Towards Intelligent Care: Human Behavior Analysis Using Energy Consumption and Door Operation Patterns in the Internet of Care Things

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Abstract: The analysis of human behavior is an interdisciplinary science aimed at recognizing, describing, and predicting patterns of human behavior and emotional states. With the development of sensor technologies and data-driven approaches, new opportunities have emerged for observing and modeling everyday human activity. This study is based on a real-world dataset collected over one month from five participants in a residential environment. The data were gathered using environmental sensors, specifically contact sensors and energy consumption sensors, which enabled monitoring of user interactions with their surroundings. A set of statistical and machine learning methods was applied, including K-means clustering, correlation analysis, time-series representation, calculation of mean values, and aggregation of correlations. The results show how contact sensors and energy consumption sensors are related, how daily load is distributed, how periodic the data are, which sensors behave in a similar way within groups and across the system, and how individual behavioral models of each user can be formed. These findings highlight the potential of sensor-based analysis for advancing behavioral research and its practical applications.

1 INTRODUCTION

The risk of social isolation in private living has been shown to increase with age. Modern approaches in the fields of automation and health sciences can reduce this risk by enhancing social and psychological resilience in older adults [1].

In the context of demographic change, the associated increase in demand for care services and shortage of nursing staff present the healthcare system with urgent challenges that require immediate attention. Digital assistive technologies could be the solution to this problem [2].

In the PräEinsamAltKI project, researchers are using innovative digital solutions to prevent loneliness: a system is being developed for a model apartment that enable automatically and at an early stage identify increasing isolation in older people. It is expected to consist of a sensor network based on Internet of Care Things (IoCT) technologies and artificial intelligence (AI) capable of identifying signs of social isolation[1].

The subjects of the study are five users. The object of the study is individual daily electricity consumption indicators, as well as the total number of door and window openings available to all users.

One of the research tasks within the project is to analyze user behavior patterns, explore relationships between sensor measurements, and evaluate the informational value of the collected data. Accordingly, this article investigates behavioral trends in residential environments using electricity consumption data and door and window opening events, examines whether a measurable relationship exists between these two sensor modalities, and evaluates the extent to which such multimodal data can provide meaningful insights that may support the early detection of changes potentially related to social isolation.

[1] https://www.hs-anhalt.de/praeeinsamaltki/uebersicht.html

2 METHODOLOGY

To address the research task, a dataset was constructed, an analysis plan defined, data processing was performed, and the result subsequently interpreted.

Common approaches include wearable sensors (accelerometers, heart rate monitors, biosensors), environmental sensors (cameras, Wi-Fi), mobile devices and self-report surveys or diaries for subjective input are used for data collecting [3], [4].

Once collected, data can be processed using methods like computer vision for video-based action recognition, or machine learning and deep learning models that extract patterns from multimodal signals. Researchers use both knowledge-driven approaches (e.g., social force models) and data-driven methods (e.g., RNNs, GCNs, GANs, reinforcement learning), with hybrid techniques combining domain expertise and AI gaining popularity [4], [5].

Energy consumption readings are processed using a time series database. As ordinary regression methods are not suitable for predicting these data, advanced algorithms such as RNN-LSTM, ARIMA, and others are applied [6].

In contrast to these technologically advanced and computationally intensive approaches, this study primarily employs statistical analysis and environmental sensor data. The analytical tools include descriptive statistics, clustering, correlation analysis, and time-dependent visualizations.

2.1 Dataset

The dataset was constructed from real sensor readings collected over one month. It consists of an array of timestamps corresponding to sensor states, each linked to specific entities.

It includes the electricity consumption data from smart plugs throughout the day for each of the five users. The contact sensor data represent the number of window or door openings per day. State values are represented in numerical format. Non-numeric observations (e.g., unavailable or NaN) were converted to zero values. The absence of data was interpreted as non-use.

The corresponding number of rows for each entity is presented in Table 1.

Thus, each entity is represented by the corresponding set of dimensions for the analyzed period.

2.2 Data Analysis Procedure

In the initial stage, the data for the entire period were visualized as time series to identify general patterns [7].

Next, mean and maximum values for each sensor were calculated by day of the week, based on which a summary table of average daily indicators was created [8]. The obtained aggregated values were used to perform unsupervised learning cluster analysis using the k-means method [9].

Additionally, heatmaps were constructed based on the average energy consumption throughout the day, which allowed to determine the load distribution pattern and the outlet usage hours.

In the next stage, the data was divided into three-time intervals, after which the Pearson correlation coefficients were calculated for each pair of features [10], [11]. The results of the correlation analysis were visualized as correlation matrices. Based on these matrices, the number of strong and moderate positive and negative correlation coefficients were calculated for each entity, indicating the prevailing direction of relationships between the sensors.

3 RESULTS

This section presents a step-by-step analysis of the procedures described in section 2.2.

The data visualization presented in Figures 1 and Figure 2 demonstrates the presence of patterns in the sensor readings. It is observed that the highest values persist for 4-5 days followed by a decrease. Five groups of peak values can be identified, indicating the periodic use of the sensors.

Thus, user behavior can be characterized as periodic, which is confirmed by the analysis of both graphs. As the individual consumption of each energy sensor increases the contact values also rise.

The average value calculated for the maximum value by day of the week for each sensor is presented in Table 1.

The maximum energy consumptions for each user occur on weekdays and the same trend is observed for contact sensors as well. For example, both are either minimal or absent on weekends.

Based on the window sensor data, the room is ventilated approximately once per day on weekdays.

From the table, it can be assumed that either the users connect different devices to their sockets or the usage times differ.

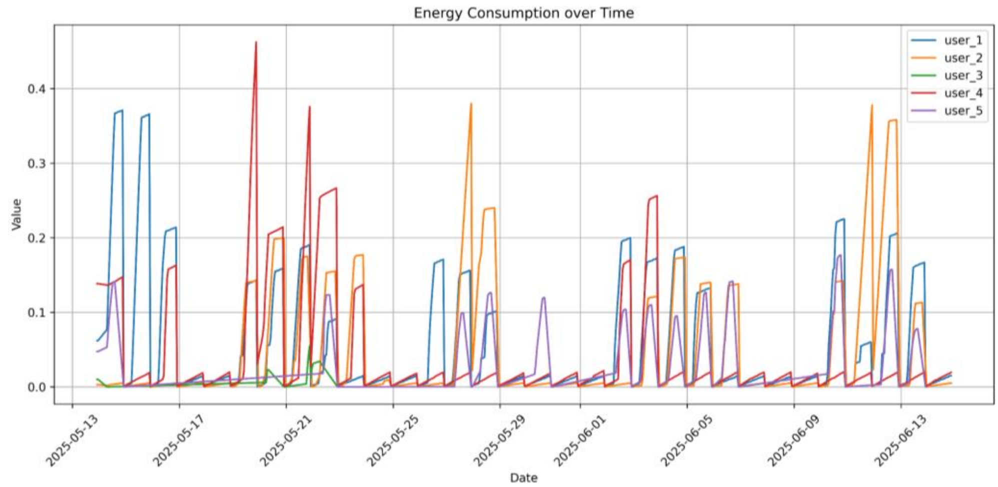

Figure 1: Time series of energy consumption sensors.

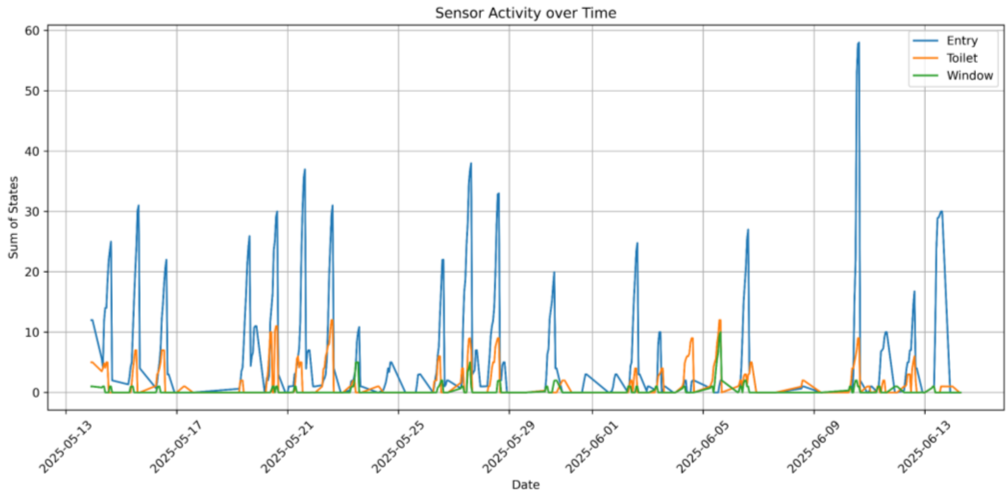

Figure 2: Time series of contact sensor values.

Table 1: Number of rows for each entity in dataset.

Energy sensors					
	user1	user2	user3	user4	user5
Rows	761	461	24	761	156
Contact sensors					
	entry		window		toilet
Rows	367		139		236

Table 2: Mean value for every sensor by day of week.

Entity	M	Tu	W	Th	Fr	Sat	Sun
user1, kW	0.132	0.155	0.198	0.162	0.085	0.014	0.014
user2, kW	0.039	0.169	0.162	0.132	0.087	0.005	0.005
user3, kW	0	0.016	0.018	0.034	0	0	0
user4, kW	0.167	0.129	0.097	0.068	0.071	0.019	0.019
user5, kW	0.104	0.108	0.107	0.135	0.113	0	0
entry	10.3	11.9	7.5	6.4	10.2	1.1	1.8
toilet	3.0	3.5	2.9	3.4	1.8	0.5	2.0
window	1.3	1.2	1.0	2.0	1.3	0.0	0

Clustering was performed to group data based on statistical features. To determine the number of clusters, the elbow method was used, which indicated that the optimal number of clusters for both groups is two.

As a result, it can be seen in Figure 3 that the behavior of the entry door differs significantly from their behavior on weekends and from that of all other contact sensors on other days. As already mentioned, the behavior of this sensor can be divided into weekday and weekend patterns. For all others, no other clearly visible useful information can be obtained. Despite the fact, that all other doors are used a far less times.

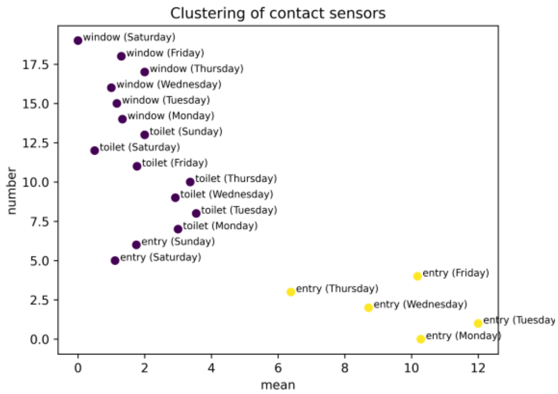

Figure 3: Clustering K-Means for contact sensor values.

The diagram obtained for the energy consumption sensors in Figure 4 appears more dispersed.

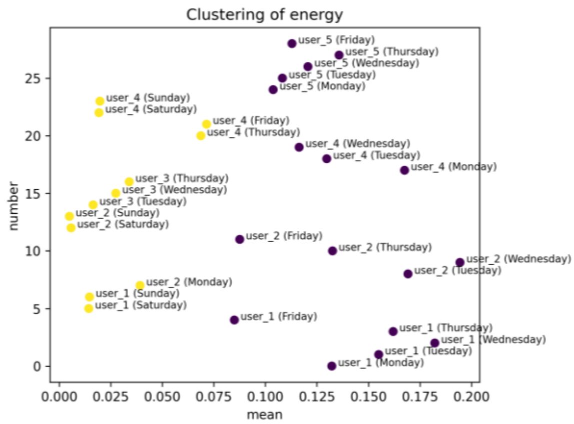

Figure 4: Clustering K-Means for energy sensor values.

User 3 stands out in that their consumption consistently remains at a low level, comparable to the weekend consumption of other users. User 5, on the contrary, is always part of the high-consumption group. The behavior of Users 1, 2, and 4 varies depending on the day of the week, showing a tendency toward higher consumption on most weekdays, which explains their assignment to both groups.

A clear periodic consumption is observed: activity on weekdays (purple group) is significantly higher than on weekends (yellow group). Thus, it can be concluded that the consumption is periodic, with higher levels during weekdays.

How does the situation develop within the weekdays themselves? The evolution if consumption patterns across weekdays is further examined through the heatmap presented in Figure 5.

In this diagram, the dark blue indicates 100% of the maximum value for each entity, while lighter shades correspond to lower levels of consumption. A striking feature of the visualization is the presence of empty cells during Saturday and Sunday. For several users, the values are either missing or remain extremely low, in many cases approaching or reaching zero.

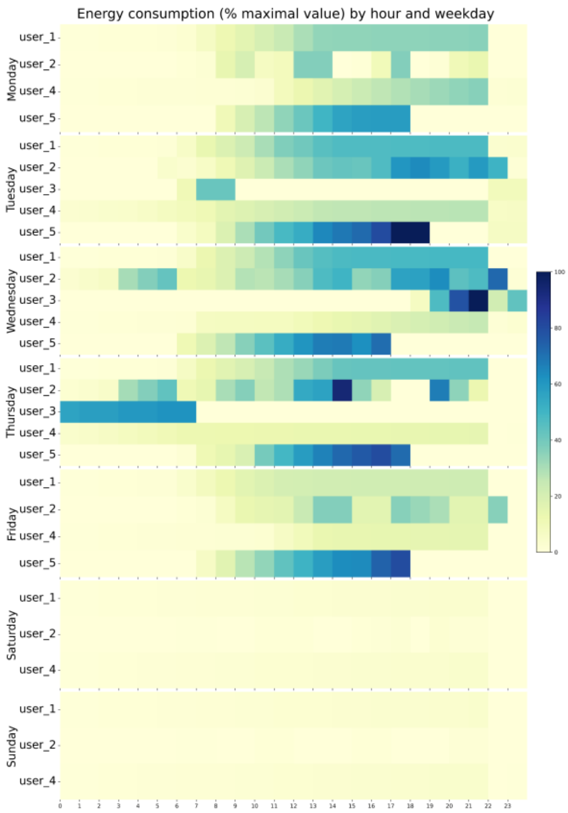

Figure 5: Hourly heatmap of consumption values expressed as a percentage of the maximum per user.

It is also evident that for many users, values gradually increase throughout the day. For example, User 1 uses it's socket from Monday to Thursday between 8 - 9 a.m. and 2 - 3 p.m., after which energy consumption stops increasing and remains stable.

User 2, in turn, uses the socket consistently from Monday to Friday. On Monday and Thursday breaks in usage are observed. Often, usage starts at 8 a.m. and continues until 3 p.m., although values are occasionally recorded in the early morning.

User 3's consumption values are logged either before 9 a.m. or after 6 p.m. Which is compared to other users can be described as abnormal.

User 4's consumption pattern is less distinct, with activity sometimes beginning at 9 a.m. and other times at 12 p.m., and ending at 3 p.m. or 10 p.m., respectively.

User 5 exhibits a more stable pattern: from Monday to Friday, the socket is used consistently between 9 - 10 a.m. and 5 - 6 p.m.

The presented values indicate that the sockets are not in use continuously throughout the day. To analyze how the individual sensors relate to one another, Pearson correlation is employed.

In the correlation heatmaps, green denotes a positive relationship, meaning that the corresponding sensors tend to increase simultaneously. Conversely, colors shifting toward red reflect a negative relationship, where an increase in one sensor is associated with a decrease in another.

Figures 6 - 12 display these correlations across all days of the week, differentiated by three distinct time periods, thereby providing a detailed view of temporal variations in sensor relationships.

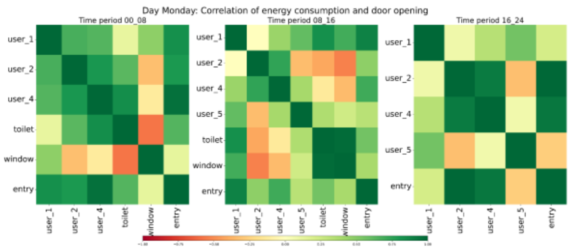

Figure 6: Pearson correlation of sensor values on Monday.

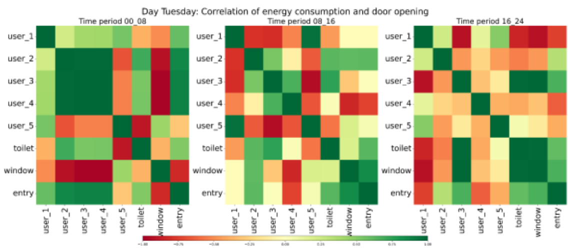

Figure 7: Pearson correlation of sensor values on Tuesday.

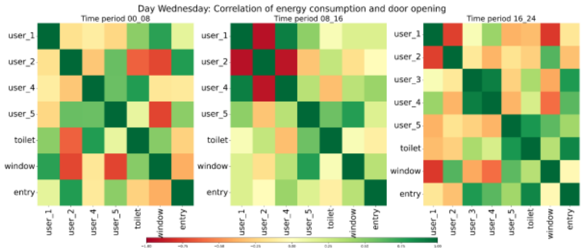

Figure 8: Pearson correlation of sensor values on Wednesday.

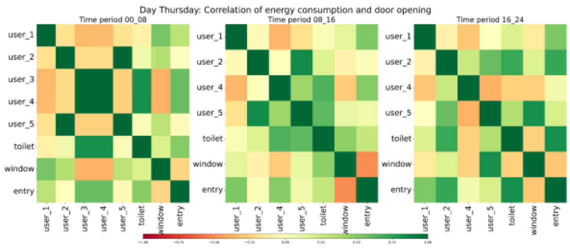

Figure 9: Pearson correlation of sensor values on Thursday.

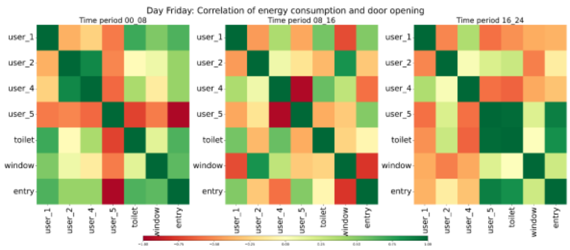

Figure 10: Pearson correlation of sensor values on Friday.

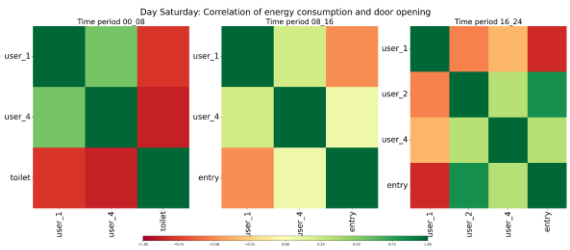

Figure 11: Pearson correlation of sensor values on Saturday.

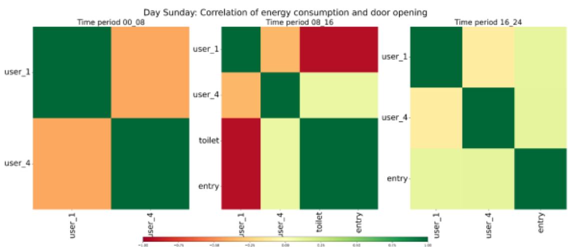

Figure 12: Pearson correlation of sensor values on Sunday.

Given the large number of correlations, a summary was created to facilitate interpretation. The average and strong correlations between entities across all periods were compiled and are presented as a bar diagram in Figure 13.

The analysis of correlations reveals distinct interaction patterns among the users and environmental sensors across different time periods (morning, daytime, and evening).

User 1 exhibits predominantly negative correlations with Users 2 and User 3 during both daytime and evening hours. In contrast, correlations with Users 4 and 5 are consistently positive across all time periods. In terms of contact sensors, correlations with all doors and the windows tend to be negative in the evening and positive in the morning. During daytime, positive and negative correlations are balanced, except for the entry door, where positive correlations are stronger.

The correlation between Users 2 and User 3 are positive at night and during the day, but becomes negative in the evening. For User 4, correlations tend to be positive during the evening and nighttime, whereas for User 5, positive and negative correlations occur with approximately equal frequency. A similar balance is observed for User 4 during daytime hours. Correlation between User 2 and the entry door remains consistently positive throughout all time periods. For the window, positive correlations dominate during the day. Correlations involving the toilet door are generally mixed, with the exception of nighttime hours, during which positive correlations predominate.

User 3 exhibits predominantly positive correlations with User 4 across all time periods, particularly at night. In contrast, correlations with User 5 are generally negative, except during the evening, when no correlation is observed. Regarding the entry door, correlations are positive in the morning and evening but absent during daytime hours. For the toilet door, correlations remain consistently positive across all periods, whereas correlations with the window are positive in the morning and neutral in the evening.

Between Users 4 and User 5, correlations are predominantly negative across all time periods. With the entry door, correlations remain consistently positive. With the toilet door, correlations are positive in the morning and during the day. In contrast, correlations with the window are consistently negative across all time periods.

Correlations between User 5 and both the entry door and the window are positive during daytime and evening hours. Correlations involving the toilet door are mixed during daytime hours but become predominantly positive in the evening.

4 CONCLUSIONS

The conducted analysis demonstrates that user behavior exhibits a clear periodic structure, with significantly higher activity levels and sensor usage during weekdays, followed by a sharp decrease or complete absence of activity on weekends. This pattern is consistent across both energy consumption and contact sensors, confirming that users tend to follow stable daily routines strongly linked to the working days.

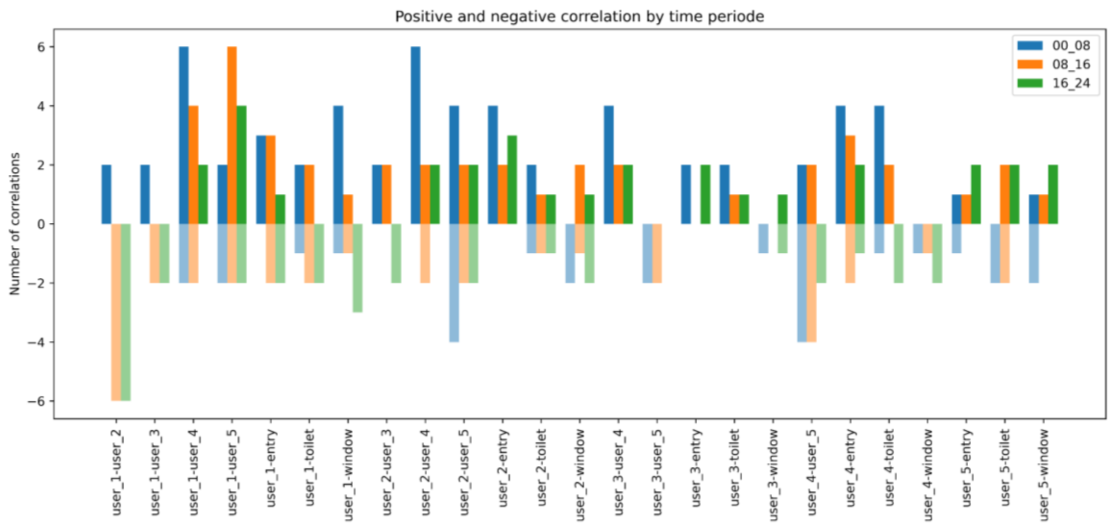

Figure 13: Positive and negative correlation by period.

Clustering analysis revealed that users can be divided into distinct groups: some consistently show higher energy consumption (e.g., User 5), while others remain at low levels (e.g., User 3), independent of the day of the week. Users 1, 2, and 4 display more variable behavior, with their consumption fluctuating depending on the weekday, yet still showing a tendency toward greater usage on working days.

The hourly heatmap analysis further confirmed these patterns by highlighting that sockets are not in continuous use but rather concentrated in specific periods, typically between morning and late afternoon. This reflects daily working rhythms and indicates that user activity is temporally bounded and highly structured.

Correlation analysis revealed both synchrony and divergence in user behavior. While Users 1, 2, and 3 tend to avoid simultaneous usage, Users 4 and 5 demonstrate stronger positive correlations with others, suggesting complementary or overlapping usage patterns. Interactions with environmental sensors such as doors and windows also exhibit temporal dependence, showing predominantly positive correlations in the morning, balanced dynamics during the day, and negative correlations in the evening.

Overall, the study demonstrates that even simple, low-cost, and non-intrusive sensors - such as energy consumption and contact sensors - can provide complementary and meaningful insights into user behavior in shared residential environments. Their combined use enables the identification of daily routines, user-specific patterns, and interaction dynamics between individuals and their environment, providing a transparent and interpretable baseline for future AI-driven systems. By establishing typical behavioral patterns for each user, this approach lays the foundation for detecting deviations that may signal changes in daily life, which could potentially support the early identification of situations associated with reduced engagement or emerging social isolation.

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