Registration page, users register with email and password (Fig. 4.7b)
3. Identity information page, users choose avatar and input username (Fig. 4.7c)
4. Cat information adding page, users input cat's information or add a cat with a code (Fig. 4.7d)

[4] `https://github.com/SUNZHIYUAN0102/PurrTime`

When the user opens the application, the program checks whether a valid token is stored locally on the current device. If not, the user is redirected to the welcome page, which means existing users need to log in again because their token has expired, while new users need to register. If a token exists, a request is sent to the server to check whether the users personal information is complete. If it is not complete, the user is redirected to the identity information page. After this condition is satisfied, the server further checks whether cat information has been added. If not, the user is redirected to the cat information adding page. When all the above checks are passed, the user is directed to the home page.



(a) Welcome page (b) Registration page (c) Information page (d) Cat adding page

Figure 4.7.: Identification pipeline

4.7.3. Navigation and main views

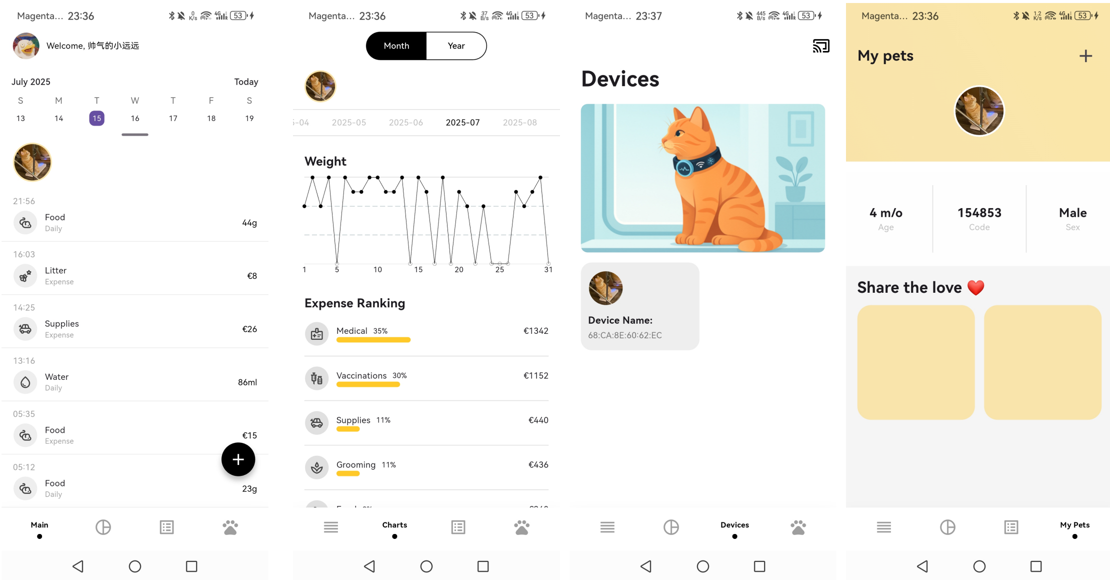
The app uses a bottom navigation bar to enable users to switch between main functions.

The Record view (Fig. 4.8a) is set as the default home page to support lightweight daily recording. It consists of three parts. The top calendar allows users to directly switch between different dates by clicking. The list below displays the cat daily life and expense records for the selected date, supporting left swipe to delete entries and opening the record detail page from the list. The button at the bottom right serves as the navigation button for creating a new record.

The charts page (Fig. 4.8b) aggregates records extracted on a monthly or yearly basis. The top line chart records changes in cat weight over time, while the bottom section categorizes and displays expense records, including percentages and specific amounts, arranged from large to small.

The Device page (Fig. 4.8c) focuses on the wearable related workflow. It lists cats that are paired with a device and enables users to enter the behavior visualization view by selecting a cat card. Through the top button, the user can view the device configuration page.

The Cat page (Fig. 4.8d) shows the users current cats and their identifiers. Users can add additional cats via an add action, and can access the cat profile editing screen by selecting the current cat avatar.



(a) Main page (b) Record chart page (c) Device page (d) Cat page

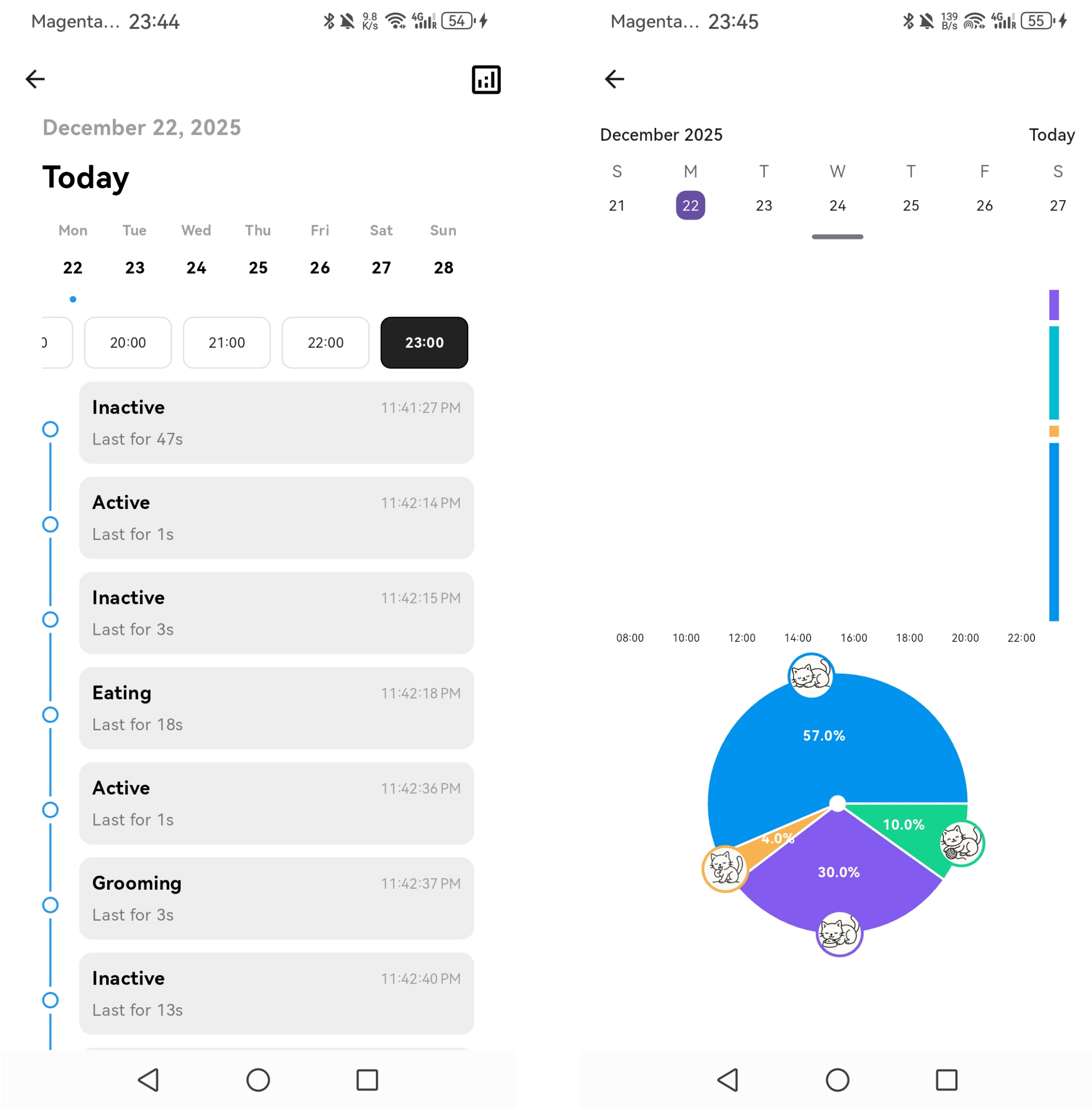
Figure 4.8.: Navigation and main views

4.7.4. Behavior visualization

To establish a connection with the WebSocket service provided by the backend, we use *web_socket_channel* to encapsulate a simple Flutter side service. It provides connection, data sending, heartbeat detection, automatic reconnection, and closing. During the rendering stage of the Behavior page, a request is sent to the backend to establish a subscription.

The Behavior page is designed to help users inspect behaviors at both the hour and day scales. The top of the Behavior page contains date switching, and the lower part displays cat behavior activities divided by hour to show behaviors within each unit time. A timeline list is used to display behaviors, containing behavior name, timestamp, and the duration of that episode. For continuous behaviors, the backend is responsible for time aggregation, so that the client receives summarized representations rather than raw second level labels, to reduce noise and improve readability (Fig. 4.9a).

Besides the timeline, the Behavior chart page provides two types of charts implemented with *fl_chart* [58]. A stacked bar chart shows the proportion and total duration of different behaviors within a unit time, and a pie chart is used to display the proportion of each behavior over a day (Fig. 4.9b).



(a) Behavior timeline (b) Behavior charts

Figure 4.9.: Behavior visualization of the four behaviors as classified by PurrTime: inactive, grooming, eating, active

5. Findings

This chapter presents the findings from the semi structured interviews conducted after participants completed the experience session. The analysis focuses on how participants made sense of behavior visualizations, what kinds of technological support they felt were needed in everyday care, and their imaginations and concerns regarding long term use.

Using thematic analysis, we identified four recurring themes across the interview transcripts. The findings are organized around these themes and their subthemes (Fig. 5.1), and each section is illustrated with representative quotes. To protect participants privacy, we refer to them using participant identifiers (P1 to P11) as listed in Chapter 3.

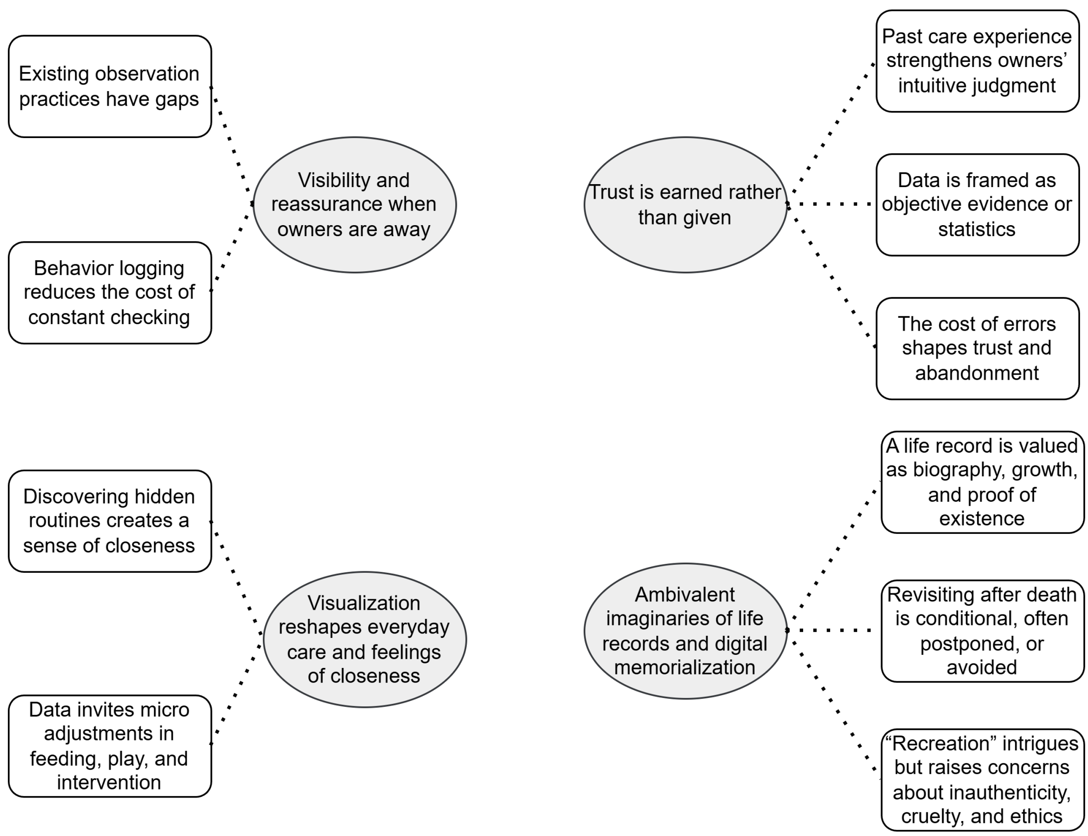


Figure 5.1.: Overview of the four themes and their corresponding subthemes

5.1. Theme 1: Visibility and reassurance when owners are away

Across interviews, participants most often envisioned using PurrTime in situations where they were away from home. They described the system as a way to reduce worry and confirm basic welfare needs when direct observation is not possible. This theme represents a specific need for remote monitoring: owners want to know what is happening at home when they cannot directly see the cat, and hope this information can be accessed easily and integrated into daily life.

Another noteworthy observation is that participants rarely attended to the reasons underlying certain behaviors. Instead, they emphasized basic questions that are hard to answer when they are away, such as whether the cat is in a safe place, whether it has eaten, and whether it is resting normally. For example, one participant summarized their goal in simple welfare term: 'Most of the time she is at home, so for me I just want to know whether she is in a safe place, has enough food, and feels comfortable.' (P9).

5.1.1. Subtheme 1.1: Existing observation practices have gaps

Some participants mentioned that they used some tools such as cameras or smart food machines which have cameras on them. However, these tools still could not meet the need for comprehensive monitoring due to some limitations of the products. For example, P1 said:

> 'I have two cats, the first cat is sneaky and often hides in corners. Even though I installed security cameras in the house, I could not capture what it is actually doing under the sofa or bed [...] The cameras are only directed at the food bowl and the litter box, and installing cameras throughout the entire home is unrealistic, so it is not possible to know exactly what they are doing. Moreover, when the camera storage becomes full, the footage cannot be reviewed, as previous records are overwritten.'

P4 further mentioned an issue she encountered when using a camera, noting that the problem did not come from the camera itself but from her own cat:

> 'So I tried the camera on the food machine before, and I used it to talk with my cat. But somehow, my cat realized that I can monitor him through the camera (I guess because of the sound), he dislikes it and always comes to beat the camera.'

Other participants who own a smart food machine (P6, P8, P11) complained about the same limitation of smart food machines. Although the device included a camera, it only provided visibility at moments that are already structured by feeding, leaving the rest of the day largely unknown. As P11 described, '[...] I only can see him when he is coming to eat.'

The above comments revealed a problem: even in todays technologically advanced society, the pet monitoring market still lacks products that could fully meet users needs.

Cameras only provided sporadic snapshots, and owners could not truly track their pets activities throughout the day. In contrast, participants thought PurrTime did not depend on a specific location in the house, and was one option that could record cat activities continuously. This was why behavior visualization was not discussed as a luxury feature, but as a solution for the current incompleteness of existing monitoring routines.

5.1.2. Subtheme 1.2: Behavior logging reduces the cost of constant checking

A second mechanism concerns effort. Even with cameras, owners still need to invest time and effort to obtain actionable information. Participant P1 especially emphasized this:

> 'As a teacher, when I go to my office, it is no longer possible to obtain information simply by occasionally checking the camera on a mobile phone. [...] Maybe I could place a tablet next to my desk to monitor in real time? But when I go to the classroom to teach students, it gets interrupted, and I still rely on spending time reviewing the videos to see whether they have eaten. But still, this takes a lot of time.'

What they wanted instead was a lower effort way to maintain awareness. In this sense, visualization becomes valuable when it transforms continuous data into some periodic abstractions.

This expectation is especially clear in P7. The participant emphasized that the system would help most when they are away and do not know what the cat is doing, and he described the preferred format as regular summaries rather than continuous inspection. As explained:

> 'Me personally really like statistics data, for example, something like an annual report. If the system could send some information every two or three hours, like some statistics about what he was doing and his conditions.'

This quote points to one specific interaction pattern. Sometimes owners do not necessarily want more data; they would like to obtain summarized data at short, regular intervals. In practice, a periodic overview can help owners confirm that everything is normal, while also making change noticeable across multiple updates.

This subtheme also has an emotional dimension. Summaries do not only save time. They can also reduce the anxiety that comes from uncertainty. When owners are away, the absence of information causes imagination, and imagination tends to focus on worst case scenarios. Periodic summaries can break this cycle by providing a simple answer to the question "what is happening right now, in general."

5.2. Theme 2: Trust is earned rather than given

Participants believed that trust in PurrTime is not given in advance, but needs to be continuously adjusted and refined over time. They suggested that they would not simply treat the system as correct or incorrect. Instead, they expected to compare its outputs with their knowledge of the cat, check whether the data aligned with their lived experience, and adjust how much they relied on the system depending on the situation. In this sense, trust appears to be an ongoing process of negotiation. Owners need to decide when to treat visualized results as evidence, when to see them as cues, and when to prioritize their own judgment.

This negotiation appears during the participants discussion of system data and intuitions. Some participants (P9, P10) framed their long term shared life with their cat as experiential expertise and a reliable basis for interpretation. Others thought data was more objective and neutral, because it afforded statistics rather than subjective impressions. The important thing here is that these two opinions have conditions. Even those pet owners who trust their own intuitions, when they feel the high accuracy of the system or when they feel uncertain, would like to use the system. And for those who are willing to trust data, they said the system must show enough accuracy to gain confidence from them.

These descriptions clarify that visualization is not default truth and that its trust is established under certain preconditions.

5.2.1. Subtheme 2.1: Past care experience strengthens owners intuitive judgment

For many participants, intuitions are not obscure speculations, but some conclusions or experience classified from long term living. Owners believe they have acute perceptions of their cats behaviors. When P9 was asked what she would do if her intuitions disagreed with the system data, she said:

> 'I will trust my intuitions, but also depend on the system accuracy. If the system has very high accuracy, I will trust the system. But in general, I will trust my intuitions more, because I think I have been living with her for 17 years, I know her enough, even better than any systems!'

The other cat owner P10, who lived with her cat for 17 years, described how to use subtle clues for daily judgments:

> 'Just by looking at him, when you live with a cat, you know when his tail is up, he is happy, if its down means he is off or not so good. And you pay attention, by intuitions.'

However, when uncertainty increases, the system can tip the decision toward actions.

> 'If my intuition tells me everything is fine, I will trust my intuition more. But if I am not sure and the system tells me something is off, I will go with her to the vet.'

Some other cat owners (P2, P4, P5) also indicated that they would trust their intuitions more when the situation is certain based on their experiences.

In conclusion, these descriptions suggested that owners did not believe that visualization could replace intuition, but rather served as part of the judgment process. When owners felt confident in their judgment, the system was less likely to override it. When they felt uncertain, the visualization could act as an auxiliary opinion. This helped explain why interpretive support was a good means. The system did not need to convince owners that it knew the truth. It needed to provide information that owners could integrate with their own sense and confidence.

5.2.2. Subtheme 2.2: Data is framed as objective evidence or statistics

Compared to participants who relied on intuition, others took a different stance. They trusted the data because it provided statistics that feel neutral and objective. P6 expressed this preference very directly:

> 'Actually data, because it gives me some statistics behaviors rather than trust my own observations I will trust the data first.'

Here, trust is grounded in a perception of measurement as more reliable than memory or momentary observation. P1 said: 'I teach chemistry, we rely heavily on instruments, we do not trust intuitions!'. P8 also stated: 'data won't lie'.

However, even for participants who trusted data first, trust was still not unconditional. Several described a need to verify the system before relying on it, and the accuracy affects their trust. P7 explained:

> 'If I find the data is correct, I will trust the data, but if I find it could be incorrect, it will be hard for me to trust it more. So will be my intuition, because I know my cat, and the app gives more functions and data, so 50:50. But first will be the data because installing the app demonstrates that is something I am searching for, and I will want to trust the data.'

5.2.3. Subtheme 2.3: The cost of errors shapes trust and abandonment

When asked under what circumstances they would stop using the system, participants most frequently talked about device accuracy. Inaccurate behavior predictions could directly affect owners decisions, leading to unnecessary worry or missing important information. Once this happens, rebuilding trust between the owner and the device becomes extremely difficult, which may cause owners to turn to other tools or return to relying on intuition.

Some participants spoke very directly about how they would react if they found the system to be inaccurate. P10 said:

> 'It will affect me a lot. If it ignores something important, I will trust my intuition more, and stop using the system and not trust it anymore.'

P6, who has adopted three disabled cats, emphasized:

> 'It would affect me a lot, because my cats are like my children. Inaccurate activity notifications could trigger many unnecessary chain reactions, such as unnecessary medical visits or suddenly rushing back home when I am outside.'

P11 said:

> 'I would start to question the system and reduce how often I use it.'

Other participants were relatively more tolerant. They proposed quantifying the error rate and stated that as long as the system remained within a relatively reliable standard, they were willing to tolerate some recognition errors. P4 said:

> 'If it is only occasional accuracy issues, it would not affect my trust, but frequent ones would. I would like the accuracy to be above 85%.'

P2 expressed a similar view:

> 'It depends on the frequency. If the error rate is below 20%, it is acceptable.'

5.3. Theme 3: Visualization reshapes everyday care and feelings of closeness

Participants not only regarded visualization as a tool for monitoring their cats behavior, but also imagined that, over long term use, having behavior records could change how they feel about their cats and how they act in everyday care. In this scenario, visualization would increase a sense of closeness between owners and pets by revealing new behavioral routines, as it uncovered aspects of the cat that owners were previously unaware of. At the same time, this approach also raised concerns. Some participants (P6, P7, P9) worried that they might become more reliant on the device rather than directly observing their cats through interaction, and that becoming more data driven could lead to a sense of distance. This theme indicates the role of visualization as a meaningful support tool in reshaping emotions, modes of interpretation, and everyday care.

5.3.1. Subtheme 3.1: Discovering hidden routines creates a sense of closeness

The underlying reason behind feeling closer is the ability to discover. Participants anticipated that, through long term use, summaries and overviews of behavior visualization data would allow them to notice details that were previously overlooked. Especially when they were not at home, this knowledge was considered a form of additional, deliberate attention that could strengthen the relationship. P10 described closeness as emerging from acts of checking and learning:

> 'I think we are closer because you give extra effort, you look at the data and see real time what he is doing'

For others, feelings of closeness stem from discovering and making sense of behaviors that are often overlooked in everyday life. P4 explained:

> 'By just looking with my eyes, I cannot fully understand her behavior. The system can answer the questions I have when interacting with her. I feel it helps me more, because I understand her better and feel closer.'

P1 expressed a similar view:

> 'More close. I am very curious about what the cat is doing when I am not at home and when cameras cannot capture it. Is he not moving at all, or moving all the time? Because when I come home, the house is always messy. I want to know when the cat actually did these things.'

P2 noted that:

> 'Visualization would make us feel closer, because at the beginning there are new discoveries, and over time it can be used to understand the cats mood and act as a barometer for monitoring his condition.'

P9 said:

> 'For me the main purpose is when I am away from the cat, I can be sure that the cat feels comfortable. It wouldnt affect our relationship, I just use it to make her life better and find some new small habits and feel more closer to her.'

These cases showed that visualization is not only valuable for discovering behavior, but can also make the cat more transparent to the owner and everyday life clearer and easier to understand.

5.3.2. Subtheme 3.2: Data invites micro adjustments in feeding, play, and intervention

Participants anticipated that the discovery of new behaviors could trigger chain reactions that potentially lead to adjustments in care practices to improve the pets comfort and welfare. As P2 speculated:

> 'Although in modern society pets are generally regarded as attached to their owners and dependent on their presence, when it is possible to respect each others living states and patterns, both sides can have a better experience.'

A common practice is that owners adjust their care practices based on the behavioral routines they have learned, in order to match the cats needs, such as play time, feeding time and frequency, and rest time. P10 described this:

> 'Yes, if I see from the app he is playing outside and having fun, I will leave him there. And if I discover some new habits, I will be more appreciative and understand him and influence a bit.'

P9 also agreed with the idea of comfort and potential adjustment:

> 'As I mentioned my main goal is to use the system to make her life better and comfortable. If I realize some new habits like when she eats or sleeps, I will adjust to her schedule and it will make her life better.'

Another pattern is using data to decide when to intervene and when not to intervene. P8 said:

> 'If the data shows when it eats, then I can know when to feed it and increase interaction with the cat. If it stays at home for a long time licking and being inactive, I will buy more toys for it to make it happier.'

P6 also connected this to inactivity:

> 'If I see them inactive, I will try to play more to let them be active.'

At the same time, increased visibility of routines sometimes tempted owners to intervene playfully, even during rest. P4 admitted:

> 'Even when I know it, I still cannot resist interrupting its behavior. For example, knowing its routines like sleeping, I might deliberately wake it up. But I will still change.'

P3 also agreed:

> 'Yes, after knowing its routines, I might deliberately try to play with it even when it is sleeping.'

5.4. Theme 4: Ambivalent imaginaries of life records and digital memorialization

When participants were invited to imagine PurrTime as a record of a cats entire life and were asked what such a digital record would mean to them, very few directly rejected the idea of a life record. Instead, participants described a persistent ambivalence: these data could be a meaningful record that preserves remembrance, but could also intensify grief and cause discomfort.

5.4.1. Subtheme 4.1: A life record is valued as biography, growth, and proof of existence

Some participants regarded the archive as a personal biography belonging to the cat. They wanted to see how the cat developed and changed across different life stages, such as what behavioral changes occurred when moving from kittenhood to adulthood. The value of the archive was not in any single day, but in the life trajectory recorded through long term use. P5 described this:

> 'I mean you can see they grow up from a kitty to a mature cat. See the pattern of how they learn something new or change their behaviors based on their age. Will be interesting.'

P9 similarly said:

> 'Personal purpose maybe its just a memory couldnt do much, some specific habits she has, schedule day to day or maybe it changes with age.'

Although P10 felt that such a life record had limited value for her because it only contained behavioral data, and she preferred images or videos, she still agreed with showing changes in life trajectories:

> 'I think it will not be important for me to have the record of his all cats life behavior data, because you also have the pictures/videos and your own memory. Maybe its good to know when he was very active when he was small but inactive when he is old. Some changes happen to him. You can create an overview of all his life. Focus on the most important stages. That could be nice.'

For others, the archive was seen as carrying proof of the cats existence. It confirms that the cat once existed and that the time spent together was meaningful. P4 described it as:

> 'Proof that it existed in the world. If I had such data, I would keep it. It is its whole life and also a very long period of memory in my life.'

P6 talked about it in this way:

> 'It will be both sad and meaningful, because they have a limited time period.'

P1 imagined a more unconventional interaction:

> 'When it passes away, the data could be stored and engraved as a QR code on the tombstone. When people scan it with their phone, they can see its whole life.'

5.4.2. Subtheme 4.2: Revisiting after death is conditional, often postponed, or avoided

Even though participants appreciated the idea of recording a cats whole life, they expressed ambivalence about whether they would revisit the data after the cats death. The same archive can both preserve memories and evoke sadness. P4 said:

> 'No, I would keep it but not revisit it. I cant accept it, it would be very upsetting.'

P5 was also uncertain:

> ‘I dont know, to be honest. I will be super sad if she passed away. I dont know whether I can look at those things without feeling sad emotions.’

P9 mentioned:

> ‘Only in case I am very sad, but it will be nice to have a memory documented.’

Others hoped that time could ease this sadness, and that after enough time had passed they might have the courage to revisit the data. P10 described this:

> ‘Probably I will be very sad. Looking at it will make it even worse. At first I will not, but it might be nice sometimes later to look again.’

P6 said:

> ‘I will probably put it in a box and review it maybe 10 years later, I cant look at it without crying.’

5.4.3. Subtheme 4.3: “Recreation” intrigues but raises concerns about inauthenticity, cruelty, and ethics

When asked about using data collected during the cats lifetime to create a cyber virtual cat that displays similar behaviors, participants expressed very different opinions. Some were curious about the idea, believing that each cat is unique and that if these specific characteristics could be extracted, the reconstructed cat would be authentic. P10 stated:

> ‘I think it will be funny, cats have their own personality. If the system can capture their habits then its authentic.’

P7 said:

> ‘I would not mind about it, but its just basic data, it couldnt really recreate 100%.’

Others felt that this idea depended strongly on actual use and experience over time. P2 said that they would like to try it but could not evaluate the long term impact. P4 felt that it was somewhat cruel for her, but still wanted to experience it first. P1, P8, and P9 expressed more positive attitudes, viewing it as a feasible way of remembrance.

Some participants explicitly rejected this proposal. They felt that what is lost is already lost and that one should not dwell on the past, as this would not feel real and could cause emotional harm. P6 said:

> ‘No, I dont want it. It would definitely make me very sad. After they are gone, I have to accept it, otherwise I will be stuck with virtual cats.’

P5 said:

> ‘Not very, because its not technically my cat. Its still not the same.’

P11 questioned its meaning, as a virtual cat could not connect him to reality:

> ‘No, because a virtual cat cannot be connected to reality. I know my cat is no longer at home. I would not have expectations for these virtual behaviors, because I cannot get any useful feedback.’

6. Discussion

In this chapter, we first discuss how the findings from the previous chapter help address the proposed research questions. We then present design implications derived from this study. Finally, we discuss the limitations of the study and outline directions for future work.

6.1. Addressing the research questions

6.1.1. RQ1: How do behavior visualizations support daily care?

Investigating this research question yielded two primary aspects: the gaps owners perceive in current monitoring practices and tools (RQ1.1), and how owners use behavior summaries for reassurance and care adjustments (RQ1.2).

RQ1.1: What gaps do owners see in current pet monitoring tools? The findings suggest that the value of PurrTime is not to fully replace existing observation practices and tools. Instead, it uses visualization as a method to complement gaps in existing observation from another perspective, supporting owners decision making in cat care. Participants pointed out that the main problem with current observation practices is that owners can only see fragmented moments of their cats day, and especially when they are away from home, it is difficult to understand the cats situation in real time. Common observation tools such as cameras, while sufficient for basic monitoring needs, have limitations such as blind spots, storage coverage, and the need for continuous checking. In contrast, behavior summaries were regarded as a way to transform fragmented everyday activities into a clearer overview of activity patterns.

RQ1.2: How do owners use behavior summaries for reassurance and care adjustments? During the experience, participants hoped to use information provided by behavior visualization to remotely confirm their cats status and to make micro adjustments to existing care practices. Through behavior summaries, participants could quickly understand the categories and timing of their cats activities throughout the day, thereby potentially reducing the cost for owners to understand their cats condition. Based on the daily routines summarized from the visualizations, owners could intervene in aspects such as feeding, play, and activity time to improve their cats quality of life and welfare. This demonstrates a direct application of the Quantified Other [33], showing that owners not only use data-driven insights to track their cats, but can also use them as a bridge to improve animal welfare through informed interventions.

These observations mainly reflect Theme 5.1 (Visibility and reassurance when owners are away) and Theme 5.3 (Visualization reshapes everyday care and feelings of closeness).

6.1.2. RQ2: To what extent do owners trust and rely on the behavior visualization system?

Investigating this research question yielded two primary aspects: the role of owners intuition in the use of the technology (RQ2.1), and owners reactions to erroneous information provided by the application (RQ2.2).

RQ2.1: What role does owners intuition play in the use of the technology? Our findings show that participants did not naturally trust the data. Instead, trust building depended on the accuracy of the device. During the process of establishing trust, participants compared system outputs with their own observations and accumulated experience. For long term cat owners, personal experience and understanding built over time gave their intuition greater authority. When the systems outputs aligned with what participants observed, they described the data as reassuring confirmation. When mismatches occurred, participants questioned the outputs. Participants further noted that if such mismatches were frequent in longer term use, they would become less willing to rely on the system and would default to intuition. This aligns with the trust calibration process proposed by Lee et al. [5], in which users compare system outputs with their own experience and continuously adjust their reliance on the system. This also connects to RQ2.2, which examines how owners react to erroneous system outputs and their perceived consequences.

RQ2.2: How do owners react to erroneous information provided by the application? How users perceived data played a crucial role in the negotiation of trust. Some participants interpreted the data as objective evidence or statistics that could provide insight in moments of decision uncertainty, rather than relying on their own uncertain intuition and observations. This understanding influenced users tolerance for errors. They emphasized that false negatives and false positives were not trivial, but could lead to unnecessary worry or the overlooking of important issues. Participants expressed a desire for the device to provide a level of accuracy that met their expectations. This reflects the cry wolf effect and rapid collapse of trust described in early automation research: false alarms can lead owners to ignore or disable potentially critical notifications, and can also quickly cause substantial damage to the fragile trust previously built through accurate monitoring [41, 42, 43].

Overall, trust between humans and devices was described as fragile and costly to rebuild. Systems should therefore communicate information in a careful and accurate manner, rather than relying on unconditional user trust. These observations mainly reflect Theme 5.2 (Trust is earned rather than given).

6.1.3. RQ3: How do long-term behavioral records influence the human-cat relationship throughout the animals life and beyond?

Investigating this research question yielded two primary aspects: how discovering hidden routines affects closeness and understanding (RQ3.1), and owners attitudes towards preserving or recreating their cats life digitally (RQ3.2).

RQ3.1: How does finding hidden routines affect closeness and understand-

ing? Participants pointed out that discovering new behavior patterns of their cats was another expectation of using the system. Uncovering hidden behaviors could increase cat owners sense of closeness to their cats. For owners, this was not only informational value but also relational value, representing a return on the care and effort invested in the relationship, in that the cat becomes more transparent and understandable in the owners eyes. Owners could combine this information with their cats comfort and preferences, allowing everyday cohabitation to become more aligned.

RQ3.2: What are owners attitudes towards preserving or recreating their cats life digitally? When imagining digital archives and virtual cats, participants expressed ambivalent feelings. On the one hand, they considered digital records to be meaningful, as they could serve as a record of the cats life and a proof of the time they lived together. At the same time, this inevitably raised concerns about the sadness and sense of loss that might be triggered when revisiting such data. Regarding the idea of a virtual cat, participants discussed limitations related to authenticity, emotional harm, and ethics.

Overall, in long term use scenarios, the system involves not only technical issues such as data storage and prediction accuracy, but also potential emotional and ethical boundaries. These observations mainly reflect Theme 5.3 (Visualization reshapes everyday care and feelings of closeness) and Theme 5.4 (Ambivalent imaginaries of life records and digital memorialization).

6.2. Design implications

Drawing from our observations and the experiences shared by our participants, we have compiled a set of design implications. Rather than absolute rules, these points are intended as practical suggestions and reflections for fellow designers working in this space. By sharing these learnings as a contribution of this thesis, we hope to provide helpful starting points for others to consider when developing similar systems.

Reducing the cost of understanding cats state Hourly and daily behavior summaries can reduce the time cost for owners to understand their cats condition when they are away. Combined with scheduled notifications, they allow owners to stay informed about their cats activities in a timely manner.

Communicating data uncertainty Trust building does not happen overnight. Behavioral labels in the interface should display the reliability of the data and guide owners to combine their own experience with the data when making judgments, rather than presenting results as absolute.

Providing privacy and emotional control for long term records Participants expressed ambivalent feelings toward long term records. Therefore, long term records should include controls over stored content and access permissions. Allowing users to selectively view or hide records can reduce emotional burden. If reminiscence features are included, they should be optional.

Treating cats comfort as a prerequisite Not all cats can adapt to wearable devices. Cats comfort and willingness are fundamental prerequisites. The system should provide guidance on proper wearing methods and suitable wearing durations, aligning with animal centered values.

6.3. Limitations

This study has several limitations that should be considered when interpreting the findings. First, not all participants cats actually used the wearable sensor device. Their owners gave answers during the interview based on their expectations and imagination rather than feedback grounded in actual use. Second, even for those participants who tried the device with their cats, the whole experience did not last long (about 1.5 hours). The short trial helped us obtain a first impression of the system but could not explain what would really happen if the system were integrated into owners daily lives over time. How does owners confidence change over time? Is it really comfortable for cats to wear it for a long time? Will they keep using it or just give up?

These limitations are mainly due to a lack of resources. Because of financial issues, when the study began, we had only one device available. This limited how many families could use the system at the same time and also limited the amount of time each cat could experience it. Therefore, this study could not address questions such as long term usage, changes in cat owners interaction behavior, and differences across families over time.

Ideally, participants should use the system for about two to three months. A longer deployment period can better reflect the constraints and difficulties of everyday use and allow users to form a habit of checking their pets status through the app. In addition, follow up interviews can be conducted at different stages during the deployment to examine whether their opinions change during long term use.

6.4. Future work

At present, due to limited data, our classification model supports only four behavior categories: inactive, active, eating, and grooming. Ideally, the system should provide more detailed behavior labels to help owners gain a more comprehensive understanding of their cats daily activities. This would require collecting longer term and more diverse behavior data from more cats.

In terms of model improvement, we aim to further increase accuracy on the existing basis. Future work can proceed in three directions. First, adjusting model architectures and training parameters to improve overall and class level recognition accuracy. Second, exploring semi supervised or unsupervised approaches to reduce the burden of manual annotation while maintaining effective accuracy. Third, the current model uses only three axis accelerometer data, while the IMU also provides gyroscope information. In the future, features from both modalities could be combined.

On the hardware side, the current device still has limited battery life and a relatively large form factor, which may, to some extent, affect cats daily activities and willingness to wear it. Future designs could consider using lower power sensors and custom configurations with modules such as the ESP32 to improve power consumption and size, and to explore more unobtrusive wearing solutions.

In terms of software and visualization, the current app provides relatively basic functions and charts. Future versions should include more layered visualization support, such as longer time scale trend review, clearer representations of uncertainty, and lightweight annotations related to everyday events. At the same time, considering the significant individual differences among cats, future systems could allow owners to upload videos of their cats activities along with corresponding accelerometer data via the app, in order to improve the accuracy of individual behavior assessment.

In addition, in this study only some participants cats experienced short term use. Many current questions, such as the negotiation of trust between people and devices, how cathuman interaction may change under long term use, and the meaning of digital beings, rely on participants imagination. Future work should carry out long term continuous deployments in more households and conduct interviews at the beginning, middle, and end stages to understand how users understanding of information, trust, and emotions develop over time.

7. Conclusion

This thesis could also explore how a wearable based behavior visualization system can support everyday cat care and improve the relationship between cats and their owners. We developed the PurrTime prototype system, which combines an IMU wearable device, a behavior classification model, and a mobile application to visualize changes in cat behavior in real time. We then conducted experience sessions and semi structured interviews to understand how cat owners interpret behavior visualizations, how they decide whether to rely on the data, and what meanings and concerns arise when imagining long term use of such a system.

The interview results could also show that participants perceived the main value of PurrTime as helping owners better understand their cats condition through behavior summaries and real time visualization, thereby reducing the cost of constant checking. Participants could make adjustments to feeding, rest, and activity based on the information summarized from the visualization. At the same time, participants rarely fully trusted the device at the initial stage. The establishment of trust was seen as a slow and negotiated process. During this process, system outputs were compared with prior experience and observation, and incorrect predictions were considered likely to cause unnecessary worry and the overlooking of important issues.

Beyond everyday monitoring, participants also imagined the impact of long term records. Many agreed on the value of digital archives as biographies of their cats and as proof of time lived together. At the same time, they inevitably associated such records with the sadness and sense of loss that might arise when a cat passes away. These responses indicate that behavior visualization in pet care involves not only functionality and usability, but also potential boundaries related to responsibility, emotion, and ethics.

Overall, this work provides a concrete prototype and explains from a practical perspective how pet owners understand behavior visualization, how trust between humans and devices is negotiated, how long term records may lead to care adjustments, and the potential implications of digital beings. The design implications revealed by these findings include: reducing the cost of understanding cats state, communicating data uncertainty, providing privacy and emotional control for long term records, and treating cats comfort as a prerequisite.

Although limited by funding, devices, participants, and cats, this study only conducted short term deployment. However, it lays a solid foundation for future long term in home studies and for improving models, hardware, and visualization techniques, in order to better support both owners and their cats.

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A. Participant Consent Form

Study title: Exploring Cat Owner Interaction Through Behavior Visualization (PurrTime)

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Purpose

This study investigates how PurrTime, a system combining a wearable device for cats and a mobile application for visualizing behaviors, may influence owners understanding, trust, and care practices.

Participation

Your participation involves two parts:

- **System experience** (approximately 1.5 hours): using the PurrTime application and wearable device with your cat.
- **Interview** (approximately 30 minutes): a semi structured discussion about your thoughts and experiences.

The total duration of participation will be approximately 2 hours. With your permission, the interview will be audio recorded for research analysis.

Participation is voluntary. You may skip any question or withdraw from the study at any time without any consequences.

Confidentiality

All information collected in this study will remain confidential. Your name and any identifying details will be anonymized in transcripts and reports. Audio recordings will be stored securely and deleted after the study is completed.

Use of Data

Your responses will be used solely for academic research purposes, such as a masters thesis or related academic publications. No identifiable information will be shared publicly.

Consent

Please indicate your consent by confirming the statements below:

- I have read and understood the information above.
- I voluntarily agree to take part in both the PurrTime system experience and the interview.
- I consent to the audio recording of the interview.
- I understand that I can withdraw from the study at any time without penalty.

Participant Name: ______________________________

Signature: ____________________ Date: ____________

Researcher Signature: ____________________ Date: ____________

B. PurrTime Interview Protocol

Introduction

Thank you very much for taking the time to join this study. We will first go through the PurrTime application and wearable device, and then conduct a short interview about your impressions and thoughts. There are no right or wrong answers. I am simply interested in your experiences and opinions. The interview will be audio recorded for research purposes only, and all information will remain confidential. Shall we begin?

Principle Explanation

A presentation slide deck was used to explain to participants the logic behind the wearable setup and the machine learning model, and why their combination can be used to predict cat behavior. Participants were informed of the overall accuracy of the classification model and the accuracy of each individual behavior.

Participant Background

- What is your age?
- What is your occupation or area of study?
- How many cats do you currently have?
- How long have you owned your cat or cats?
- How would you describe your experience with technology? (Low, Medium, High)

Cat Background

- What is your cats name?
- How old is your cat?
- What is their sex and breed?
- How would you describe your cats personality?
- Does your cat have any particular habits or health conditions that you pay attention to?

Experience Session

(Approximately 1.5 hours)

- Open the PurrTime application and create your personal account.
- Add your cats profile (name, age, sex).
- Add one feeding record for your cat.
- Add one weight record.
- Add one expense record.
- View the record chart page and explore how the data is visualized.
- Put the wearable device on your cat.
- Pair the device with your cats profile in the application.
- Let your cat move freely for approximately one hour.
- Check the activity log and view the collected behavior data and charts.

Evaluation and Reflection

Part 1. Daily Routines and Existing Habits

- In your daily life, how do you typically keep track of your cats well being?
- In your daily life, which behaviors or situations do you pay the most attention to?
- If the systems data and your own intuition disagree, which would you trust more, and why?

Part 2. Trust and Dependence

- If the device alerts you to a problem but you see nothing unusual, what would you do?
- Are you concerned that you might become too dependent on the system and interact less directly with your cat?
- If the system gives false positives or misses something important, how would that affect your trust in it?

Part 3. Emotions and Relationship

- If you had a continuous digital record of your cat, how do you think it would impact the bond between you?
- Do you feel that visualization makes your cat feel closer or more distant?
- Are you worried that quantifying behaviors makes your cat feel like a monitored object?

Part 4. Ethics and Privacy

- If this data were shared with veterinarians, researchers, or other pet owners, how would you feel?
- Do you think cats have a form of privacy? Could this system violate it?
- In a household context, would you be concerned that the data might be misused?

Part 5. Long Term Use and Imagination

- If you could see your cats activity data every day, do you think it would change how you interact with them?
- Do you worry that long term reliance might reduce the joy of caring for your cat, making it too rational or data driven?
- If in the future the system could predict your cats emotions, how far would you want it to go?

Part 6. Life Record and the Digital Being

- Imagine the system could record your cats entire life. How would you view such a digital archive?
- After your cat passes away, would you want to revisit or re-experience these records?
- Would you see such a digital being as a form of memorial, companionship, or as something inappropriate?
- If the system could recreate your cats behavior, for example as a virtual cat, would you want to experience that, or would it feel inauthentic?
- In your opinion, should there be ethical boundaries for an animals digital life?

Closing Questions

- What is your biggest hope or expectation for a system like PurrTime?
- What is your biggest concern or fear regarding potential risks or negative effects?
- If you could give one piece of advice to the design team, what would it be?