CATCHING POKÉMON AND IN-GAME FRIENDS' HOME ADDRESSES

Jouni Ikonen (1), Antti Knutas (1), Laura Anna Ripamonti (2), Giovanni Livraga (2), Sonja Hyrynsalmi (1)*

(1) Software engineering, LUT University, Lappeenranta;
(2) Computer science, University of Milan, Milan
(1) Finland, (2) Italy

* Corresponding Author, e-mail: Jouni.Ikonen@lut.fi

Abstract: While location-based games are widely popular, the interpersonal privacy risks players pose to one another remain under-researched. These risks can lead to harassment and stalking. This paper presents an experimental study investigating how the in-game gift mechanic in Pokémon GO can be exploited to reveal players' sensitive locations. We employed a mixed-methods approach consisting of a 37-day "in-the-wild" play experiment (n=20), questionnaires, and semi-structured interviews. Our results demonstrate that in-game gift metadata allowed for the identification of over 60% of participants' home addresses within a 100-meter radius. These findings highlight critical privacy implications for location-based game design and the need for increased user awareness.

Key words: location-based games, geospatial privacy, inference attack, gamification risks, open source intelligence.

1. INTRODUCTION

Modern location-based games generate hundreds of millions of dollars in monthly revenue [1, 2]. The gameplay of a location-based game blends the physical environment with a virtual game world, requiring players to collaborate, communicate, and move around to achieve in-game objectives [3]. Location-based games can bring benefits such as promoting physical exercise [4], but moving around in real life during gameplay and using real environments can also create new challenges and ethical concerns [5].

Niantic has developed some of the most popular location-based games. Notable examples include the alternate reality game Ingress (released in 2013), Pokémon Go (2016), Pikim Bloom (2021), Peridot (2022) and Monster Hunter Now (2023) which are all free-to-play games. In this paper, we focus on Pokémon Go as it has been the most impactful location-based game, with the highest revenues and the largest number of active players [1, 2].

Pokémon Go requires players to physically move around and interact with virtual objects, which are tied to real-world locations [6]. It can also be categorized under the augmented reality (AR) game genre as AR can be used as part of the playing experience. However, it is primarily considered a location-based game as its core mechanics and fundamental nature rely on location data and the physical movement of players to different locations [7]. In Pokémon Go, players use their mobile devices to view a map of their surroundings with virtual objects superimposed. Two of the virtual objects are PokéStops and Gyms, which provide players with game items like balls for catching Pokémon and gifts that can be sent to other players. Action to get items is later referred as “spinning”. In this study, we focus on gifts because they contain information about places that players have visited, and we propose that information about a player's location history can be inferred from gifts they have sent.

Although prior studies have analysed privacy threats posed by game providers, the impact of other users on privacy has received little attention. In this work, we present an analysis of privacy concerns caused by player’s gift exchanges in Pokémon Go and focus on the following research question:

- Is it possible to predict where other players live or work from in-game data available to players? If so, what level of accuracy can be attained?

We approached these questions by conducting an in-the-wild [8] study with a group of volunteers. The research team interacted with the participants until most of them had reached the status of “Ultra Friends” with our research player, that is, they had interacted with the research player in the game for at least 30 days. The in-the-wild study was accompanied by a pre-questionnaire, two post-questionnaires, and an optional interview. The core data sources of our research were the in-game gifts that users sent to each other.

The remainder of this paper is organized as follows. Section 2 reviews related work regarding privacy in location-based games, differentiating between provider-side and player-side threats. Section 3 contextualizes the study by detailing the specific in-game motivators, such as gift exchanges and friendship levels that encourage data sharing. Section 4 outlines our mixed-methods approach, including the 'in-the-wild' play experiment and the specific algorithms developed to estimate player home locations from gift metadata. Section 5 presents our analysis and findings, quantifying the accuracy of these location attacks and visualizing the results. Finally, Section 6 concludes the study, discussing the implications of these privacy risks and suggesting avenues for future research.

2. RELATED WORK

Pokémon Go has gained significant academic attention regarding its impact on health, social interaction, and privacy. While studies highlight benefits such as increased physical activity [9], improved mood, and cognitive enhancement [10], the game’s core mechanics rely heavily on location data, introducing distinct ethical and privacy challenges.

Successful gameplay involves social elements, such as raids and gift exchanges, which foster community but also expose users to peer-to-peer privacy. Prior research on Location-Based Games (LBGs) has predominantly focused on privacy threats posed by service providers, including data collection, surveillance, and third-party sharing [11, 12]. However, threats posed by other players are increasingly critical. Interactions in

Pokemon GO such as defending Gyms or sharing items have been discussed to be able to reveal a player's sensitive locations, such as homes or workplaces, potentially leading to cyberbullying or stalking [5, 13].

Due to the reliance on geolocation data, Pokémon Go has also raised substantial privacy concerns (see, e.g. [14]). These can be clustered into three main areas: data collection and use, third-party access and data sharing, and potential data breaches. Pokémon Go continuously accesses and collects detailed location data from players to populate the game environment with virtual creatures and user-created points of interest (i.e., PokéStops and Gyms), thus raising concerns about the extent and sensitivity of the information gathered (see, e.g., [13, 15, 16]). Similarly, the game can build detailed profiles of user behaviour, including movement patterns and frequently visited locations, which could be misused if not properly protected [13]. Another possibility is that the service provider (Scopely in our case) could share collected data with third-party service providers for analytics and other purposes, raising concerns about data handling and protection [11].

3. IN-GAME MOTIVATORS FOR PLAYERS

In-game motivators are not a new concept, and Pokémon Go is not the only game that uses them to encourage users to keep playing. The competition between mobile games for players' attention is intense, and game companies need to maintain players' attention and continue offering new content, especially for long-term players [17–19].

Pokémon Go has regularly received new features to maintain players' attention [17]. When the gift feature was added 2018, it raised discussion in the Pokémon Go community about the safety of the shared location information as, a player could open the map on their mobile phone and see the exact location of the PokéStop where the gift was obtained directly [20]. Nonetheless, the feature was received with enthusiasm, and players quickly became excited about exchanging information and gifts with each other. The game mechanics for gifts in Pokémon Go are straightforward. Typically, a player can hold 30 gifts in an inventory and select which gift they want to send to another player. The player is restricted to sending only one gift to a specific friend per day. Each gift includes a picture of the PokéStop or Gym where it was obtained, a textual description, and the name of the player sending it. Textual descriptions can be used to understand whether the PokéStops are located in the same city or the same country, but they do not directly contain information about how the PokéStops are positioned related to each other. While the game does not explicitly display coordinates on the gift card, the specific location of many PokéStops are retrievable via third-party mapping services. Consequently, while players may view gifting as a mechanism for game progress, they are inadvertently sharing a granular history of their physical movements with other users. This creates a tension between the game's incentive structure and the user's location privacy, a gap this study aims to explore.

At the same time as adding the gift feature to the game, Niantic also introduced friendship levels [17, 21], which are designed to maintain engagement. As of January 2026, there are six friendship levels in Pokémon Go: Friends, Good Friends, Great Friends, Ultra Friends, Best Friends and Forever Friends. Users must interact for several days to progress to the next friendship level. There are multiple possible interactions that contribute to friendship levels, of which opening a gift is one. The point rewards for reaching each level also vary, with players earning 0, 1000, 10000, 50000, 100000 and 150000 points and other in game perks, for the friendship levels, respectively. In addition, there are occasional in-game events that speed up friendship progress, which could affect the expected time to reach the next.

Figure 1 presents an example view of an in-game gift that a player has received. In the middle of the picture is an area with a textual description of the PokéStop from where the sender obtained the gift. The textual description includes the name of the PokéStop, the city where it is located, the region, the country, and the sender's nickname (which is blurred out here for privacy reasons). These data do not include any geographical coordinates, but it is possible to ask other players where the PokéStop is on a map or use third-party services (e.g., Telegram bot or a website) to obtain the coordinates from PokéStop name.

Figure 1. An in-game gift that a player has received from another user (screenshot from main author's gameplay). Pokémon GO is a trademark of Nintendo, used here for non-commercial scholarly analysis under fair use.

4. METHODOLOGY

The research started from a hypothesis of privacy risks in the Pokémon Go game, in which players could learn the whereabouts of other players via in-game gifts. A literature search did not reveal any research on using Pokémon Go gifts to find the whereabouts of other players, so we concluded that we had identified an unverified potential privacy problem. The research was constructed as a mixed-methods study, including an experiment to investigate whether it is quantitatively possible to deduce, from the in-game data, where other players physically live, and qualitative questionnaires to investigate players' privacy perceptions. The research was designed as a field study, following the 'in-the-wild' methodological framework established by Rogers [25]. We utilized this established approach to observe players performing their normal play routines. While the methodological framework is well-established, its application to the specific privacy implications of the Pokémon GO gift mechanic is, to our knowledge, entirely novel. A field study was essential as we needed to collect real play data to develop an estimation of players' home locations.

We played Pokémon Go with the volunteers for five weeks and recorded interaction data between the participants and our test player, which forms our gameplay data set. We gathered additional data via three questionnaires and in-person interviews.

4.1. Research process

The research process is presented in Figure 2. It starts with identification of the potential problem, research design, participant recruitment and pre-questionnaire to collect basic information about the participants (Questionnaire 1). Next phase is a 37-day data collection period during which participants send in-game gifts to the researcher's game account. After that participants are invited to fill in the post-data collection questionnaire to provide more information on their playing habits and form a baseline for participants' attitudes and perceptions regarding privacy and data security (Questionnaire 2). In the end the initial findings from the game data are presented to the participants, followed by a questionnaire regarding whether the participants' attitudes and perceptions regarding privacy and data security were changed (Questionnaire 3).

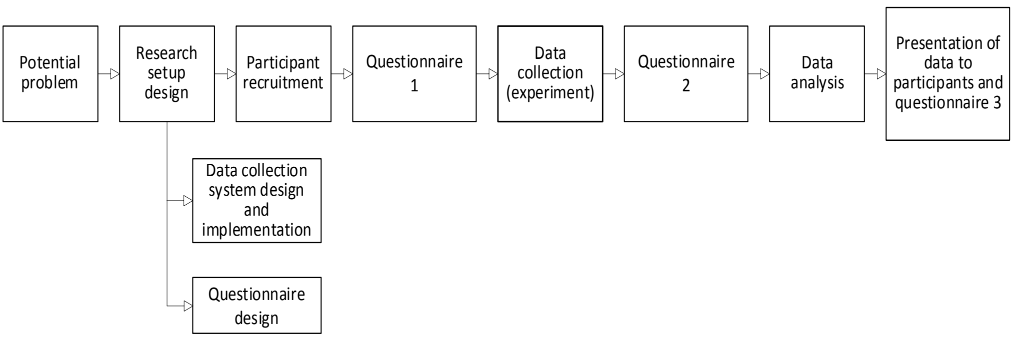

Figure 2. The research process

The participants were recruited by advertising the possibility of assisting in the research in the local Pokémon Go players' Telegram group, which had 182 members at the time. Telegram messaging is not part of the Pokémon Go game but is used by some players to communicate with other players and coordinate events. We selected the first 20 volunteer players to participate. Each participant was explained that they would be participating in research and would be asked to fill in surveys and send a daily Pokémon Go gift. All the participants were presented with research guidelines, and they gave consent to participate in the research. All the participants were adults. In early stages of the research, we realized that one of our participants was playing with two game accounts, so we had 19 persons and 20 game accounts participating in the research. This was decided to be acceptable as it could provide insights if it is possible to identify from data if players are playing together. In processing of questionnaire data the two accounts were treated as one.

4.2. Estimation of players' home locations from in-game gift data

In the 37-day data collection period (March – May 2023), we asked each participant to send daily an in-game gift to our research player. We opened the received gifts daily to extract the senders' nicknames and the location descriptions. Methods that could be used to acquire data are as follows:

- Manually open each gift and record the player nickname whom it was from and the location of the originating PokéStop.
- Hack the Pokémon Go network protocol and write a client to receive and open gifts.
- Connect a mobile phone to a PC and remotely control the phone by sending commands to it.
- Use an emulator to run Pokémon Go software on a PC, automate playing in the emulator, and build data extraction on that.

Method 1 was rejected due to the manual labour involved. Method 2 would be the preferred methodology, but due to games network protocol and security measures that was not seen as viable option. Method 3 was selected as it is relatively easy to send commands to an Android phone via the Android Debug Bridge (ADB).

We scripted a software robotics system to open and save images of the received gifts automatically. Automatic text recognition was used to extract the name of the location and the user nickname from each image.

Opening of the gifts was implemented using a Linux laptop connected to an Android phone by a USB cable. The phone was set to developer mode so it could be connected by USB and controlled with ADB commands. The basic algorithm for the data collection was as follows:

1. Open the friend list (see Figure3, left side) in Pokémon Go in the mobile phone.
2. Take a screenshot from the friend list.
3. Identify the coordinates of each visible gift in the screenshot.
4. Click on each gift visible in the screenshot.
   a. Click on the gift to show where it is from and take a screenshot.
   b. OCR to extract text from the gift.
   c. Store player and PokéStop names, and location description.
   d. Open the gift.
5. If there are remaining entries in the friend list, scroll to show more friends and return to step 2.
6. Close the friend list by clicking the close button.

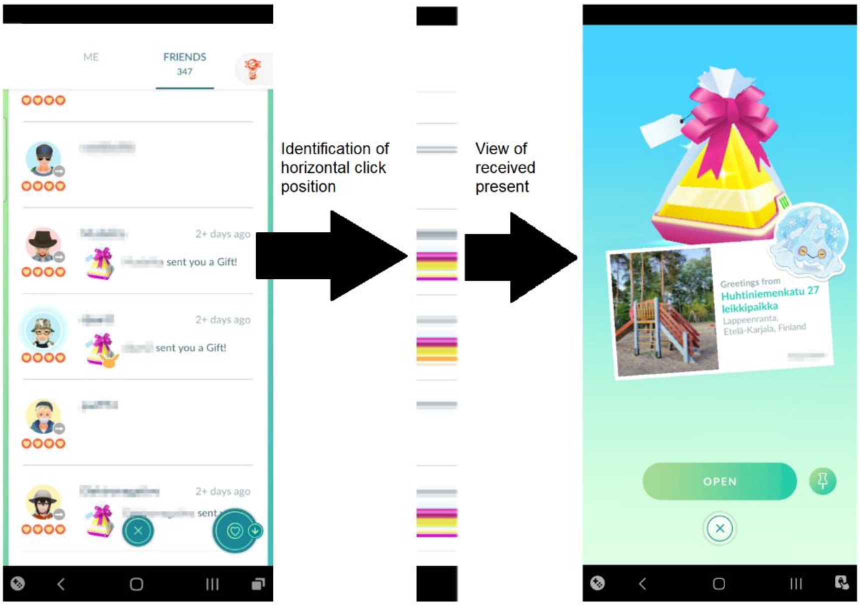

Figure 3. Identifying gifts from a friend list by analysing colours. Image created by the authors using screenshots from Pokémon GO.

To detect gifts in the friends list, a small program was written to identify gifts. The identification was performed by taking a one-pixel-wide vertical slice of the screenshot chosen to pass through all the bows of the gifts, and if shades of red were detected at a given position, it was recorded as the position of a gift. The detected horizontal positions were then used to click on each received gift. An illustration of this is shown in Figure 3 (middle) in which the one-pixel-wide vertical slice has been stretched for legibility.

5. ANALYSIS AND FINDINGS

The data used in this research were collected from the participants through questionnaires, in-game gifts sent by the participants to our research player, and interviews. The data extracted from the gifts (PokéStop information and username) were collected during the gift-opening process, but had to be checked manually to identify and correct errors in OCR processing. One typical error was the name of the PokéStop being split into multiple parts.

During the 37-day research session, our test player received 698 gifts from 388 different PokéStops or Gyms and four different countries (Table 1). 77% of the gifts were from the area of the city where the research was conducted. We used a Telegram bot called PortMapBot to look for the GPS coordinates of each PokéStop and Gym, and we were able to find them for all but one location, corresponding to a success rate of 99.7%.

Table 1. Descriptive statistics of received in-game gifts.

	Data per player			
	Gifts sent	PokéStops	Cities	Countries
Min.	26	13	1	1
Max.	37	32	11	2
Average	34.9	28.85	4.3	1.125
Median	36	24	4.5	1

In the analysis, the coordinate data of the gifts were inspected separately for each player. These data were used to make an educated guess about places the player spent a large amount of time; we devised multiple algorithms to make these determinations. The results were then compared with the home addresses of the participants and were also presented to the participants, who were asked to comment on whether a location important to them had been correctly identified. To present the results to participants, they were visualized with the QGIS geographical information system software using OpenStreetMap as background data. An example of one of these visualizations can be seen in Figure 4 (published with the permission of the participant). The circles identify the places the user has sent a gift from and the numbers indicate how many gifts have been sent from there.

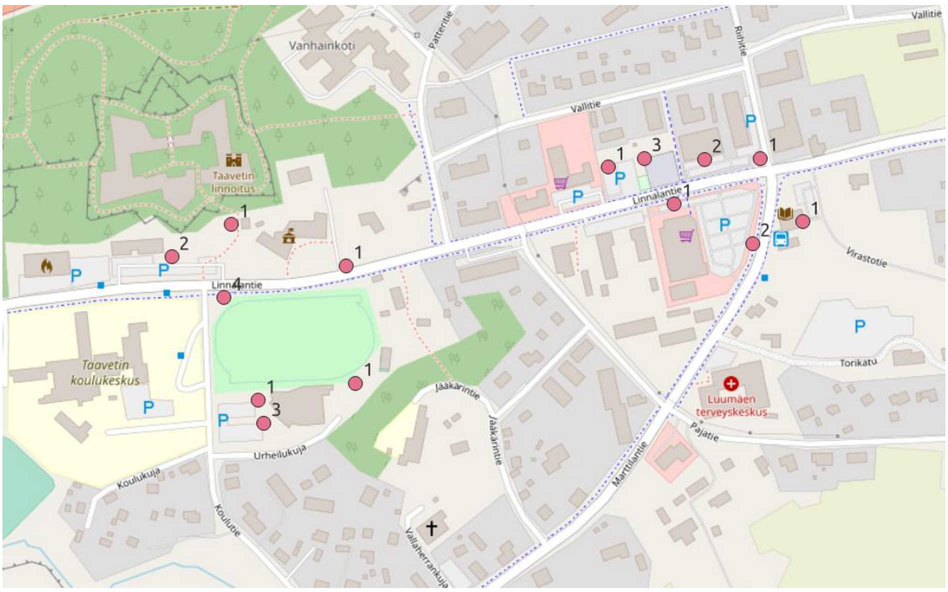

Figure 4. A close-up of clusters of received gifts from a participating user illustrated on a map. Source: authors' own work and background map © OpenStreetMap contributors.

The following four algorithms were used to make an educated guess about the most significant location for the user:

1. Visually analyse collected data on the map and guess where the participant resides.

2. Select the PokéStop where most gifts are from.
3. Select two PokéStops where the most gifts are from.
4. Select the PokéStop with the most gifts and then select the PokéStop within 700 meters with the second highest number of gifts.

The data visualization for each participant was inspected by researchers. By looking at the collected data for each user on a map, the researchers made their best guess at each player's home address. For most of the users, the data formed one or two clusters, which researchers assumed were significant places for the participant, like homes, workplaces, or schools. For algorithm 2 the PokéStop from which the most gifts were received was identified and this was assumed to be a meaningful place for the player. The distance between this PokéStop and the participant's home address or other address given by the player was then calculated. If there were multiple PokéStops with an equal number of gifts, then the distances from each of these PokéStops to the participant's meaningful location were averaged. For algorithm 3 the two PokéStops where the most gifts were received from were selected and their midpoint was assumed as the significant location. If there were more than two PokéStops with an equal number of gifts, then their midpoint was used. The distance between the assumed significant position and the home address or other address given by the participant was calculated. For algorithm 4 The PokéStop where most gifts were sent from was identified. Then, of the PokéStops within 700 meters of this, the PokéStop with the second largest number of gifts was selected. If there were more than two PokéStops with an equal number of gifts within the range, then their midpoint was used.

The proposed algorithms were used for each participating player account (N=20). Table 2 presents the results for all the players and all four algorithms. The table provides the calculated minimum and maximum distances from the home addresses of the players, the median, and the average, each measured in meters. In addition, the table presents the percentage of participants whose home addresses were identified to be within 100 meters. Algorithm 2 was able to identify 60% of players' home addresses to this accuracy. When we showed the results to participants, we learned that for multiple participants, their home was far from the calculated location, but they had another significant location close by. These included workplaces and partners' homes. Later, when we included these places in our analysis, we were able to detect homes or other significant locations with 100 m accuracy for 70% of players with algorithm 2. The researchers' guesses from the visual analysis (algorithm 1) identified 9 (45%) participants' home addresses to within 100m and, with the other significant places included, 11 (55%).

Table 2. Distances from estimated locations to home addresses for all players (in meters).

	Algorithm			
	1	2	3	4
Min.	26	20	26	26
Max.	10211	66850	1473478	66653
Median	128	92	1402	111
Average	1531	5674	79662	4673
within 100m accuracy	45%	60%	15%	35%

Most critically, our analysis shows that sophisticated profiling is not required to reveal a player's home location. The most effective method was also the simplest, Algorithm 2, which merely tracked the most frequently sent gift location. This rudimentary heuristic performed better than complex spatial averaging or human visual analysis, achieving a median accuracy of 92 meters. This finding suggests that the barrier to entry for potential stalkers is dangerously low, as no complex data processing is required to compromise a user's privacy.

The results indicate a strong possibility that a player can deduct from the in-game data where their in-game friend lives, with an accuracy in the tens of meters. We conclude that we have answered our first research question, “Is it possible to predict where other players live or work from in-game data available to players? If so, what level of accuracy can be attained?”

6. CONCLUSION

This study investigated the potential for privacy concerns in Pokémon Go by analysing in-game gift data. We show that a malicious actor can find out the home or other significant locations of 70% of the players with a spatial precision of 100 meters. Although players might not be aware of this potential information leakage, our findings highlight a potential privacy risk that deserves consideration. This research should be replicated in different countries, considering the impact of PokéStop and population distributions. Future work could also include larger sample sizes, which would allow us to deepen our research by analysing whether different subgroups show different behaviours, for example, based on age and gender (e.g., it is probable that younger generations would have different perceptions and behaviours from older age groups). Moreover, game data also potentially reveal paths that users normally use as well as their social networks, which we plan to investigate in the future. Hopefully, this study will encourage users to be mindful of the privacy implications inherent in location-based games and advocate for increased transparency and user control over data collection and usage.

REFERENCES

[1] *Annual revenue generated by Pokémon GO worldwide from 2016 to 2025*, 2025, URL: https://www.statista.com/statistics/882474/pokemon-go-all-time-player-spending/, (Visited on 06.02.2026).

[2] *Pokémon Go Revenue and Usage Statistics*, 2026, URL: https://www.businessofapps.com/data/pokemon-go-statistics/, (Visited on 21.01.2026).

[3] Leorke, D. *Location-Based Gaming: Play in Public Space*, Springer, 2019.

[4] Khamzina, M., Parab, K.V., An, R., Bullard, T., Grigsby-Toussaint, D.S. Impact of Pokémon Go on physical activity: a systematic review and meta-analysis. *American Journal of Preventive Medicine*, vol.58, 2020, pp.270–282.

[5] Hyrynsalmi, S.M., Rantanen, M.M., Hyrynsalmi, S. Towards ethical guidelines of location-based games: challenges in the urban gaming world. *Software Business: 11th International Conference, ICSOB 2020*, Karlskrona, Sweden, November 16–18, 2020, Proceedings 11, 2021, pp. 134–142.

[6] Paavilainen, J., Korhonen, H., Alha, K., Stenros, J., Koskinen, E., Mayra, F. The Pokémon GO experience: a location-based augmented reality mobile game goes mainstream. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, 2017, pp. 2493–2498.

[7] Spallazzo, D., Mariani, I. *Location-Based Mobile Games: Design Perspectives*, Springer, 2018, (98 p.).

[8] Rogers, Y., Marshall, P. *Research in the Wild*, Morgan & Claypool Publishers, 2017, (97 p.).

[9] Giller, M., Kowal, T., Likus, W., Brzęk, A. Pokémon GO, Went, Gone…—Physical activity level, health behaviours, and mental well-being of game users: A cross-sectional study. *Healthcare*, vol.13, 2025. https://doi.org/10.3390/healthcare13182334.

[10] Lee, J.E., Zeng, N., Oh, Y., Lee, D., Gao, Z. Effects of Pokémon GO on physical activity and psychological and social outcomes: A systematic review. *Journal of Clinical Medicine*, vol.10, 2021. https://doi.org/10.3390/jcm10091860.

[11] Fiesler, C., Hallinan, B. "We Are the Product": public reactions to online data sharing and privacy controversies in the media. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 2018, pp. 1–13.

[12] Zuboff, S. *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*, New York: PublicAffairs, 2019.

[13] Rauti, S., Laato, S. Location-based games as interfaces for collecting user data. *Trends and Innovations in Information Systems and Technologies*, 2020, pp. 631–642.

[14] Brückner, S., Sato, Y., Kurabayashi, S., Waragai, I. The handling of personal information in mobile games. *Advances in Computer Entertainment Technology: 14th International Conference, ACE 2017*, London, UK, December 14-16, 2017, Proceedings 14, 2018, pp. 415–429.

[15] Zhao, B., Zhang, S. Rethinking spatial data quality: Pokémon Go as a case study of location spoofing. *The Professional Geographer*, vol.71, 2019, pp.96–108.

[16] Rossow, A.L. Gotta catch . . . a lawsuit? A legal insight into the intellectual, civil, and criminal battlefield Pokemon Go has downloaded onto smartphones and properties around the world. *John Marshall Review of Intellectual Property Law*, vol.16, 2017, pp.329.

[17] Alha, K., Koskinen, E., Paavilainen, J., Hamari, J. Why do people play location-based augmented reality games: a study on Pokémon GO. *Computers in Human Behaviour*, vol.93, 2019, pp.114–122.

[18] Rasche, P., Schlomann, A., Mertens, A. Who is still playing Pokémon Go? A web-based survey. *JMIR Serious Games*, vol.5, 2017.

[19] Fernandez del Rio, A., Guitart, A., Periánẽz, Á. A time series approach to player churn and conversion in videogames. *Intelligent data analysis*, vol.25, 2021, pp.177–203.

[20] *Player Safety: giving Gifts and Your Location in Pokemon GO*, July 2018, URL: https://pokemongohub.net/post/article/player-safety-giving-gifts-and-your-location-in-pokemon-go/, (Visited on 06.02.2026).

[21] *Friend List & Friendship Levels*, 2026, URL: https://niantic.helpshift.com/hc/en/6-pokemon-go/faq/2847-friend-list-friendship-levels-1614900279/, (Visited on 20.01.2026).

Information about the authors:

Jouni Ikonen – is an Associate Professor in the department of Software Engineering in LUT University, Finland. His research interests include networking protocols and technologies, online collaboration, data sharing between applications, games, education and privacy.

Antti Knutas – is an Associate Professor in the department of Software Engineering at LUT University. His research focuses on human factors in software engineering, software communities, and civic technology. His work combines qualitative and quantitative methods to produce actionable insights for system and software design.

Laura Anna Ripamonti – is an Associate Professor in the Department of Computer Science at the Università degli Studi di Milano, Italy, where she leads the research laboratory PONG – Playlab fOr inNovation in Games. Her research focuses on video games, particularly the interplay between technology and game design.

Giovanni Livraga – is an Associate Professor in Department of Computer Science at Università degli Studi di Milano. His research focuses on data protection, privacy, and security in data release, outsourcing, and emerging scenarios.

Sonja Hyrynsalmi – is a Postdoctoral Researcher in LUT University, Department of Software Engineering. Her research focuses on Human Capital in Software Engineering, skills, career and diversity, equity and inclusion in software engineering. She has strong background also in the software-intensive software engineering and IT ethics.

Manuscript received on 25 January 2026