Using Machine Learning to Identify Common Engagement-Related Behaviours Demonstrated by Older Adults with Dementia While Playing Mobile Games

by

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Abstract

Background: Dementia causes impairment of a person's memory, cognitive abilities, and behaviour, making it difficult for a person to complete daily tasks. Dementia affects the behavioural, psychological, and social dimensions of older adults living with the disease. Older adults living with dementia may demonstrate engagement through behaviours that differ from those without dementia when they participate in activities such as playing mobile games. This study aims to identify the most common engagement-related behaviours along with their personal characteristics, technical issues, and environmental disturbances to determine their applicability to dementia. This project could be a useful option to help rehabilitation professionals identify clients experiencing dementia based on their engagement-related behaviours while performing leisure activities such as mobile games.

Methods: Participants included five individuals living with dementia and 10 individuals without dementia. The secondary analysis of a single case design was conducted. The Chi-squared, and Fisher's exact tests were used for statistical analyses. Then, four Random Forest models were trained to identify the relevant engagement-related behaviours demonstrated by older adults with dementia from those without dementia. Random Forest Gini index was used to identify the strongest predictors of engagement-related behaviours of dementia.

Results: 30/47 (64%) of engagement-related behaviours were statistically significantly different in the two groups (older adults living with/without dementia). The accuracy (F1 score) of the Random Forest models for identifying engagement-related behaviours demonstrated by older adults with dementia from those without dementia was 78% using engagement-related behaviours only, 88% using engagement-related behaviours along with personal characteristics, 79% using engagement-related behaviours along with environmental disturbances, and technical issues, and 91% using engagement-related behaviours, personal characteristics, technical issues, and environmental disturbances features. The area under the receiver operating curve for the final model was 99%.

Conclusion: The findings show differences in frequencies of engagement-related behaviours demonstrated by older adults with and without dementia. The Random Forest model could be an accessible way to identify engagement-related behaviours commonly demonstrated by older adults with dementia while playing mobile games.

Preface

This thesis is an original work by Melika Torabgar. The research project, of which this thesis is a secondary analysis, received research ethics approval from the University of Alberta Research Ethics Board, Project Name " Vibrant Minds - Evaluating the usability and effectiveness of three tablet-based serious games for older adults ", No. Pro00069138, September 17, 2018. Results from this thesis were used for the poster presentation at the Reverse EXPO, AI4Society Conference on February 18, 2022.

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1. Introduction

1.1. Problem statement

According to the data from World Health Organization (World Health Organization, 2022), by 2050, the number of older adults who live with dementia will be increased to over 139 million people worldwide. It is also considered that 40 percent of people over 65 experience memory impairment (Alzheimer Society of Canada, 2021). The total number of people living with dementia in 2017 was 750,000 in Canada, with 72% of them being women. It is estimated that by 2038, the number of Canadians who live with dementia will increase dramatically, reaching 1.1 million people (Feldman & Estabrooks, 2017). In addition, the total economic cost caused by dementia increased from US$279.6 billion in 2000 to US$948 billion in 2016 globally (Xu, Zhang, Qiu, & Cheng, 2017). Thus, dementia has a tremendous economic impact not just on people who are living with it but also on society.

Mild cognitive impairment (MCI) is a phrase used to describe a state that falls between normal aging and dementia (Petersen, 2004). MCI is a clinical condition marked by a mild deterioration in one or more cognitive processes while maintaining autonomy in everyday activities. MCI causes symptoms in cognition, psychology, and behaviour (Corbo & Casagrande, 2022). Common behavioural changes associated with MCI are memory issues, lack of interest or engagement in activities and being apathetic to one's surroundings (Quail, Carter, Wei, & Li, 2020). Generally, MCI affects around 17% of persons over 60, and its frequency rises dramatically as people age (Lydon, Nguyen, Nie, Rogers, & Mudar, 2022).

Dementia is a chronic or progressive clinical syndrome in which problem-solving abilities, memory, and language deteriorate (Egas-López, et al., 2022). There is a slight degradation of certain cognitive skills in MCI, which is frequently regarded as the prodromal stage of dementia; nonetheless, it does not affect the patients' ability to carry out ordinary everyday activities (Egas-López, et al., 2022). However, people living with dementia require full-time care and support with basic everyday activities such as showering, clothing, and toileting (Herrmann & Gauthier, 2008). Therefore, it is critical to detect cognitive decline or dementia as early as possible in the disease's progression. Early diagnosis might be quite advantageous in terms of receiving treatments to slow down the progression of this disease (Brunet, 2013). Cognitive decline is usually monitored by health professionals during routine clinical exams or when an adverse event, such as a fall, occurs. Examples of screening tools for detecting and monitoring MCI and dementia are the Montreal Cognitive Assessment (MoCA) and the Mini-Mental State Examination (MMSE) (Ciesielska, et al., 2016). The MoCA test is a 30-point questionnaire which can be administered in 10 minutes (Jia et al., 2021). The MoCA test assesses cognitive domains such as attention and concentration, executive functions, memory, language, visuoconstructional skills, conceptual thinking, calculations, and orientation (Tsai, et al., 2016). A total point of 26 or higher is considered a normal cognitive function (Papastefanakis, et al., 2021; Malek-Ahmadi, et al., 2015). The MMSE test takes five to ten minutes to examine functions such as registration (repeating named prompts), attention, calculation, recall, language, the ability to follow simple commands and orientation (Jones & Gallo, 2000). The overall score for the test is 30. A score of 23 or less is generally accepted cut-off point attributing to the presence of cognitive impairment (Ruchinskas & Curyto, 2003; Fitriana, et al., 2021; Crum, Anthony, Bassett, & Folstein, 1993). MoCA is more suitable than MMSE for people over 60 who need screening tests to detect MCI (Ciesielska, et al., 2016).

Despite many advantages of MCI and dementia screening tools, the MoCA and MMSE have limitations. The MMSE's usefulness in screening for cognitive deficits has been questioned. According to several experts, when given to those with higher levels of education, the MMSE has low sensitivity for detecting moderate cognitive impairment (Stewart, O'riley, Edelstein, & Gould, 2012). Because the MMSE lacks questions that test verbal fluency, reasoning/judgment, and cued verbal memory and does not provide adequate sensitivity, it is less effective in detecting cognitive impairments associated with different disorders (Stewart, O'riley, Edelstein, & Gould, 2012; Yu, et al., 2020). The MoCA also has limitations. The biggest disadvantage of the MoCA is that its administration takes longer than other cognitive screening tests (Manjavong, Limpawattana, & Sawanyawisuth, 2021). Another limitation of the cognitive screening tools is that they create anxiety in older adults when taking the test (Meltzer, et al., 2017), which might be a reason for older adults to avoid doing the test.

Older adults living with dementia may find it challenging to engage in various activities for a variety of reasons, including a reduced motivation to participate in an activity and a lack of ability to self-engage in a task (Trahan, Kuo, Carlson, & Gitlin, 2014). Memory, language, and spatial recognition difficulties place distinct challenges when engaging this population in an activity (Trahan, Kuo, Carlson, & Gitlin, 2014). Engagement is a psychological and emotional state, which refers to the term known as "involvement" in different activities (Kappelman, 1995) and is associated with immersion, presence, psychological absorption, and flow (Brockmyer, et al., 2009). Báldy et al. (2021, p.2088) defined engagement as "the intensity and emotional quality of a user's involvement in initiating and carrying out activities." Chanel et al. (2008) described engagement as a positive-excited emotion. Although the definitions of engagement are inconsistent in different studies, the most common concepts include emotional, behavioural, and cognitive aspects (Fredricks, Filsecker, & Lawson, 2016).

Engagement-related behaviours could help get information about the presence and progression of dementia. Older adults living with dementia can demonstrate unique behaviours while engaged in an activity (Jøranson, et al., 2016). Different studies investigated the behavioural changes of older adults living with dementia when interacting with humans (e.g., other older adults, caregivers, and family members) (Teri, Logsdon, McCurry, Pike, & McGough, 2020; Perugia, et al., 2018) and non-humans (e.g., playing board games, playing with robots, and interacting with therapeutic dogs) (Jøranson, et al., 2016; Perugia, et al., 2018; Olsen, Pedersen, Bergland, Enders-Slegers, & Ihlebæk, 2019). It is noticeable that the engagement-related behaviours of individuals with MCI who later progress to dementia could differ from those of older adults without dementia (Grady, 2012). As a result, the engagement-related behaviours of older adults may provide valuable information regarding cognitive decline and dementia.

Previous research has investigated the behaviours demonstrated by older adults living with dementia while interacting with technology. For example, Perugia et al. (2018) identified engagement-related behaviours of older adults living with dementia while playing board games and playing with a robot. This study showed that older adults identified relevant engagement-related behaviours such as movement of torso, head, and gaze toward the activity. Jøranson and colleagues (2016) explored different engagement-related behaviours while older adults living with dementia interacted with the seal robot PARO. Authors identified relevant engagement-related behaviours demonstrated by older adults living with dementia, such as observing the robot, communicating with the robot, and smiling/laughing toward the robot. The authors found that older adults living with dementia demonstrate engagement-related behaviours while playing with a robot.

With rapid advancement of technology, there is increasing use of serious computer games to enhance cognitive skills in older adults (Khalili-Mahani, et al., 2020). Serious computer games aim for non-entertainment purposes such as rehabilitation, education and training on complex task performance to allow participants to make mistakes without facing risks (Ye, Backlund, Ding, & Ning, 2020; Tashiro & Dunlap, 2007). Serious computer games can be enjoyable when they provide a good balance of difficulty, reward, and competitiveness (Khalili-Mahani, et al., 2020). Also, serious computer games could have a therapeutic effect on older adults (Whitlock, McLaughlin, & Allaire, 2011), including developing their skills, providing a playful experience that generates positive emotions, and changing behaviour and attitudes (Nguyena, et al., 2017). When older adults living with dementia are immersed in playing a serious computer game, they exhibit certain behaviours (Ning, Li, Ye, Zhang, & Liu, 2020; Iborra, Rios, Martinez, Moron, & Corachan, 2020) and engagement in an activity. Thus, older adults, including those living with dementia, who play serious computer games may exhibit certain behaviours. In this study, serious computer games are referred to as mobile games.

Although dementia and MCI can be identified by health professionals with different screening tools (e.g., MoCA), they have some limitations, as mentioned. To mitigate some of these limitations, Artificial Intelligence (AI) and specifically Machine Learning (ML), a subset of AI, could be a useful option to help health professionals to identify behaviours demonstrated commonly by older adults with dementia. This approach has been used in recent studies. Bayat and colleagues (2021) used the Global Positioning System (GPS) data loggers to analyze driving behaviours with the ML technique for identifying older adults with dementia. The best model consisted of driving features, age, and APOE4 status (This gene is the strongest risk factor for Alzheimer's disease (AD)), with an accuracy of 91% to identify older adults living with dementia. This finding showed that driving patterns as described by GPS driving could serve as an accurate digital biomarker for identifying preclinical AD. Padhee and colleagues (2021) identified dementia from verbal utterances with an ML model. They used the Pitt Corpus dataset, a resource from the DementiaBank repository, for identifying dementia. This dataset contained 550 transcripts and recordings, describing the Cookie Theft picture; the picture depicted a woman, a man, and a girl working in the kitchen. The highest accuracy achieved was 81% with the binary classification, i.e., people with AD vs. individuals without AD. Refaee and colleagues (2020) used the data from The AD Neuroimaging Initiative (ADNI) on different areas of the brain and the Clinical Dementia Rating Scale Sum of Boxes (CDRSB), along with demographic information such as gender, marital status, and age as well as genetic information such as APOE4 for identifying dementia. The model that included the CDRSB feature achieved the highest accuracy, i.e., 95.2% (Refaee, et al., 2020).

The current research shows that there have been some approaches to recognize dementia based on older adults' behaviours, i.e., older adults' driving behaviours. Although driving behaviours provide useful information for the recognition of signs of AD, most people who get older are unable to drive. In addition, driving for older adults who live with AD may be considered unsafe, restricting older adults' access to this activity (Amjad, Roth, Yasar, Wolff, & Samus, 2016). In low-income settings, older adults may not have access to a car. Other studies demonstrated that AD could be identified using ML applied to data from different areas of the brain, CDRSB and demographic information. Identification of dementia based on these features is possible when there are data from those specific activities, but the analysis might be time-consuming and costprohibitive. In addition, in low-income settings, older adults may not have access to neuroimaging tests. In contrast, mobile games may be more accessible for most seniors, as mobile games are relatively inexpensive, safe and enjoyable.

In a literature review conducted by the author of the present document, it was found that although some studies have used ML to recognize engagement-related behaviours in people while playing mobile games, there is no ML model to recognize engagement-related behaviours of older adults. The age of participants in such studies was below 55 years. This finding shows a gap in knowledge since older adults' facial expressions and other behaviours are different from those younger when expressing engagement and emotions (Arioli, Crespi, & Canessa, 2018). Older adults might demonstrate unique facial expressions, vocalization and verbalization when they get engaged in playing a mobile game compared with younger people. For example, older adults may use specific words of the baby boomer generation when they get nervous or excited while playing. As a result, there is a lack of ML algorithms that have been fed by engagement-related behaviours of older adults.

The present study seeks to address this knowledge gap. In doing so, it focuses on constructing an appropriate method using ML to accurately recognize the differences in engagement-related behaviours demonstrated by older adults with and without dementia while playing mobile games. Thus, the objective of this project is to use supervised ML techniques to test the ability of a dataset of engagement-related behaviours demonstrated by older adults while playing mobile games. Using alternative means such as playing mobile games may be more interesting or engaging for older adults than the application of standardized screening tools. Because of the advancement in technology, most older adults may use mobile games for their leisure activities, and they can demonstrate different behaviours while playing these games. Further, this study seeks to determine which behaviours and features may help discriminate for signs of dementia. The relevance of this project relies on the fact that ML can potentially help rehabilitation professionals detect cognitive decline and dementia in older adults by observing their engagement-related behaviours while performing leisure activities. This will help rehabilitation professionals monitor relevant behaviours in a manner that can be implemented on a regular basis and in an enjoyable way which is not always possible with the utilization of cognitive screening tools.

1.2. Questions and Hypothesis

Question 1. What are the most common engagement-related behaviours observed in older adults living with dementia and those without dementia while playing mobile games?

Question 1.1. What are the frequencies of each engagement-related behaviour observed in older adults living with dementia and those without dementia who played mobile games?

Question 1.2. Are there any differences in frequencies of the engagement-related behaviours between older adults living with dementia and those without dementia while playing mobile games?

Hypothesis 1: There are significant differences in engagement-related behaviours of older adults living with dementia and those without dementia while playing mobile games.

Question 2. What distinct patterns of engagement-related behaviours along with personal characteristics, technical issues and environmental disturbances are demonstrated by older adults with dementia?

Hypothesis 2: A dataset of engagement-related behaviours along with other characteristics such as personal characteristics, environmental disturbances, and technical issues generates distinct patterns for the presence of dementia in older adults while playing mobile games.

2. Literature Review

This chapter will start by presenting dementia and its progression. Then the concept of engagement-related behaviours in older adults living with dementia will be covered, followed by the topic of using AI to identify dementia in older adults. Finally, the use of ML to identify engagement-related behaviours while playing serious computer games will be addressed.

2.1. Dementia in older adults

Dementia is a type of cognitive impairment that impairs a person's memory, cognitive abilities, and behaviour, making it difficult for them to complete daily tasks (World Health Organization, 2019). Dementia is an umbrella term that is used to describe several behavioural and psychological symptoms, such as hyperactivity (agitation and irritability), psychosis (delusions and hallucinations), affective symptoms (depression and anxiety), and apathy (Deardorff & Grossberg, 2019). These symptoms result from various diseases such as Alzheimer, Lewy body dementia, Vascular dementia, Frontotemporal dementia, and other conditions such as Parkinson's and Huntington's diseases (Chiu, Chen, Yip, Hua, & Tang, 2006). The most common cause of dementia is AD, counting roughly 60-80% of the cases of dementia; while vascular dementia, Lewy body dementia, and Frontotemporal dementia are the next common cause of dementia, with 5-10% of the cases (Alzheimer's association, 2022). In addition, two different types of dementia may occur simultaneously, which is known as "Mixed dementia," usually caused by AD and vascular dementia. Only 5% of individuals are diagnosed with dementia before the age of 65 (Evans, 2018). In all regions of the world, the prevalence of dementia rises exponentially with age. The prevalence of dementia doubles every 5.5 years of age in North America, 6.5 years in West and Central Europe, 6.6 years in South Asia, and 10.6 years in Southeast Asia (Evans, 2018).

As people age, their cognitive skills may decrease considerably. The transition between normal cognition and dementia is referred to as MCI (Kryscio, Schmitt, Salazar, Mendiondo, & Markesbery, 2006). Dementia is a degenerative neurological disorder that affects older adults, leading to a decline in cognitive functioning, increasing dramatically in older people (Wang, Xu, & Pei, 2012). Dementia affects the brain and cognitive functioning, deteriorating the performance of activities of daily living (Thies & Bleiler, 2012). Although dementia does not have an effective cure, researchers are focusing on different strategies to reduce or delay cognitive impairment progression. For example, different activities such as cognitive games could be one of the applicable methods for older adults with and without dementia to keep them active and stimulated to potentially slow down the cognitive decline of this group (Tong, Chan, & Chignell, 2017).

Different screening tools are used to detect cognitive decline and dementia. Examples are the MMSE and the MoCA. The MMSE assesses orientation, attention, recollection, language, and the ability to follow orders to diagnose cognitive impairment and dementia (Burrell & Piguet, 2015). The test has a total score of 30. A score of 23 or less is commonly used as a cut-off point for determining whether or not someone has dementia (Folstein, Folstein, & McHugh, 1975; Schultz-Larsen, Lomholt, & Kreiner, 2007) and the test takes five to ten minutes to complete (Jones, Moyle, & Sung, Engagement of a Person with Dementia Scale: Establishing content validity and psychometric properties, 2018; Ruchinskas & Curyto, 2003; Fitriana, et al., 2021). The MMSE can be administered in a doctor's office or clinical environment; however, it is a brief and effective test that may also be performed in the home (Schultz-Larsen, Lomholt, &

Kreiner, 2007). Scoring the exam is straightforward, and family members or loved ones may manage the administration and scoring procedure without prior training (Carnero-Pardo, 2014). The MoCA is a screening tool for dementia (Nasreddine, 2016). MoCA tests visuospatial skills, executive functioning, visuoperception, naming, memory, attention, language, abstraction, and orientation, among other cognitive areas. Even in older persons with MCI who have a low level of schooling and varying literacy, the MoCA has good concurrent and criterion validity (Julayanont, et al., 2015). The MoCA is a 30-item screening test and can be administered in ten to 15 minutes to detect cognitive deficits (Julayanont, et al., 2015; Jia, et al., 2021). The cut-off score of diagnosis MCI is 26 (ranging from 19-25) and the cut-off point for diagnosing mild AD is 22 (ranging from 11-21) (Nasreddine, 2016). The typical cognitive function is defined as a higher score of 26 (Papastefanakis, et al., 2021). This test needs training and certification to be administered by the health professionals who intend to administer, score, or interpret the MoCA test (Nasreddin, 2016).

These screening tools have some limitations. First, they have different levels of sensitivity. The MoCA is far more sensitive than the MMSE but is more time-consuming. The additional information the MoCA provides makes it a more effective clinical cognitive tool than the MMSE. Second, the MoCA test can only be administered by health-care professionals. In addition, the MMSE requires some training before using it, and access to these tests is frequently unavailable to underserved communities (e.g., poor health, low income, and rural areas) (Khaw, et al., 2021). Third, doing these cognitive screening tests may produce anxiety in older adults (Meltzer, et al., 2017). When anxiety becomes so overwhelming that older adults can't focus or think clearly, may explain why older people refuse to take the test.

Dementia affects the behavioural, psychological, and social dimensions of older adults living with the disease. Dementia may lead to behavioural changes, which could impact a person's personality. For instance, a person who has lived with their beloved pet may suddenly change their desire and not want to have the pet anymore. The psychological dimension of dementia is related to depression or mental health problems (Jones, Moyle, & Sung, 2018). The most common mental health conditions associated with people living with dementia are anxiety, depression, and psychosis (Qassem, Tadros, Moore, & Xhafa, 2014). People with dementia may feel threatened by the environment (Jones, Moyle, & Sung, 2018), feeling that they are in the wrong place because the environment does not seem right or familiar. As a result, people with dementia may not be interested in participating in group activities and often have no group to communicate with, which could be the reason for their difficulty in social interaction (Birt, et al., 2020). By reducing their participation in activities, people living with dementia could feel worthless and useless, increasing the risk of developing depression (James I. A., 2010) and reducing their engagement in social activities. Dementia affects behaviour, mood, and socialization, which can negatively impact the person's life (Wright, 2020).

Disruption of social activities, such as loss of community connections and altered relationships with family and friends, could be an early sign of cognitive impairment in older adults (Kotwal, Kim, Waite, & Dale, 2016). Older adults living with dementia demonstrate less engagement in social activities due to their cognitive impairment levels (Khosla, Chu, Khaksar, Nguyen, & Nishida, 2021). In addition, challenging behaviours such as disruptive vocalizations, aggression, and communication deficits could be all symptoms of dementia (Trahan, Kahng, Fisher, & Hausman, 2011). Therefore, it is possible to believe that behaviours demonstrated by older adults can provide information about the presence of dementia.

2.1.1. Summary and gaps

In summary, as people get older, the prevalence of facing dementia will increase. The number of older adults who live with dementia is increasing worldwide. Dementia affects older adults' engagement in meaningful activities. Dementia is usually identified with screening tools such as MoCA and MMSE by trained personnel. These cognitive screening tools may produce anxiety among older adults, making them avoid taking the test or affecting their performance. Since dementia affects the behavioural component of older adults, it is possible that behaviours demonstrated by older adults can provide valuable information about the presence of dementia. Therefore, there is a need for alternative ways to detect dementia in more natural ways, for example, recognizing the engagement-related behaviours of older adults while engaging in activities.

2.2. Engagement-related behaviours in older adults living with dementia

Engagement is defined as active involvement in a specific activity in contrast to a lack of interest, apathy, or superficial participation (Ninaus, et al., 2019). The first step of immersion in activity is engagement. A condition of absolute absorption or engagement in an activity is referred to as flow (Ljubin-Golub, Rijavec, & Jurčec, 2018). Mihaly Csikszentmihalyi (2014) coined the term "flow" after conducting hundreds of interviews to learn about people's motivation to participate in a variety of activities. Flow has been described as "a subjective state that people report when they are completely involved in something to the point of forgetting time, fatigue, and everything else but the activity itself" (Csikszentmihalyi, Abuhamdeh, & Nakamura, 2014). Flow is a cognitive and psychological state that may occur while performing challenging activities in which the task complexity is matched to the person's ability level (Payne, Jackson, Rim Noh, & Stine-Morrow, 2011). For example, individuals feel in improving cognitive ability and being less conscious about time passing. This may result in to increase the engagement while doing an activity, e.g., playing games (Cowley, Charles, Black, & Hickey, 2008).

Engagement is a complex construct that has behavioural, cognitive, and affective dimensions (Hookham & Nesbitt, 2019). The behavioural dimension of engagement refers to effort and task persistence, participation, attention, and effort (Ninaus, et al., 2019). The cognitive dimension relates to the attention and concentration an individual achieves when doing an activity. This dimension corresponds to the mental contribution to activities such as learning (Fredricks, et al., 2016). The affective dimension of engagement is related to valence (the level of the pleasantness of a stimulus, ranging from negative to positive), arousal (the level of emotional intensity elicited by stimuli, ranging from calm to excited), and emotions such as curiosity and control (Rowe, Shores, Mott, & Lester, 2011; Lee, Hsu, & Cheng, 2022). The affective dimension of engagement could be described as an emotional reaction (Ninaus, et al., 2019). Thus, the engagement dimensions could vary both situationally and dispositionally (Mills, et al., 2013). People may demonstrate engagement-related behaviours when they are doing activities.

Although not abundant, some researchers have investigated the engagement-related behaviours of older adults living with dementia. Jøranson and colleagues (2016) employed a Paro robot to explore the distinct engagement behaviours in older adults living with dementia during a 30-minute session. Paro is designed to look like a baby seal, with a swivelling head, moving legs and tail, and speakers that mimic the sounds of an actual baby harp seal. This robot adapts to its environment, recognizes voices, and responds to repeated speech. A total of 30 older adults with mild and severe dementia participated in a 12-week intervention with Paro. The study participants were over 65 years of age and diagnosed with mild, moderate, or severe dementia. All participants' sessions with the Paro were recorded during weeks 2 and 10. From the recordings, an ethogram was created to characterize participants' behaviours. As an outcome, during the session, participants with severe dementia appeared to struggle to keep their attention on Paro. As the intervention progressed, participants showed an increase in interactions with Paro. The findings of this study showed that older adults living with dementia demonstrate some behaviours while engaging in interactions with Paro, including observing Paro, observing other participants, having physical contact with Paro (e.g., having Paro on the lap), observing other things, talking to Paro, and smiling/laughing toward Paro and other participants. In addition, these findings showed that older adults with different degrees of dementia could demonstrate differences in their engagement-related behaviours. For instance, there was a significantly higher percentage of the time spent observing Paro among older adults with mild to moderate dementia compared to that in participants with severe dementia. In contrast, older adults with severe dementia had a statistically significantly higher percentage of the time spent observing other things compared to older adults with mild to moderate dementia.

Perugia and colleagues (2018) pointed out that engagement-related behaviours of older adults living with dementia are measured with three methods, including observational rating scales, ethograms, and coding systems. The authors developed a coding system of engagement-related behaviours of older adults living with dementia and interpreted those behaviours with a mixed approach. Authors developed the Ethographic and Laban-Inspired Coding System of Engagement and the Evidence-based Model of Engagement-related Behaviour. The authors developed two ethograms to describe the participants' behaviour in two activities, game-based cognitive stimulation (including board games: jigsaw puzzles, shape puzzles and a game with dominoes) and free play with a robot (a pet robot Pleo). The authors utilized Laban Movement Analysis to find a common structure in the two ethograms' behaviours and combine them into a single coding system. Fourteen participants whose ages ranged from 69 to 92 years old and who had been diagnosed with mild to moderate dementia were included in this study. Two independent researchers scored participants' videos. The coding system's inter-rater reliability for cognitive games achieved kappa = 0.78, and for robot play had kappa = 0.74. This study showed that the most relevant categories of engagement-related behaviours of older adults living with dementia were related to head, torso, arms, gestural support, postural support, and hands movements while playing board games and interacting with the toy robot.

Olsen et al. (2019) recorded engagement-related behaviours of 21 older adults living with dementia who participated in a group animal-assisted activity intervention in nursing homes and 28 home-dwelling older adults living with dementia who attended a day program centre. All subjects were above 65 and had dementia or cognitive impairment. The aim of this study was to investigate the engagement-related behaviours among older adults living with dementia in group animal-assisted activity intervention and home-dwelling older adults living with dementia. For 12 weeks, all the participants interacted with a dog and its handler for 30 minutes twice a week. Early and late in the intervention, groups of animal-assisted activity were filmed, and distinct behaviours seen during the filming were carefully identified. The Solomon Coder, a behaviour coding software, was used to analyze all of the videos. This software allows for the quantification of behaviour. The results showed that older adults living with dementia in both nursing home and day program centres showed engagement-related behaviours in group animal-assisted activity. These positive engagement-related behaviours included looking at the dog-related activity (e.g., facing the dog or activities involving the dog), smiling, laughing, talking, looking at other people, and petting the dog. In addition, the results showed that older adults with different degrees of dementia demonstrated a few different behaviours. Participants with severe dementia slept (e.g., sleep, sit still with eyes closed for a minimum of one minute) significantly more than older adults with mild dementia. Participants with severe dementia also spent significantly less time looking at the dog-related activity than those with mild dementia.

2.2.2. Summary and gaps

In summary, few studies have investigated the engagement-related behaviours of older adults living with dementia in different activities. These activities were playing board games, interacting with robots, and interacting with dogs in an animal-assisted intervention. All activities proved that older adults living with dementia demonstrate engagement-related behaviours while doing activities.

This review revealed a lack of research using technologies, for example, mobile tablets, for investigating engagement-related behaviours of older adults. In addition, none of the studies compared the engagement-related behaviours of older adults living with dementia and those without dementia.

2.3. Using artificial intelligence to identify dementia in older adults

The appearance of AI in many aspects of life is feasible, especially in health-care systems (Khan, 2020). ML is the subset of AI performing equally to the human brain by predicting accurate decisions based on data or previous experience (Alpaydin, 2020). AI can perform accurate tasks and help health-care systems in several ways. First, AI can be used in the healthcare systems to identify patients' characteristics and provide appropriate intervention strategies with high accuracy (Bærøe, Miyata-Sturm, & Henden, 2020). For example, merging a large amount of data provides valuable information to mitigate errors in health-care settings to reduce treatment costs. Second, with the help of human intelligence, the machine could also improve decision-making in health-care (Bærøe, Miyata-Sturm, & Henden, 2020). For example, health-care professionals can interpret data and check information with their patients and the decision that was made by machine. Third, ML techniques offer significant benefits to health professionals in evaluating large amounts of complex health-care data (Ngiam & Khor, 2019). For example, ML algorithms can analyze diverse data types such as demographic data, laboratory findings, imaging data, and doctors' free-text notes.

A literature search was conducted to find studies that have used AI, especially ML, to identify older adults with dementia from those without dementia. In doing so, a literature search was conducted using the following search engines and databases: Discovery Service for University of Alberta Libraries, Scopus, and Google Scholar. Different combinations of terms and the Booleans "AND" and "OR" were used as follows:

(identif* OR measur* OR track* OR assess* OR recognize OR monitor OR detect* OR monitoring OR discern* OR perceiv* OR perception OR classif* OR modeling OR models) AND (behaviour OR behavior OR movement* OR expression* OR engag* OR motion* OR recognition) AND (dementia OR "cognitive impairment" OR "mild cognitive impairment" OR "moderate dementia" OR "severe dementia" OR Alzheimer’s) AND (Algorithm* OR "machine learning" OR "artificial intelligence").

The results of this literature search show that there are a few recently published studies for identifying dementia with ML. Bayat et al. (2021) aimed to identify dementia based on older adults' driving behaviours. Authors installed the in-vehicle GPS into the participants' vehicles and used GPS data loggers to identify AD using ML methods. In this study, a total of 64 older adults with preclinical AD and 75 older adults without preclinical AD were included. The GPS data logger, together with custom software, comprises the Driving Real-World In-Vehicle Evaluation System (DRIVES), which recorded the date, time, latitude and longitude coordinates, and speed every 30 seconds when a vehicle was being driven. To detect preclinical AD, four Random Forest (RF), an ML algorithm, were trained with four sets of input variables. The first model contained age and APOE4 (a risk-factor gene to develop the disease) status, the second model had the driving behaviours only, the third model included driving behaviours and age, and the last model had driving behaviours, age, and APOE4 status. The greatest predictors of preclinical AD were identified using the RF Gini index. Results show that the F1 score, the model's accuracy, of the RF models for detecting preclinical AD was 85% when APOE4 status and age were used, 82% when GPS-based driving behaviours were used alone, 88% when age and driving behaviours were used together, and 91% when age, APOE4 status, and driving behaviours were used together. The final model with the driving behaviours, age, and APOE4 status had the highest accuracy compared to other models. Finally, the findings showed that GPS driving behaviours might serve as a useful and accurate digital biomarker for recognizing preclinical AD in older adults. In addition, the finding of this study showed that the five most important features to identify preclinical AD were APOE4 status, age, and three driving behaviours (average jerk, number of night trips, and radius of gyration).

Padhee et al. (2021) used a Support Vector Machine (SVM), an ML algorithm, for a multi-class problem to learn from verbal utterances to identify between adults without dementia and adults with MCI and AD. The authors used the Pitt Corpus dataset, including 550 transcripts and recordings of 310 English-speaking participants to describe the Cookie Theft picture (the picture depicted a woman, a man, and a girl working in the kitchen). This dataset is a resource from the DementiaBank collection, comprising 209 persons at various stages and types of dementia and 102 individuals without dementia aged between 45-90 years. The findings indicated that the SVM model was able to accurately identify 81.3% of AD cases (possible AD, diagnosing when there is an atypical or mixed presentation of the disease and probable AD, diagnosed when the person meets all the core clinical criteria) vs. participants without dementia. Thus, the accuracy in detecting dementia was excellent. Also, it had more than 50% accuracy for a three-class classification (i.e., individuals without dementia, people with MCI, and probable AD model for recognizing the early signs of progressive MCI. In a multi-class setting (i.e., people without dementia, people with MCI, probable AD and possible AD), this study demonstrated that ML models such as SVM could be used to identify early signs of cognitive decline as well as several forms of AD (possible AD and probable AD) from individuals without dementia based on their verbal utterances.

Refaee et al. (2020) employed different ML algorithms to identify AD from MCI and older adults without dementia. They used data from the ADNI (Petersen, et al., 2010). The ADNI dataset contains 20 characteristics that are known to be relevant in the diagnosis of AD. It has 819 Control Subjects, 399 cases of patients living with dementia, and 1050 cases of people with MCI. All features used in this analysis contained neuroimaging data from different regions of the brain and the CDRSB along with characteristics including demographic data such as age, gender, marital status, and APOE4. The average age of the participants with the AD (74.87) group was greater than that of the MCI (72.88) and individuals without dementia (72.84). In total, five different ML models were trained and evaluated against the dataset using a nested ten-fold cross-validation for model selection and assessment: Gradient Boosting Decision Trees (XGBoost), Neural Network, RF, SVM and Linear Discriminant Analysis. The results of this study showed that by including the CDRSB feature, XGBoost exhibited the best results with the greatest performance with 95.20% accuracy among the five different ML algorithms. Age was also a contributing factor in identifying AD from MCI and individuals without dementia. The results showed that the accuracy of the model without including the CDRSB feature was 84.44 %. Therefore, this study showed that the neuroimaging data, along with other features such as demographic data, improved the performance of the model to identify AD from MCI and older adults without dementia.

Finally, Sánchez-Reyna et al. (2020) utilized the ADNI dataset (adni.loni.usc.edu) to identify the presence of AD. The dataset included information on the individuals' age (75.16 +/- 6.68 years), gender (264 Female, 364 Male), MMSE, APOE4, and diagnosis of 628 older adults. One hundred ninety of whom were non-dementia, 305 with a diagnosis of MCI, and 133 with a diagnosis of AD. MCI and AD were combined in this study to provide a binary dilemma to the ML model. Four different algorithms were used in this step: logistic regression (LR), artificial neural networks (ANN), SVM, and RF. The ADNI database was separated into two groups throughout the classification analysis: training and testing. The training subset contained 70% of the data, whereas the test subset contained 30%. An area under the curve (AUC) was created as a validation statistic for the model with the greatest accuracy. Although the AUCs of the ANN, LR, and SVM models are close to each other, the LR model had the greatest AUC of 0.842 for identifying non-dementia from AD. These results show that ML models can be used for the classification models to identify the presence of AD.

2.3.1. Summary and gaps

Only a few papers have explored the use of ML to identify dementia. Different activities were employed to recognize dementia, including driving and describing a picture. Research shows that GPS data loggers can be an accurate digital biomarker to identify dementia, ML algorithms were used based on contextual and psycholinguistic aspects to learn linguistic biomarkers from verbal utterances and aid clinical diagnosis of various stages and forms of dementia and the ADNI dataset, which contained the neuroimaging data from different regions of the brain, could help to identify the presence of AD.

Despite the advances in this area in the last four years, some gaps have been identified. Models still rely greatly on biomarkers (e.g., APOE4) and people in low-income settings with weak health-care systems may not have access to genetic analysis. The complexity of activities may also include some limitations; for instance, older adults may have some driving difficulties, including vision, hearing, and motor issues, and in some low-income countries, they may not have access to a car. In addition, no dataset included behaviours of older adults. This literature search shows the lack of research on use of ML techniques to identify engagement-related behaviours demonstrated by older adults with dementia. Engagement-related behaviours can provide valuable information but have not been extensively used in research. It is clear that there is a need for the development of methods using ML to identify the distinct patterns of engagement-related behaviours demonstrated by older adults with dementia.

2.4. Using ML to identify engagement while playing serious computer games

Serious games are the type of games with a therapeutic purpose (Susi, Johannesson, & Backlund, 2007). All games with the primary goal of education, physical or mental training or stimulation are identified as serious games (Susi, Johannesson, & Backlund, 2007). The aim of cognitive activities such as serious games is to provide a series of repeated and standardized tasks to target specific cognitive domains (e.g., attention and memory) (McCallum & Boletsis, 2013). Individuals may like to play a serious game for fun or entertainment, which might have a therapeutic effect on their brain. As a result, serious games have grown in popularity in several population groups, including older adults, to train cognitive skills.

To identify the existing methods for recognizing engagement in players while playing video games, a systematic literature review was conducted. In doing so, two databases were explored (Scopus and Web of Science), which retrieved a total number of 1006 papers. After deduplication, a total of 753 abstracts were screened (253 papers were duplicates). During title and abstract reading, 53 of the publication met the inclusion criteria. Finally, 16 studies were included for data extraction in the full paper reading phase. Papers were extracted from databases using five different combinations of terms and the Booleans "AND" and "OR "as follows:

(engagement OR "emotional engagement" OR distraction OR focus OR attention OR concentrat* OR participation OR involvement OR immersion OR interact OR interaction) AND (measur* OR track* OR assess* OR recognize OR monitor OR detect* OR monitoring OR discern* OR perceiv* OR perception OR classif* OR modeling OR models) AND (game OR games OR gaming OR gamer* OR "online learner") AND (temperature OR ((facial OR face OR eye OR hand OR hands) W/3 (movement* OR expression* OR motion* OR recognition)) OR eye-tracking OR skin-response* OR dermal-reaction* OR blood-volume-pulse OR skinconductance OR sensor* OR biosignal OR electroencephalogra* OR eeg) AND (Algorithm* OR "machine learning" OR "deep learning").

Papers that met the inclusion criteria were used to extract data. The inclusion criteria were:

1. Studies that:

a) reported on technologies to automatically recognize engagement.

b) Used as games, video games, mobile games, virtual reality, PlayStation, X-box, Nintendo, Computer, and smartphone.

c) provided information about the algorithms (e.g., performance) or technologies (e.g., brand, model, price) used to recognize engagement-related behaviours.

2. Documents:

a) papers published in scientific journals or conference proceedings.

b) published between 2010 and 2020.

c) written in English.

Sixteen studies were included and screened for data extraction by two independent readers and followed PRISMA guidelines (Liberati, et al., 2009). The author of the present document acted as the main rater. Table 1 shows the findings of this literature review. It can be seen that there are three main methods for recognizing engagement: bio-signal, body movements, and the mixture of bio-signals and body movements to recognize people's engagement-related behaviours (See Table 1, column Categories). Also, these three categories used different algorithms to identify engagement-related behaviours, such as SVM, RF, K-nearest neighbour, Naïve Bayas and some other algorithms to receive the desired accuracy. It was clear that SVM was used for all categories in different studies. Furthermore, the age of people who were tested in all studies was between 8 and 55.

Table 1.
Different algorithms with different bio-signals, body movements, and ages of participants.

Categories	Subcategories	Algorithms	Average age of participants	Study
Bio-Signal	EEG	Emotiv's proprietary engagement algorithm, The CI algorithm, Wrapper algorithm, GAAM, Clustering algorithm	Between 20 and 25. (Rejer & Twardochleb, 2018)	(Andujar, Ekandem, Gilbert, & Morreale, 2013), (Seo, Noh, & Jeong, 2018), (Rejer & Twardochleb, 2018)
	Multiple Signals	SVM, Emotiv EPOC internal algorithms, POSM, IDOL, Reinforcement learning algorithm	Between 20–37. (Ozkul, Palaska, Masazade, & Erol-Barkana, 2019)	(Balducci, Grana, & Cucchiara, 2017), (Ozkul, Palaska, Masazade, & Erol-Barkana, 2019)
Body Movements	Facial expressions	SVM, Classification algorithm over the dataset, Classification via Clustering (k-means), Bayes Net (Confusion), Updateable Na ̈ive Bayes, Bayes Net (Engagement), Bayes Net (Frustration), Logistic Regression	23.69 ± 4.25 (Ninaus, et al., 2019) Eighth- and ninth-grade students (predominately 13–15 years old) (Bosch, D'Mello, Ocumpaugh, Baker, & Shute, 2016)	(Ninaus, et al., 2019), (Bosch, D'Mello, Ocumpaugh, Baker, & Shute, 2016)

Categories	Subcategories	Algorithms	Average age of participants	Study
	Movement of body segments	SVM, Multimodal affective recognition algorithm	From 8 to 10 (Psaltis, Apostolakis, Dimitropoulos, & Daras, 2018)	(Psaltis, Apostolakis, Dimitropoulos, & Daras, 2018)
Body Movements	Facial expressions and body movements	ZeroR, Classification Tree, Naïve Bayes, GAO, RFC, Genetic programming	35.1± 14.54 (Blom, Bakkes, & Spronck, 2019), Between 23 and 28 years (Blom, Bakkes, & Spronck, 2019), 29.79± 5.92, min: 20, max: 45 (Harteis, Fischer, Töniges, & Wrede, 2018)	(Blom, Bakkes, & Spronck, 2019), (Harteis, Fischer, Töniges, & Wrede, 2018)
Bio-signals and body movements		SVM, MLP, KNN, The pseudo-code for the TimeOnTask threshold computation algorithm, Deep Neural Network, Random Decision Forest, Random Decision Jungle, RFC	27±7 (Ghergulescu & Muntean, 2016), 20.87 (McMahan, Parberry, & Parsons, 2015), 28 (Čertický, et al., 2019) Between 18 and 35 (Benlamine, Dombouya, Dufresne, & Frasson, 2017)	(Ghergulescu & Muntean, 2016), (Henderson, et al., 2019), (McMahan, Parberry, & Parsons, 2015), (Wei, Zhang, Dang, & Li, 2017), (Čertický, et al., 2019), (Benlamine, Dombouya, Dufresne, & Frasson, 2017)

Notes.
GAAM= Genetic Algorithm with Aggressive Mutation, SVM= Support vector machines, POSM= Partially Ordered Set Master, IDOL= increment/decrement one level algorithms, GAO= Gradient Ascent Optimisation algorithm, RFC= Random Forest Classifier, MLP= Multi Layer Perceptron, KNN= K-nearest neighbours classifiers.

Bio-signals (e.g., EEG) to recognize engagement were used in five studies. The Emotive EPOC 14-channel wireless Electroencephalography (EEG) headset was used in three studies to detect neural signals of engagement. Different algorithms were used to recognize engagement where SVM had the highest accuracy, 92% (Balducci, Grana, & Cucchiara, 2017).

Body movements were used in five papers containing three sub-categories: facial expression, body movements, and the mixture of facial expression with body movements. Five studies used eye movements to recognize engagement-related behaviours. Most studies used algorithms with medium to high accuracies ranging from 44% to 85%. SVM achieved 85% accuracy (Psaltis, Apostolakis, Dimitropoulos, & Daras, 2018), which was the highest in detecting the movement of body segments for engagement-related behaviour recognition.

The mixture of bio-signals and body movements for recognizing engagement-related behaviours was found in six studies. SVM and Random decision forest had high accuracy, 97% and 96%among other algorithms (Wei, Zhang, Dang, & Li, 2017).

The results show that fifteen studies used six different algorithms to identify engagement, EEG was used in nine of the studies, the SVM algorithm was used in all categories (i.e. bio-signals, body movements, and the mixture of bio-signals and body movements) and achieved the highest accuracy in all categories, and the Random Decision Forest algorithm achieved the second-highest accuracy, 96%, in the bio-signals and body movements category.

2.4.1. Summary and gaps

In summary, the literature shows that engagement while playing video games has been recognized using ML mainly through analyzing participants' bio-signals (e.g., EEG) and their body movements. ML has played a significant role in identifying behaviours during gameplay. Different ML algorithms, such as SVM, RF, Genetic algorithms, and Deep Neural networks, were used to recognize engagement.

This review revealed gaps in the area. Most of the participants included in the studies were young, i.e., the range of age was between 8 and 55 years, and there were no studies focusing on using ML to detect engagement in older adults while playing video games. Facial expressions and body movements could differ when expressing engagement and emotions as people age. Younger adult datasets cannot be used to identify the engagement-related behaviours of older adults since older adults may exhibit distinctive facial expressions, vocalisation, verbalization, and body movements while engaging in games. Therefore, there is a lack of ML models with older adults' dataset to identify engagement-related behaviours while playing mobile games.

3. Methodology

The present study is the secondary analysis of the primary study with the single case design to analyze individuals' engagement-related behaviours over the time. This chapter will begin by describing the data source and original dataset, then proceed to explain the final dataset and preprocessing data. The rest of the chapter will cover statistical and ML analysis.

3.1. Data Source and Original Dataset

This research from a primary study approved by the ethics board of the University of Alberta in Edmonton, Alberta, Canada (Pro00069138) (Rios Rincon, Daum, Miguel Cruz, Liu, & Stroulia, 2022). In the primary study, over the period of eight weeks, participants, including 14 older adults without dementia and six older adults living with dementia, played four serious games, Bejeweled, Whack-A-Mole, Mahjong, and Word-Search (Rios Rincon, Daum, Miguel Cruz, Liu, & Stroulia, 2022). Over this period of eight weeks, participants played one of these games during 16 sessions for 30 minutes each session. Each session took place in a room with all the participants seated at a table. Some sessions were recorded for the analysis of engagement-related behaviours. The video footage captured each participant's face, trunk, and upper limbs and was recorded at least once. The video footage was taken with cameras at different angles in the room. The videos of 21 participants were used to create a coding system of engagement-related behaviours. The engagement-related behaviours coding system contained 29 codes related to engagement with ten categories consisting of gaze, eyes, head, torso, limbs, face, voice, gameplay, concentration, and breath. Eighteen codes were related to disengagement with the same categories except for breath (Rios Rincon et al., 2020). In total, 47 main behaviours were identified and assigned to a code composed of a combination of letters (Rios Rincon et al., 2020). The behaviours and codes are presented in Table 2.

The data used for the present study corresponds to a dataset of engagement-related behaviours that were manually curated in the context of the mentioned previous study. For developing the dataset, three independent raters watched 15 video footage of 15 older adults playing video games and annotated the engagement-related behaviours (Rios Rincon et al., 2020). The age of these 15 participants ranged between 59 and 89 years, with an average age of 78.66 (SD = 8.12 years); 6 (40%) of the individuals were male, and 9 (60% were female; five were living with mild or moderate dementia (33%) and 10 were older adults without dementia (67%). The dataset of engagement-related behaviours was developed as follows. Three research assistants were trained in using the coding system by watching the recorded videos from older adults while playing video games. The raters coded the older adults' behaviours in intervals of 15 seconds according to the coding system. A research assistant was assigned to be the main rater based on their educational background and experience. Codes from two raters were compared with those scored by the main rater for calculating inter-rater reliability. By comparing all codes, raters achieved high inter-rater reliability (Kappa = 0.87) (Rios Rincon, et al., 2020).

A similar methodology has been used in previous studies. Jøranson et al. (2016) investigated behaviours in individuals living with dementia by analyzing their behaviours recorded every second. The authors recorded the videos of older adults when participants were interacting with the seal robot Paro. Video recording was conducted for 30 minutes each session, and an ethogram was used to identify different behaviours in participants from the recordings. Olsen et al. (2019) identified older adults' engagement-related behaviours when older adults interacted with therapy dogs. Each session contained 30 minutes to interact with the dog and its handler.

All behaviours were categorized using an ethogram, and the time participants demonstrated behaviour was registered in seconds. Bayat and colleagues (2021) recorded driving behaviours such as average trip distance, a number of unique destinations, average speed etc., every 30 seconds in older adults with and without AD. Thus, previous research has used intervals between 1 and 30 seconds to curate behaviours.

Table 2.
Description of Engagement-related behaviours Categories

Category of the behaviour	Name of the behaviour	Code of the behaviour	Description of behaviour
Gaze	Gaze toward game	*E-GTG	Looking at the game/device
	Away from game	*D-GAG	Looking at something other than the game/device
Eyes	Saccadic eye movements	E-ESM	Small movements of the eyes as fixation moves from one point of the screen to another
	Scanning behaviour	E-ESB	Movements of the eyes to follow along with game action (could be in any direction)
	Squinting at screen	E-ESS	In an attempt to get a clearer or sharper view of something in the game
	Closed eyes	D-ECL	Participants close their eyes and keep them closed for a second or longer. This code does not pertain to blinking.
	Eyes fixed on a point	D-EFX	Participant fixes their eyes in a point (No eye movements)
Head	Scanning behaviour	E-HSB	Moving the head to follow along with game action (could be in any direction)
	Head leaning toward game	E-HLT	Moving the head closer to the device to get a better view of game action
	Head oriented away from the display	D-HOA	Turning or moving the head in any direction away from the game/device
Torso	Lean forward	E-TLF	Torso leaned in towards the device
	Upright posture	E-TUP	Sitting upright, attentively
	Slouched posture	D-TSL	Body sliding down low in their seat (opposite of sitting straight/at attention)
	Turning away from the game	D-TTA	Turning the torso in any direction that takes bodily orientation away from game

Category of the behaviour	Name of the behaviour	Code of the behaviour	Description of behaviour
Limbs	Scanning behaviour	E-LSB	Moving the hand back and forth near the screen to follow along with game action
	Adjust the position of the tablet	E-LAT	Pulling the tablet closer or into a more comfortable position
Limbs	Play arm position adjustment	E-LPA	Moving the playing arm into a more comfortable position or advantageous position for gameplay
	Non-play hand at mouth	E-LNM	Non-play handheld near mouth or lips. The finger may be between lips or teeth. Should be for more than 3 sec.
	Play hand away from device	D-LHA	Participant moves play the hand (e.g., right hand) away from device for a moment or longer (more than 3 seconds)
	Play hand movements unrelated to the game	D-LSH	Participant moves play a hand in any fashion not directly related to game play. This could include shaking their play hand, tapping their hand on the table, scratching their head for an extended period of time, etc. (more than 3 seconds)
	Smacking face	D-LSF	Participant smacks face in frustration at the situation
Face	Neutral expression	E-FNT	A plain face, indicative of focus. No obvious smile or other expressions.
	Lip behaviour	E-FPO	Pouting, pursing lips, biting lip, mouthing words
	Eyebrow movement	E-FEM	Furrowed brow, raised eyebrows
	Playful grimace	E-FPG	An apparently pained expression in response to something happening in the game
	Open mouth	E-FOM	A more prolonged case of the mouth hanging open, likely due to deep absorption in gameplay
	Surprised expression	E-FSP	A briefly held expression with mouth open and/or eyebrows raised
	Smiling	E-FSM	Could be a big smile, or a milder smile
	Tongue behaviour	E-FST	Tongue either comes out between closed lips, or hangs out of an open mouth
	Pained expression	D-FGR	A facial expression of pain that appears to have to do with own body, the environment, situation, the technology, or as a reaction to the level of difficulty of the game being too high or too low. Might have to do with problems with the functionality of the technology or distractions in the room.
	Angry expression (e.g., baring teeth)	D-FBT	Anger apparently directed at situation, environment, level of difficulty of the game, or the function of the device.
	Frowning	D-FFR	Participant displays negative affect, with eyebrows furrowed and corners of lips turned downward
	Yawning	D-FYA	The participant yawns, indicating fatigue and lack of absorption in gameplay

Category of the behaviour	Name of the behaviour	Code of the behaviour	Description of behaviour
Voice	Voiced utterance	E-VAU	Participant uses their voice out loud to communicate something that may or may not involve real words. Participant's affect seems to be positive. The Participant does or does not expect a response from someone else. Participant comments at something in the game or something related to gameplay. This is like talking to oneself. Examples: "Oh"(surprise), "Ooh"(interest),"What?"(surprise/confusion),"Oops/Whoops" (surprise/displeasure), "Ok" (self-talk), Cursing
Voice	Voiceless utterance	E-VMW	Same as above, except that the participants voice is quiet (i.e., no vocal vibration). Examples: Talking under breath, whispering
	Laughing	E-VLA	Participant laughs at something in the game or something related to gameplay
	Frustrated exclamation	D-VFE	As with the pained and angry facial expressions above, the coder is required to interpret whether such expressions have to do with the environment, situation, technology, or level of game difficulty being too high or too low. This might have to do with problems with the functionality of the tablet or with distractions in the room.
	Refusal ("I quit" "I won't do it anymore")	D-VRF	Participant verbally expresses their refusal to continue with the activity
Gameplay	Physical interaction with the screen	E-GPP	Touching the screen in response to game activity
	Keeping up with the game	E-GKU	Adjusting pace of play in response to increases in speed/difficulty of the game. e.g., responding more quickly to events on the screen
	Not physically interacting with the screen	D-GNP	Participant stops--or fails to start--attempting to engage with the device/game
	Not keeping up with a game	D-GNK	The participant's gameplay is inattentive or incapable, leading them to fall behind the action in the game.
Concentration	Not distracted by external stimuli	E-CND	No signs of distraction when non-gameplay activity occurs around the participant (e.g., not turning to look at the source of a loud noise)
	Playing while doing something else	E-CAS	E.g., putting one's phone away or out of sight, picking up something that fell, carrying on conversation with someone
	Stopping play to attend to another stimulus	D-COS	Includes social interactions such as asking for help, engaging in conversation with someone else, gesturing to other people, and looking for other people, and non-social behaviours such as looking at one's phone or other personal items.
Breath	Rhythmic breathing	E-BRB	Evenly paced breathing, without overtly deep inhales or exhales

Note: *E- corresponds to the Engagement behaviours. D- corresponds to the Disengagement behaviours

The original data set was composed of 15 separate coding sheets on the Excel files. In total, 1774 labelled data were collected from 15 older adults. Besides, the original dataset contained engagement-related behaviours alone.

3.2. Final Dataset and preprocessing data

The author of this research integrated all 15 Excel files in one file, making the codes consistent and reliable required integrating and preparing all codes in a compatible file for data preparation. It was important to add more relative variables to the original dataset, such as personal characteristics, environmental disturbance, and technical issues. For example, personal characteristics included age, gender, education, familiarity with serious games, and experience with computer games; environmental disturbance included disruption in the session, interruption of the game, communications with others; and technical issues, including some problems to start the game or the game crashes. The relevance of each of these features may result in recognition of dementia. For instance, age may be one of the reasons for facing dementia; as a person gets older, the risk of having dementia may increase (Canton-Habas, Rich-Ruiz, Romero-Saldana, & Carrera-Gonzalez, 2020). Also, gender may be relevant for having dementia (Mielke, 2018). It is important to know if education, familiarity with serious games, and experience with games have an effect on developing dementia (Baumgart, et al., 2015). In addition, the environmental disturbance and technical issues can give valuable information on whether these features affect dementia identification. All information about each participant from these additional features was extracted from the participant's files and added to the final dataset as it is explained below.

In the original dataset, age was recorded as a continuous variable. When running the ML models, it was noticeable that age was the main predictor of older adults with dementia. These results were biased because the total number of participants included in this study was low and each participant had a unique age. Therefore, the machine identified older adults with dementia based on the age of the participants. To solve this problem, in the final dataset, age was transformed with the visual binning method (SPSS Statistics, 2016). This method was used to generate binned categories based on the mean and standard deviation of the distribution of this sample. This method was performed in IBM SPSS Statistics version 23.

The environmental disturbance and technical issues were coded from field notes taken by the research team in the primary study. In the primary study, the research team involved in data collection recorded any event that happened during each session. The author of the present study reviewed all notes and generated a coding system for environmental disturbance and technical issues. Table 3 shows the coding system for these features. Then, two raters watched all the 15 videos and annotated the environmental disturbance and technical issues based on the coding system. The author of this document acted as the first rater.

The primary rater compared all scores of videos for calculating the inter-rater reliability. The agreement in observation of environmental disturbances and technical issues between the two raters was high. The high score of agreement in observation between two raters and the highly symmetrically imbalanced marginals results in the low-kappa score, which is called the low-kappa paradox (Feinstein & Cicchetti, 1990). Cohen's kappa is defined with the difference in expected probability with observed probability divided by one minus expected probability. The inter-rater reliability was low because of the high observed probability between the two raters. Because of the high agreement and low-kappa paradox, inter-rater reliability was measured using the chance-adjusted index Bennett S score rather than Cohen's kappa (Zorron Cheng Tao Pu, et al., 2020). In Bennet S score, the difference in the calculation is mainly on expected probabilities, dividing over one minus the one over the number of categories. Thus, the environmental disturbance and technical issues' inter-rater reliability S scores were S = 0.92 and S = 0.96, respectively, which showed excellent inter-rater reliability.

Table 3.
Indicators, variable operationalizations, and definitions

Features	Indicator	Operationalization	Definition
Personal characteristics	Age	Below 78 = 0, Equal and above 78 = 1	Age at the moment of data collection in years
	Gender	Woman = 1, Man = 0	Women and men participants in this study
	Education	School education = 0 Diploma/vocational training/ university degree = 1	Class 0 indicates school education such as Elementary, Junior high, High school Diploma. Class 1 indicates college diploma, vocational tr Bachelor's, Master's, and Doctorate degree
	Technology literacy	Daily, occasional use of one device = 0 Daily use of 2 or 3 devices = 1	Class 0 indicates daily or occasional use of one device (computers or tablets or smartphones). Class 1 indicates daily use of 2 or 3 devices, such as computers, tablets, and smartphones.
	Previous experience with Serious games	No = 0, Yes = 1	Class 0 indicates no previous experience with Serious games. Class 1 indicates from a few times a year to daily experience
Environmental disturbance	Disruption, Interruption, Communications with others	No = 0, Yes = 1	Class 0 indicates no interruption or disruption during the gameplay. Class 1 indicates the frequency in which each indicator occurred during the session such as the research assistant talks about something not related to the game with the participant, research assistants or other participants making some noise (e.g., people laughing or talking in the room). Noise of the street (e.g., siren) Mobile phone ringing, and unexpected situations (e.g., smoke in the air)
Technical issues	Connectivity/ Problem to start or the game crashes	No = 0, Yes = 1	Class 0 indicates no technical problem during gameplay. Class 1 indicates the frequency in which each indicator occurred during the session, such as charging the the battery of the tablet, tablet crashes and need to restart the game, internet connectivity

Artificial intelligence, mainly supervised ML, needs input and output data (Holzinger, 2016). To create an adequate dataset for the machine to learn from the final dataset, the total columns of 55 of engagement-related behaviours along with personal characteristics, environmental disturbance, and technical issues were constructed. Because the codes were made up of a mixture of letters, the data could not be used as it was in the Excel file. Each category had different codes, representing the behaviour of engagement or disengagement (See Table 2). In some instances, more than one code was entered in a single behaviour category; for example, the category face has eight codes: E-FNT, E-FPO, E-FEM, E-FPG, E-FOM, E-FSP, E-FSM, and E-FST of engagement, and D-FGR, D-FBT, D-FFR, and D-FYA of disengagement. By separating each behaviour and movement code in a column, along with personal characteristics, environmental disturbance, and technical issues, 54 features with different codes were used for the input data. It was essential to convert categorical code into numerical by assigning a one-hot encoding method, a way of preprocessing categorical features to new binary features (Al-Shehari & Alsowail, 2021), to transform data and prepare it for an algorithm to improve prediction. With one-hot encoding, each category value was converted into a new categorical column and given a binary value of 1 or 0. Thus, a binary vector was used to represent each integer value. For instance, if a behaviour or a movement happened in a given interval of 15 seconds, that code would be equal to one, and if it did not occur, that code would be equivalent to zero.

We considered the prediction model as a ML problem with a binary output, health condition, with class 0 representing older adults without dementia and class 1 representing persons living with dementia. See Figure 1.

E-CND	D-GNK	D-GNP	E-GKU	E-GPP	D-VRF	D-VFE	...	D-GAG	E-GTG	AGE	Gender	Education	Technology literacy	Previous experience with serious games	Environmental disturbance	Technical issues	Health condition
0	0	0	0	1	0	0	...	0	1	0	1	0	0	1	0	0	1
1	0	0	0	1	0	0	...	0	1	1	1	1	1	0	0	0	0
1	0	0	0	1	0	0	...	0	1	1	1	1	0	0	0	0	0
1	0	0	0	1	0	0	...	0	1	1	0	1	0	0	0	0	0
1	0	0	0	1	0	0	...	0	1	1	0	1	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1	0	0	0	1	0	0	...	0	1	0	0	0	0	1	0	0	0
1	0	1	0	1	0	0	...	0	1	1	1	1	0	0	0	1	0
1	0	0	0	1	0	0		0	1	1	1	1	0	0	0	0	0

Figure 2

The one-hot encoding dataset of engagement-related behaviours along with personal characteristics, environmental disturbance features, and technical issues

3.3. Statistical analysis

The first step for statistical analysis was the analysis of demographics. All demographics, including age, gender, education level, technology literacy, and previous experience of older adults with serious games, were analyzed using descriptive statistics.

For answering the first part of question 1 (question 1.1), the frequencies of each behaviour and their percentages were estimated using descriptive statistical analysis, which involved summarizing data by calculating the occurrence of each behaviour, as well as their percentages. To answer the second part of question 1 (research question 1.2.), the Chi-squared test with contingency 2*2 table and Fisher's exact test were used with a significance level of 0.05 to compare the behaviours of engagement and disengagement between older adults living with dementia and older adults without dementia (Portney & Watkins, 2009). For expected frequencies less than five occurrences, Fisher's exact test was employed to reduce the risk of incurring in the Type I error for 2*2 tables (Portney & Watkins, 2009).

3.4. Machine learning analysis

To answer research question 2, the dataset was split into training and testing sets. The training data was used to create four ML models, which were then used to make predictions. A more advanced method, stratified K-fold cross-validation was used, which is a type of cross-validation (Mate, Potdar, & Priya, 2020). Because the ratio of older adults living with dementia vs. older adults without dementia was 0.33, the stratified K-fold method was employed to maintain the ratio for each fold (James & Vimina, 2021). This method was used to ensure that each fold has the same proportion of observations with a given label. The dataset was divided into K different folds or subsets. As a result, the model was repetitively run K number of times. The dataset was trained on the K-1st fold in each iteration, and the test dataset was used to evaluate the Kth fold. In this study, a value of 4 was assigned to K. Therefore, 75% of the data was used for training and 25% for testing. Once the model had been completed, the final results were derived by averaging values from test samples across four iterations.

The RF classifier, a supervised ML model, was used to identify the relevant engagement-related behaviours demonstrated by older adults with dementia from those without dementia for this study. RF, an ensemble learning method, are a robust tree-structured ML technique that is good at dealing with high-dimensional data and a high number of features and is resistant to outliers (Bayat, et al., 2021). Four RF models with four sets of input variables were trained.

1- engagement-related behaviour features only, 2- engagement-related behaviours features and personal features,

3- engagement-related behaviours features, environmental disturbance and technical issues features,

4- engagement-related behaviours features, environmental disturbance features, technical issues, and personal features.

Each model was trained on a large number of hyperparameters containing the parameters that values are used for the learning process, and the models that performed the best were chosen. To evaluate the performance, the precision, recall, and F1 score were calculated with 95% confidence intervals and compared to the four models. For the models, precision is the measure of participants that were correctly identified by the model as having dementia out of all participants actually having it. In other words, the ratio of the true-positives (who have dementia) over the total number of predicted Positives values (true-positives + false-positives). Recall (or sensitivity) is the measure of the model that identifies true positives correctly. For all participants who actually have dementia, recall tells how many times dementia data was correctly identified. In other words, recall is the ratio of True Positive predictions over the total number of true-positive and false-negative ones. The model needs a trade-off between precision and recall to achieve accuracy. For this purpose, the F1 score was calculated. Table 4 describes all measurements used for this study with their definitions and formulas (Priyaa, Garga, & Tigga, 2020).

A receiver operating curve (ROC) was generated to visualize the true positive rate (TPR) against the false positive rate (FPR) at various thresholds. Finally, the area with the curve and the axes as the boundaries called AUC was computed for each model. This area is considered a metric of a good model, with the metric ranging from 0 to 1. The model with a high value (close to 1) is called a model with good skill (Subchan & Andayani, 2021). The AUC is a useful approach to summarise the test's overall diagnostic accuracy (Mandrekar, 2010).

Table 4.
Measurements for model evaluation

Measurements	Definition	Formula used for this study
Precision	The positive predictions made by the model which are truly relevant.	$\frac{True\ Positive}{True\ Positive + False\ Positive}$
Recall	The measure of how many truly relevant results are detected.	$\frac{True\ Positive}{True\ Positive + False\ Negative}$
F1 score	The harmonic mean from precision and recall.	$2 \times \frac{(Precision\ \times\ Recall)}{Precision + Recall}$

Finally, the feature importance method was used to recognize older adults with dementia from those without dementia with engagement-related behaviours, environmental disturbance, technical issues, and personal characteristics. In the feature importance method, the importance of each feature is calculated by providing a score for each feature (Artasanchez & Joshi, 2020). If the feature achieves a high value, it will be an important feature for the machine's prediction. Feature importance is calculated with the decrease of node impurity, a metric used in the construction of Decision Trees to identify how the features of a dataset should be divided into nodes in order to form the tree, reaching the probability of that node (Ronaghan, 2018). To find the decrease in node impurity, the RF Gini index was used. The Gini index degree ranges from zero to one, with 0 denoting that all elements belong to one class or that there is only one class and 1 denoting that the elements are randomly distributed among different classes (Kaur, 2020). The formula is as follows (Shang, et al., 2006):

$$\text{Gini Index} = 1 - \sum_{i=1}^{n} (P_i)^2$$

Therefore, the relevant features to identify the engagement-related behaviours of older adults with dementia from those without dementia were generated with this method. In addition, the selection of the relevant features was arbitrary, in this study, the relevant features with a higher score of 0.05 in a decrease in mean impurity were selected.

4. Results

This chapter will begin with the results of the demographic variables. The second section will address the results from the first research question. The last part of this chapter will cover the results from the second research question.

4.1. Demographic variables

Table 5 presents the descriptive statistics relating to the age of the participants, gender, educational level, technology literacy, and their previous experience with the game. On average, older adults without dementia were 3.1 years older than participants living with dementia. The ratio of women to men in both groups was equal, 60% women. The most common highest level of education for older adults in both groups was a high school diploma, and ten percent of older adults without dementia had a master's degree. Both groups used at least one or a combination of two information and communication technologies (ICT). Forty percent of older adults living with dementia used computers or computers and tablets. Computers were the ICT used the most by older adults without dementia. Both groups had similar previous experiences with serious gaming.

Table 5

Demographic variables

Variables	Dementia (n = 5)	Without dementia (n = 10)
Age, year	76.6 ± 6.8	79.7 ± 8.8
Gender, % female	60%	60%

Variables		Dementia (n = 5)	Without dementia (n = 10)
Highest educational level	% Elementary school	0%	10%
	% High school diploma	40%	30%
	% Trade/vocational training	20%	0%
	% College diploma	20%	20%
	% Bachelor's degree	20%	30%
	% Master's degree	0%	10%
Technology literacy (ICT used)	% Computer	40%	60%
	% Computer & Tablet	40%	0%
	% Computer & Smartphone	0%	10%
	% Computer, Tablet, & Smartphone	20%	30%
Previous experience with serious games, %		60%	60% 10% missing data (one participant)

4.2 Research Question 1

To answer research question 1.1, a descriptive analysis was used for each engagement-related behaviour with their frequencies and percentages. In total, older adults living with dementia had 591 opportunities (i.e., total amount of 15-sec intervals) to demonstrate each behaviour while older adults without dementia had 1,183 opportunities to demonstrate each behaviour. See Table 6 (column frequency of behaviours).

It was noticeable that the most frequent behaviours occurring more than 70% in both groups were related to the categories of *gaze,* e.g. gaze toward game (E-GTG), *eyes,* e.g. scanning behaviour (E-ESB), *head,* e.g. scanning behaviour (E-HSB), *face* e.g. neutral expression (E-FNT), *gameplay,* e.g. physical interaction with a screen (E-GPP), and *concentration,* e.g., not distracted by external stimuli (E-CND).

Older adults without dementia demonstrated the Lean forward (E-TLF) behaviour more than older adults living with dementia. E-TLF was demonstrated 47% of the time; however, older adults living with dementia had a frequency of 2% of E-TLF behaviour. In addition, older adults without dementia had Eyebrow movement (E-FEM) 27% of the time intervals, compared to older adults living with dementia, who demonstrated this behaviour only 4% of the time. On the other hand, older adults living with dementia showed higher frequencies in some behaviours compared with older adults without dementia, including upright posture (E-TUP) having a 100% of the time in older adults living with dementia vs. 54% of the time in older adults without dementia, voiced utterance (E-VAU) 28% of the time interval in older adults living with dementia compared with less than 1% of the time in non-dementia ones, and playing while doing something else (E-CAS) 26% of the time in older adults living with dementia compared with the other ones (9% of the time).

Interestingly, there were behaviours with zero frequencies in the categories of *eyes, torso, limbs, face, voice, and gameplay* in the group of older adults living with dementia. Older adults living with dementia did not demonstrate some engagement behaviours such as saccadic eye movements (E-ESM), squinting at the screen (E-ESS), play arm position adjustment (E-LPA), and keeping up with the game (E-GKU), with the zero frequency of these behaviours. Older adults living with dementia did not demonstrate some disengagement behaviours as well, for example, slouched posture (D-TSL), smacking face (D-LSF), angry expression (D-FBT), yawning (D-FYA) and refusal (D-VRF). It can be noticed that slouched posture (D-TSL) behaviour was not observed in both groups, i.e., older adults living with dementia and older adults without dementia.

To answer the research question 1.2, the Chi-squared and Fisher's exact test with the level of their significance were calculated. The Chi-squared and Fisher's exact test showed that there were significant differences in engagement-related behaviours between older adults living with dementia and those without dementia. The comparison between the frequencies of the 47 engagement-related behaviours along with their statistics and significance values (P-value), are presented in Table 6.

Table 6

Chi-squared and Fisher's exact tests

Behaviour code	Observation	Frequency of behaviours		Total frequencies	Chi-square [a] or Fisher's exact test [b]	
		Dementia (n = 591)	Without dementia (n =1183)		Statistics	P-value
E-GTG	Yes	585 (99%)	1,182 (99.9%)	1,767 (99.6%)	8.685	0.006[b]*
	No	6 (1%)	1 (0.1%)	7 (0.4%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-GAG	Yes	42 (7.1%)	68 (5.7%)	110 (6.2%)	1.250	0.263[a]
	No	549 (92.9%)	1,115 (94.3%)	1,664 (93.8%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-ESM	Yes	0 (0%)	119 (10%)	119 (6.7%)	63.724	< 0.001[b]*
	No	591 (100%)	1,064 (90%)	1,655 (93.3%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		

Behaviour code	Observation	Frequency of behaviours		Total frequencies	Chi-square [a] or Fisher's exact test [b]	
		Dementia (n = 591)	Without dementia (n =1183)		Statistics	P-value
E-ESB	Yes	587 (99.3%)	1,173 (99.1%)	1,760 (99.2%)	0.142	1.000[b]
	No	4 (0.7%)	10 (0.9%)	14 (0.8%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-ESS	Yes	0 (0%)	2 (0.2%)	2 (0.1%)	1.000	0.317[b]
	No	591 (100%)	1,181 (99.8%)	1,772 (99.9%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-ECL	Yes	1 (0.2%)	2 (0.2%)	3 (0.2%)	4.775	1.000[b]
	No	590 (99.8%)	1,181 (99.8%)	1,771 (99.8%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-EFX	Yes	8 (1.4%)	0 (0%)	8 (0.5%)	16.086	< 0.001[b]*
	No	583 (98.64%)	1,183 (100%)	1,766 (99.5%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-HSB	Yes	587 (99.32%)	1,178 (99.6%)	1,765 (99.5%)	0.504	0.491[b]
	No	4 (0.68%)	5 (0.4%)	9 (0.5%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-HLT	Yes	4 (0.6%)	154 (13%)	158 (8.9%)	73.981	< 0.001[b]*
	No	587 (99.4%)	1,029 (87%)	1,616 (91.1%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-HOA	Yes	25 (4.2%)	34 (2.9%)	59 (3.3%)	2.254	0.159[a]
	No	566 (95.8%)	1,149 (97.1%)	1,715 (96.7%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-TLF	Yes	9 (1.5%)	551 (46.6%)	560 (31.6%)	370.321	< 0.001[a]*
	No	582 (98.5%)	632 (53.4%)	1,214 (68.4%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		

Behaviour code	Observation	Frequency of behaviours		Total frequencies	Chi-square [a] or Fisher's exact test [b]	
		Dementia (n = 591)	Without dementia (n =1183)		Statistics	P-value
E-TUP	Yes	589 (99.7%)	636 (53.8%)	1,225 (69%)	388.545	< 0.001[b]*
	No	2 (0.3%)	547 (46.2%)	549 (31%)		
	Total	591 (100%)	1,183 (100%)	1,774(100%)		
D-TSL	Yes	0 (0%)	0 (0%)	0 (0%)	-	-
	No	591 (100%)	1,183 (100%)	1,774 (100%)		
	Total	591 (100%)	1,183 (100%)	1,774(100%)		
D-TTA	Yes	2 (0.3%)	14 (1.2%)	16 (1%)	3.148	0.107[b]
	No	589 (99.7%)	1,169 (98.8%)	1,758 (99%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-LSB	Yes	410 (69.4%)	738 (62.4%)	1,148 (64.7%)	8.433	0.003[a]*
	No	181 (30.6%)	445 (37.6%)	626 (35.3%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-LAT	Yes	16 (2.7%)	8 (0.7%)	24 (1.3%)	12.181	0.000[a]*
	No	575 (97.3%)	1,175 (99.3%)	1,750 (98.7%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-LPR	Yes	462 (78.2%)	1,049 (88.7%)	1,511 (85.2%)	34.411	< 0.001[a]*
	No	129 (21.8%)	134 (11.3%)	263 (14.8%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-LPA	Yes	0 (0%)	3 (0.3%)	3 (0.2%)	1.501	0.555[b]
	No	591 (100%)	1,180 (99.7%)	1,771 (99.8%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-LNM	Yes	5 (0.9%)	136 (11.6%)	141 (8%)	61.098	< 0.001[a]*
	No	586 (99.1%)	1,047 (88.4%)	1,633 (92%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		

Behaviour code	Observation	Frequency of behaviours		Total frequencies	Chi-square [a] or Fisher's exact test [b]	
		Dementia (n = 591)	Without dementia (n =1183)		Statistics	P-value
D-LHA	Yes	26 (4.4%)	23 (2%)	49 (2.8%)	8.844	0.002[a]*
	No	565 (95.6%)	1,160 (98%)	1,725 (97.2%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-LSH	Yes	6 (1%)	1 (0.1%)	7 (0.4%)	8.685	0.006[b]*
	No	585 (99%)	1,182 (99.9%)	1,767 (99.6%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-LSF	Yes	0 (0%)	2 (0.2%)	2 (0.1%)	1.000	0.317[a]
	No	591 (100%)	1,181 (99.8%)	1,772 (99.9%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-FNT	Yes	491 (83%)	1,112 (94%)	1,603 (90.4%)	53.944	< 0.001[a]*
	No	100 (17%)	71 (6%)	171 (9.6%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-FPO	Yes	347 (58.7%)	373 (31.5%)	720 (40.6%)	120.775	< 0.001[a]*
	No	244 (41.3%)	810 (68.5%)	1,054 (59.4%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-FEM	Yes	24 (4%)	310 (26.2%)	334 (18.8%)	126.448	< 0.001[a]*
	No	567 (96%)	873 (73.8%)	1,440 (81.2%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-FPG	Yes	6 (1%)	7 (0.6%)	13 (0.7%)	0.971	0.324[a]
	No	585 (99%)	1,176 (99.4%)	1,761 (99.3%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-FOM	Yes	8 (1.4%)	72 (6%)	80 (4.5%)	20.498	< 0.001[a]*
	No	583 (98.6%)	1,111 (94%)	1,694 (95.5%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		

Behaviour code	Observation	Frequency of behaviours		Total frequencies	Chi-square [a] or Fisher's exact test [b]	
		Dementia (n = 591)	Without dementia (n =1183)		Statistics	P-value
E-FSP	Yes	24 (4%)	4 (0.3%)	28 (1.6%)	35.160	< 0.001[b]*
	No	567 (96%)	1,179 (99.7%)	1,746 (98.4%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-FSM	Yes	128 (21.7%)	78 (6.6%)	206 (11.6%)	87.144	< 0.001[a]*
	No	463 (78.3%)	1,105 (93.4%)	1,568 (88.4%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-FST	Yes	12 (2%)	23 (2%)	35 (2%)	0.015	0.902[a]
	No	579 (98%)	1,160 (98%)	1,739 (98%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-FGR	Yes	2 (0.3%)	2 (0.2%)	4 (0.3%)	0.502	0.604[b]
	No	589 (99.7%)	1,181 (99.8%)	1,770 (99.7%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-FBT	Yes	0 (0%)	25 (2.1%)	25 (1.4%)	12.667	0.000[b]*
	No	591 (100%)	1,158 (97.9%)	1,749 (98.6%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-FFR	Yes	2 (0.3%)	56 (4.7%)	58 (3.3%)	24.074	< 0.001[b]*
	No	589 (99.7%)	1,127 (95.4%)	1,716 (96.7%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-FYA	Yes	0 (0%)	6 (0.5%)	6 (0.4%)	3.007	0.187[b]
	No	591 (100%)	1,177 (99.5%)	1,768 (99.6%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-VAU	Yes	164 (27.7%)	8 (0.7%)	172 (9.7%)	329.927	< 0.001[a]*
	No	427 (72.3%)	1,175 (99.3%)	1,602 (90.3%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		

Behaviour code	Observation	Frequency of behaviours		Total frequencies	Chi-square [a] or Fisher's exact test [b]	
		Dementia (n = 591)	Without dementia (n =1183)		Statistics	P-value
E-VMW	Yes	105 (17.8%)	29 (2.5%)	134 (7.5%)	132.378	< 0.001[a]*
	No	486 (82.2%)	1,154 (97.5%)	1,640 (92.5%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-VLA	Yes	21 (3.5%)	11 (1%)	32 (1.9%)	15.313	< 0.001[a]*
	No	570 (96.5%)	1,172 (99%)	1,742 (98.1%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-VFE	Yes	3 (0.5%)	22 (1.9%)	25 (1.4%)	5.185	0.030[b]*
	No	588 (99.5%)	1,161 (98.1%)	1,749 (98.6%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-VRF	Yes	0 (0%)	1 (0%)	1 (0%)	0.499	1.000[b]
	No	591 (100%)	1,182 (100%)	1,773 100%)		
	Total	591 (100%)	1,183 (100%)	1,774 100%)		
E-GPP	Yes	574 (97.1%)	1,181 (99.8%)	1,755 (99%)	27.265	< 0.001[b]*
	No	17 (2.9%)	2 (0.2%)	19 (1%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-GKU	Yes	0 (0%)	86 (7.3%)	86 (4.8%)	45.152	< 0.001[b]*
	No	591 (100%)	1,097 (92.7%)	1,688 (95.2%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-GNP	Yes	24 (4%)	28 (2.4%)	52 (3%)	3.975	0.046[a]*
	No	567 (96%)	1,155 (97.6%)	1,722 (97%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-GNK	Yes	2 (0.3%)	2 (0.2%)	4 (0.2%)	0.502	0.604[b]
	No	589 (99.7%)	1,181 (99.8%)	1,770 (99.8%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		

Behaviour code	Observation	Frequency of behaviours		Total frequencies	Chi-square [a] or Fisher's exact test [b]	
		Dementia (n = 591)	Without dementia (n =1183)		Statistics	P-value
E-CND	Yes	433 (73.3%)	1,178 (99.6%)	1,611 (90.8%)	326.994	< 0.001[a]*
	No	158 (26.7%)	5 (0.4%)	163 (9.2%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-CAS	Yes	149 (25.2%)	5 (0.4%)	154 (8.7%)	305.494	< 0.001[a]*
	No	442 (74.8%)	1,178 (99.6%)	1,620 (91.3%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
D-COS	Yes	42 (7.1%)	62 (5.2%)	104 (5.9%)	2.485	0.114[a]
	No	549 (92.9%)	1,121 (94.8%)	1,670 (94.1%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		
E-BRB	Yes	289 (48.9%)	298 (25.2%)	587 (33%)	100.068	< 0.001[a]*
	No	302 (51.1%)	885 (74.8%)	1,187 (67%)		
	Total	591 (100%)	1,183 (100%)	1,774 (100%)		

Notes.
[a] Chi-squared test; [b] Fisher's exact test; * $p < 0.05$

E-GTG=Gaze toward game; D-GAG=Away from game; E-ESM=Saccadic eye movements; E-ESB=Scanning behaviour; E-ESS=Squinting at screen; D-ECL=Closed eyes; D-EFX=Eyes fixed on a point; E-HSB=Scanning behaviour; E-HLT=Head leaning toward game; D-HOA=Head oriented away from the display; E-TLF=Lean forward; E-TUP=Upright posture; D-TSL=Slouched posture; D-TTA=Turning away from the game; E-LSB=Scanning behaviour; E-LAT=Adjust the position of the tablet; E-LPR= Play hand ready; E-LPA=Play arm position adjustment; E-LNM=Non-play hand at mouth; D-LHA=Play hand away from device; D-LSH=Play hand movements unrelated to the game; D-LSF=Smacking face; E-FNT=Neutral expression; E-FPO=Lip behaviour; E-FEM=Eyebrow movement; E-FPG=Playful grimace; E-FOM=Open mouth; E-FSP= Surprised expression; E-FSM=Smiling; E-FST=Tongue behaviour; D-FGR=Pained expression; D-FBT=Angry expression(e.g., baring teeth); D-FFR=Frowning; D-FYA=Yawning; E-VAU=Voiced utterance; E-VMW=Voiceless utterance; E-VLA=Laughing; D-VFE=Frustrated exclamation; D-VRF=Refusal; E-GPP=Physical interaction with the screen; E-GKU=Keeping up with the game; D-GNP=Not physically interacting with the screen; D-GNK=Not keeping up with a game; E-CND=Not distracted by external stimuli; E-CAS=Playing while doing something else; D-COS=Stopping play to attend to another stimulus; E-BRB=Rhythmic breathing.

Each engagement-related behaviour was assigned with the degree of freedom of one for two tests.

Table 6 shows that 30/47 engagement-related behaviours, 64% were significantly different in frequencies between the two groups i.e., older adults living with dementia and those without dementia. The *face* category, which contained more behaviours than the other categories, had eight out of 12 (66.6%) behaviours statistically significantly different between the two groups.

On the other hand, the slouched posture behaviour (D-TSL) was not observed in both groups. As a result, neither the Chi-squared test nor Fisher's exact test was calculated for this behaviour.

4.3 Research Question 2

To answer the research question 2, four different RF models were trained to achieve the highest F1 score for choosing the best model. Then, the relevant engagement-related behaviours demonstrated by older adults with dementia from those without dementia were recognized. The results of these models are presented below.

4.3.1. Random Forest models

Table 7 shows the precision, recall, F1 score and the AUC of four models. When the input variables were the engagement-related behaviours alone (model 1), the model correctly identified older adults with dementia 69% (precision) of the time. The 0.93 recall score means that among the participants living with dementia, the model correctly identified 93%. The predictive model achieved an F1 score of 78% and an AUC of 0.96%. When adding more variables to the engagement-related behaviours features, the performance of each model increased, indicating higher F1 score.

The higher precision scores indicate the model's lower FPR (i.e., predicted dementia, but the subject did not have dementia). In addition, the higher recall shows the model's lower false-negative rate (i.e., predicted the subject did not have dementia, but the subject had). The higher F1 score shows the higher harmonic average from precision and recall, and the higher AUC indicates the better performance of the model at identifying between classes.

The environmental disturbance and technical issues are not relevant in older adults with dementia; having these features with engagement-related behaviours resulted in model three to achieve only a 1% F1 score higher than model one. Finally, model 4 had the highest F1 score, and AUC compared to other models. The AUC, F1 score, recall and precision for the model 4 were 99%, 91%, 97%, and 85%, respectively. Therefore, model 4 was chosen as the best model.

Table 7

Model performances on test sets with the 95% confidence intervals in parentheses

Model	Input variables	Precision	Recall	F1-score	AUC
1	Engagement-related behaviours	0.69 (0.654-0.715)	0.93(0.843-1.000)	0.78(0.770-0.813)	0.96(0.939-0.970)
2	Engagement-related behaviours and personal features	0.81(0.780-0.839)	0.98(0.958-1.000)	0.88(0.872-0.902)	0.99(0.984-1.000)
3	Engagement-related behaviours, environmental disturbance and technical issues	0.68(0.634-0.730)	0.94(0.875-1.000)	0.79(0.774-0.815)	0.96(0.949-0.965)
4	Engagement-related behaviours, environmental disturbance, technical issues, and personal features	0.85(0.724-0.990)	0.97(0.930-1.000)	0.91(0.851-0.963)	0.99(0.984-1.000)

The AUC for identifying older adults with dementia with the engagement-related behaviours alone (model 1) was excellent, 0.96 (95% CI 0.939–0.970), and improved with the environmental disturbance, technical issues, and personal characteristics feature with 0.99 (95% CI 0.984 -1.00) (model 4). Figure 2 shows the AUC value between 0 to 1, where a value close to one reflects an accurate test while an AUC value of 0.5 suggests no ability to recognize older adults living with dementia versus those without dementia. As model 4 was trained with the stratified 4-fold, each fold generated the AUC. The result shows that the fourth model (mean AUC) had an AUC of more than 0.9, which is considered an exceptionally accurate test.

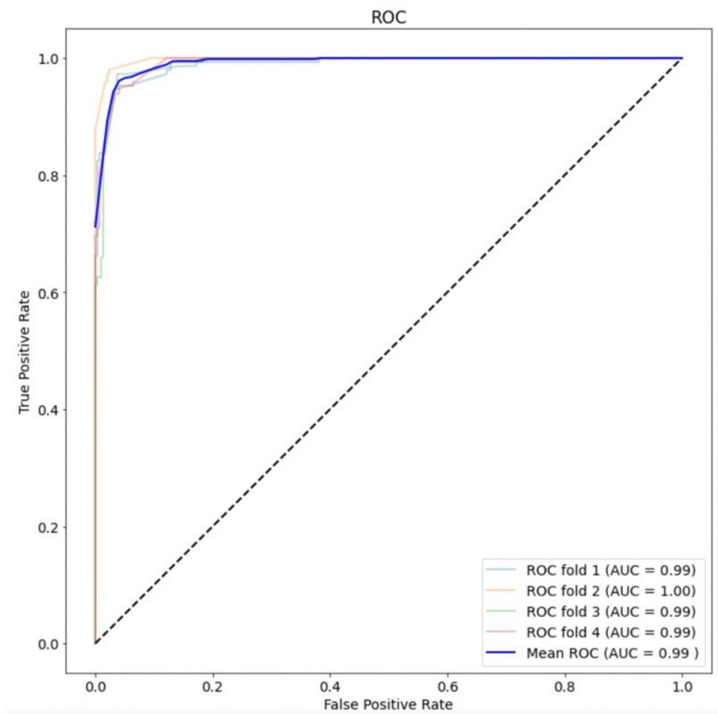

Figure 2

The AUC for engagement-related behaviours, personal features, environmental disturbance, and technical issues

4.3.2. Engagement-related behaviours importance

Figure 3 presents the ranked importance of the features that identified engagement-related behaviours demonstrated by older adults living with dementia from those without dementia. The mean decrease in impurity shows that the higher the impurity, the more relevant the behaviour will be. With the decrease in impurity, the importance of the behaviour will be reduced. The mean decrease in impurity will be reduced to zero importance, meaning the behaviour is not relevant to older adults with dementia.

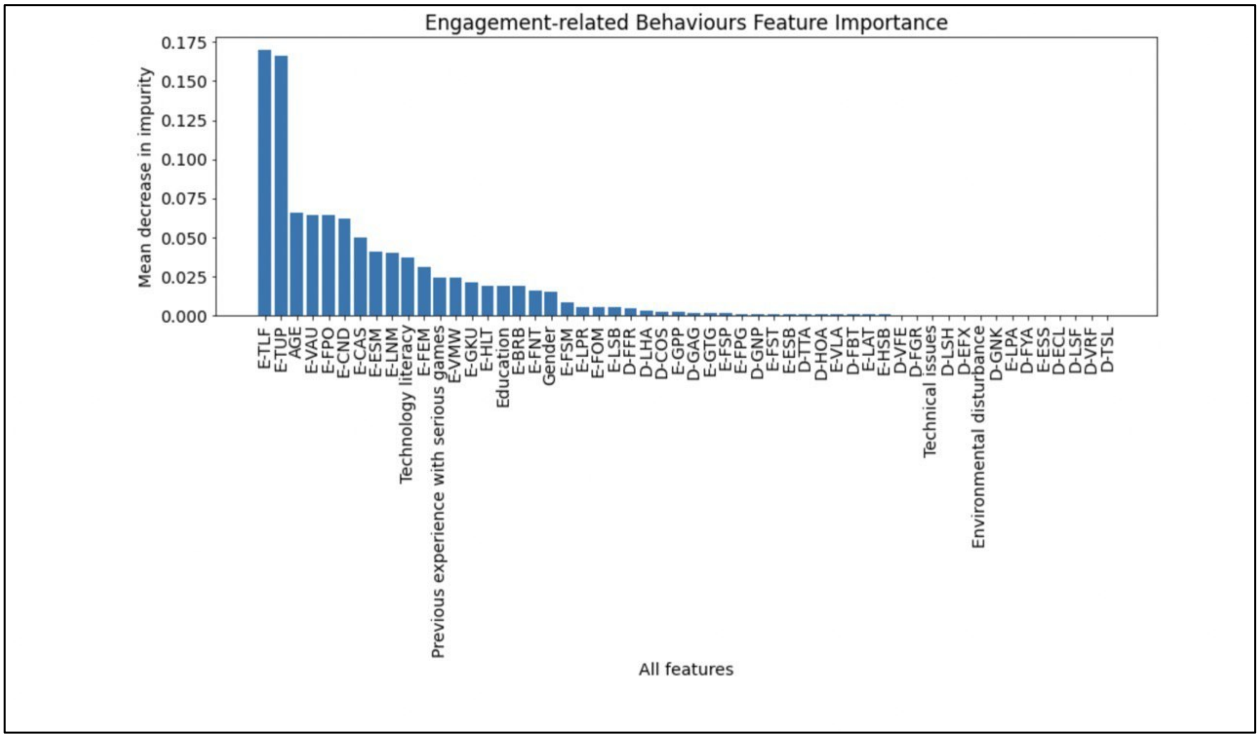

Figure 3

Feature importance of all features

As shown in Figure 3, the seven most relevant features with their mean decrease in impurity to recognize dementia were:

1) engagement- torso lean forward (E-TLF),

2) engagement- torso upright posture (E-TUP),

3) Age,

4) engagement-voiced utterance (E-VAU),

5) engagement- face pouting (E-FPO),

6) engagement- concentration with no distraction (E-CND) and,

7) engagement – concentration while doing something else (E-CAS)

It was found that behaviours in the category *torso,* i.e., engagement- torso lean forward (E-TLF) and engagement- torso upright posture (E-TUP) were the most relevant . for identifying variation in behaviour between older adults living with dementia and those without dementia It was noticeable that older adults with dementia demonstrated more upright posture (E-TUP) behaviours than older adults without dementia. However, older adults without dementia leaned forward (E-TLF) to the game more frequently than older adults with dementia. Also, age was one of the relevant features in older adults with dementia; as people age, the prevalence of having dementia may increase. Older adults with dementia demonstrated voice utterance (E-VAU) and face pouting (E-FPO) behaviours more frequently than the other group. In addition, older adults without dementia could concentrate with no distraction (E-CND) compared with older adults with dementia, and those with dementia tended to distract more frequently, concentrating while doing something else (E-CAS) behaviour. Interestingly, none of the seven important behaviours were related to disengagement behaviours.

5. Discussion

This study aimed to answer the research questions 1.1. What are the frequencies of each engagement-related behaviour observed in older adults living with dementia and those without dementia who played mobile games? 1.2. Are there any differences in frequencies of the engagement-related behaviours between older adults living with dementia and those without dementia while playing mobile games? and 2. What distinct patterns of engagement-related behaviours along with personal characteristics, technical issues and environmental disturbances are demonstrated by older adults with dementia? The main findings of this study showed that the most common behaviours demonstrated by older adults were related to the behaviour categories of gaze, eyes, head, face, gameplay, and concentration; 64% of engagement-related behaviours were statistically significantly different in the two groups (i.e., older adults living with dementia and those without dementia); and the most relevant features for identifying cases of older adults with dementia from those without dementia were related to the behaviour categories of the torso, age, voice, face, and concentration. This chapter discusses the findings regarding each of the study's research questions and hypotheses, followed by a discussion about the clinical implications, limitations, and future research.

In research question 1.1. the frequencies of each engagement-related behaviour observed in older adults living with dementia and those without dementia who played mobile games. The descriptive statistics for engagement-related behaviours showed that the most frequent behaviours demonstrated by older adults were related to the categories of *gaze* (e.g. gaze toward game), *eyes* (e.g. scanning behaviour), *head* (e.g. scanning behaviour), *face* (e.g. neutral expression), *gameplay* (e.g. physical interaction with screen) and *concentration* (e.g. not distracted by external stimuli). Similarly, Perugia et al. (2018) identified that head movements had the leading role in engagement-related behaviour in older adults living with dementia, followed by torso movement, arms/hands movement, gaze toward activity, gestural support, and postural support in older adults living with dementia. There were some differences in the engagement-related behaviours found in the present study compared to Perugia et al.'s (2018) work. Perugia and colleagues focused on behaviours related to body movement, whereas, in the present study, the concept of engagement included behavioural, cognitive, and affective dimensions (Hookham & Nesbitt, 2019). As a result, the coding system used for creating the engagement-related behaviours dataset had codes related to not only movement but also affect and cognition. In addition, the analysis of engagement-related behaviours in different activities could generate different results. For example, Perugia et al. (2018) engaged older adults by playing board games and interacting with a robot toy; in contrast, older adults played mobile games on tablets in this study.

In the present study, older adults living with dementia demonstrated a higher percentage of torso behaviour (100% of the time intervals) of the upright posture (E-TUP) compared with older adults without dementia (54% of the time intervals). However, the results showed that older adults without dementia demonstrated a higher percentage of torso behaviour, leaning forward (E-TLF) (45% of the time intervals), compared to older adults living with dementia (2% of the time intervals). Perugia and colleagues (2018) found that the torso movement toward the activity sequenced into arms and hands movements was the common behaviour among older adults living with dementia. The difference in behaviours in the present study and Perugia et al.' (2018) work was related to leaning forward (E-TLF). This difference can result from using different activities in the two studies. Perugia et al. (2018) used board games to make older adults engaged. Board games are usually placed horizontally on a table, so older adults tend to lean forward and play the game. The environment could have an impact on the engagement-related behaviours of older adults. For example, for playing the board game, participants may tend to lean forward toward the game as the board games should be placed on the table. However, when they are playing with tablets, they can put them horizontally on the table, use the tablet stands, or play the game while holding the tablet. However, in the present study, 80% of participants in each group (i.e. four out of five older adults living with dementia and eight out of ten older adults without dementia) decided to use tablet stands to angle the tablet screen to improve the view of the game. Therefore, in the present study, the environmental condition seems not to have impacted the torso behaviours of older adults as they equally preferred to use the tablet stands to angle the tablet in the two groups.

Another behaviour that was demonstrated primarily by older adults living with dementia was voiced utterance (E-VAU), i.e., older adults living with dementia demonstrated almost 30% of the time intervals the voiced utterance (E-VAU) behaviour. In comparison, older adults without dementia showed this behaviour less than 1% of the time intervals. The voiced utterance (E-VAU) behaviour is defined as communication that does not involve real words (e.g., wow, oh, hm). The higher use of voiced utterances in the older adults living with dementia group might be to the fact that people living with dementia had difficulties in communicating with real words, so they expressed their emotions through voiced utterances such as "oh" (showing interest) or "oops" (being surprized) rather than words or phrases. These results are aligned with previous research that shows older adults living with dementia had difficulty with verbal communication due to their memory impairment (Hubbard, Downs, & Tester, 2003; Martínez-Sánchez, Meilán, Carro, & Ivanova, 2018). According to the World Health Organization (2019), the common signs and symptoms of dementia are changes in mental abilities, including forgetfulness, issues with problem-solving, and difficulty communicating or finding words. The literature on communication-related to dementia highlighted the consequences of cognitive decline on linguistic expression and meaning comprehension and also observed the relative retention of communicative abilities including nonverbal information, as well as the desire to communicate in older adults living with dementia (Smith, et al., 2011).

The behaviour of playing while doing something else (E-CAS) was more frequent in older adults living with dementia (25% of the time intervals) than in older adults without dementia (less than 1% of the time intervals). This result may indicate that older adults living with dementia were easily distracted while playing the games compared with older adults without dementia. The literature shows that external stimuli could quickly distract older adults living with MCI and dementia due to the decline in cognitive function (Wargnier, et al., 2015; Hamdy, et al., 2017). For example, Hamdy et al. (2017) described how a 68-year-old man with MCI or possibly dementia was prone to start fixing tasks that he could not finish or from which he was quickly distracted.

Older adults without dementia demonstrated eyebrow movement behaviour (E-FEM) more than older adults living with dementia (27% versus 4% of the time). The results showed that older adults without dementia demonstrated some facial expressions, furrowed brows or raised eyebrows more often than the group living with dementia. Similarly, Smeddinck et al. (2013) found that older adults without dementia demonstrated emotional facial expressions such as smiling, frowning, and sadness when playing motion-based games. Thus, the results suggest that eyebrow movement is a common behaviour exhibited by older adults without dementia while engaged in playing games.

Results from the research question 1.2. revealed that 30 out of 47 (64%) of engagement-related behaviours were statistically significantly different in older adults living with dementia compared with older adults without dementia. The results support hypothesis 1.2. There are significant differences in engagement-related behaviours of older adults living with dementia and those without dementia while playing mobile games. Therefore, the results of this study showed that older adults living with dementia could demonstrate behaviours that could be different from older adults without dementia.

These statistical analyses showed that some behaviours had a huge difference in the two groups, achieving the smallest p-values. The most statistically significantly different engagement-related behaviours were pertinent to the upright posture (E-TUP), lean forward (E-TLF), voiced utterance (E-VAU), concentration with no distraction (E-CND), concentration while doing something else (E-CAS), voiceless utterance (E-VMW), eyebrow movement (E-FEM), face pouting (E-FPO), rhythmic breathing (E-BRB), head leaning toward game (E-HLT), saccadic eye movements (E-ESM), and non-play hand at the mouth (E-LNM), achieving the $p<0.001$ for all of these behaviours. Interestingly, six of these engagement-related behaviours, including E-TUP, E-TLF, E-VAU, E-CND, E-CAS, and E-FPO, are related to the most relevant features demonstrated by older adults with and without dementia. This will be discussed later in this section.

The frequencies of the eyebrow movement (E-FEM), head leaning toward game (E-HLT), saccadic eye movements (E-ESM), and non-play hand at the mouth (E-LNM) behaviours were statistically significantly higher in older adults without dementia than in older adults living with dementia. As it was mentioned before, older adults without dementia didn't distract easily, and they showed their engagement with some facial expressions such as eyebrow movements. In addition, non-dementia individuals tended to lean forward to the game (E-TLF). The statistically significant difference in this behaviour between the two groups can be interpreted as older adults without dementia felt comfortable in their surroundings because previous research showed that older adults living with dementia could not trust their environment and felt uncomfortable in their surroundings (Burton & Kaszniak, 2006). In addition, it is likely that the leaning forward to the game behaviour (E-TLF), was related to the head leaning toward the game (E-HLT) behaviour which explains why both behaviours were higher in the non-dementia group. Regarding the saccadic eye movements (E-ESM), our results align with Krebs et al.'s (2021) results, which tested the feasibility of eye-tracking during a puzzle game and developed adjunct markers for cognitive markers performance using eye-tracking metrics between older adults without dementia and those living with dementia. They have found that saccadic eye movements were shorter, and fixations were longer in AD participants than in older adults without dementia. Non-play hand at the mouth (E-LNM) behaviour was an indicator of engagement in older adults without dementia. This behaviour could be related to those individuals without dementia who were concentrated more on playing games, and they could demonstrate this concentration by the movement of their non-play hand at their mouth when thinking and engaging in the game.

Finally, voiceless utterance (E-VMW) was demonstrated mostly by older adults living with dementia. In the voiceless utterance (E-VMW) behaviour, the participant's voice is quiet (e.g. talking under his breath, whispering). The results of older adults living with dementia having more voiceless utterance (E-VMW) behaviour than the non-dementia group is aligned with Rajagopal et al.' findings who placed individualized textual prompts on the dinner table of three women with cognitive impairment at an assisted-living facility. Authors found that the vocal-verbal behaviour was emitted after five seconds of silence and consisted of whispering to themselves, moving lips without any vocalization, grunting, coughing, and other non-words behaviours (Rajagopal, et al., 2022).

The results of this study support hypothesis 2, a dataset of engagement-related behaviours along with other characteristics such as personal characteristics, environmental disturbances, and technical issues generates distinct patterns for the presence of dementia in older adults while playing mobile games. Model 1, the engagement-related behaviours alone, achieved an accuracy (F1 score) of 78%. It was noticeable that personal characteristics along with engagement-related behaviours had the most impact on the model, increasing the accuracy from 78% to 88%. However, the environmental disturbances, technical issues along with engagement-related behaviours increased the model's F1 score to 79%. This means that these additional features did not improve the model's prediction as it increased only by 1%. The results show that the highest F1 score for identifying older adults with dementia was 91% in the model that included the engagement-related behaviours, personal characteristics, technical issues, and environmental disturbances features (model 4). Notice that environmental disturbances and technical issues improved the model prediction only by 3% (from 88% to 91%) in model 4. In this study, there were not many problems with the technology and disturbances in the environment due to the controlled environment. However, these results might be different in real, uncontrolled sessions. For example, in real scenarios, people could talk about something not related to the game with older adults, which may distract them easily or make some noises, e.g., talking or laughing with the older adult. In addition, their tablets may run out of battery, or the tablet might crash during the gameplay.

The most relevant engagement-related behaviours demonstrated by older adults with dementia from those without dementia were lean forward (E-TLF), upright posture (E-TUP), age, voiced utterance (E-VAU), face pouting (E-FPO), concentration with no distraction (E-CND), and concentration while doing something else (E-CAS). Similarly, Bayat et al. (2021) identified dementia with a 91% F1 score and found the important driving behaviours of older adults living with dementia. Achieving similar accuracies showed that playing mobile games could be a safe and low-cost activity to identify older adults with and without dementia with their engagement-related behaviours, compared to driving, which could be a more complex, risky and costly activity for this population.

In total, all models had a higher recall (the measure of how many true relevant results, actual dementia disease, are detected) compared to precision (with all predictions of dementia made by the model, how many are truly relevant). Achieving a higher recall is more important than getting a high precision (Arroyo, Corea, Jimenez-Diaz, & Recio-Garcia, 2019). In other words, detecting behaviours as many people with dementia as possible is more desirable than predicting people's behaviours who do not have dementia but actually have (false-negative results). The higher recall score indicated the model's lower false-negative rate. Therefor in health-care settings, it may be desirable to lower the false-negative rate; for example, if a person has dementia, but the health-care professional diagnosed that a person does not have dementia (false-negative) may have some detrimental consequences (e.g. not delaying the progression of the disease or not accessing to the required health care services) for the patient and their families by the wrong diagnosis. Thus, it is important to mitigate the false-negative prediction.

It was hypothesized that a dataset of engagement-related behaviours along with other features such as personal characteristics, environmental disturbances, and technical issues generates distinct patterns for the presence of dementia in older adults while playing mobile games. The results show that personal characteristics, especially age, along with engagement-related behaviours, are the most relevant features demonstrated by older adults with dementia.

Two engagement-related behaviours in the torso category were the most relevant features demonstrated by older adults with dementia, i.e., lean forward (E-TLF) and upright posture (E-TUP). As mentioned, previous research has found that people living with dementia are often not comfortable with their surroundings, feel threatened by the environment, and they have difficulties in social interaction (Brittain, Corner, Robinson, & Bond, 2010; Jones, Moyle, & Sung, 2018). This might be why older adults living with dementia feel unsecured, resulting in sitting upright (E-TUP) or attentively while playing mobile games. The statistical analysis shows that older adults living with dementia demonstrated upright posture (E-TUP) 100% of the time compared with older adults without dementia. Also, this behaviour was statistically significantly different ($p<0.001$) between the two groups. The results also showed that older adults without dementia leaned forward (E-TLF) toward the game 47% of the time compared with older adults living with dementia (2% of time intervals), and the frequencies were statistically significantly different ($p<0.001$) between the two groups. As mentioned before, 80% of both groups, older adults living with dementia and those without dementia, angled the tablet screen to improve the view of the games while playing. The fact that the same proportion of participants in both groups angled the tablet suggests that the tablet position did not influence the differences in these behaviours. A possible explanation for these results is that older adults without dementia felt more comfortable with their surroundings than older adults living with dementia while playing, which is supported by previous studies (Brittain, Corner, Robinson, & Bond, 2010).

Results show that age, voice behaviour, and facial behaviour are the other relevant features demonstrated by older adults with dementia. Interestingly, age was the third relevant feature which was the only variable related to personal characteristics in older adults with dementia. Similarly, Bayat et al. (2021) found that age was the second important feature in identifying dementia. As people age, the risk of acquiring dementia will increase (Canton-Habas, Rich-Ruiz, Romero-Saldana, & Carrera-Gonzalez, 2020). In addition, age has been identified as the strongest risk factor for MCI and dementia (Wahl, et al., 2019). This may explain why age results in a feature for older adults with dementia in the present study.

Voiced utterance (E-VAU) behaviour was the fourth relevant feature demonstrated by older adults with dementia. Similarly, the literature showed that people with MCI could demonstrate differences in their speech and phonation compared with older adults without dementia (Martínez-Nicolás, Llorente, Martínez-Sánchez, & G. Meilán, 2021). One of the most important characteristic symptoms of dementia is speech problems, which can appear from memory disorders (Barragan Pulido, et al., 2020). Padhee and colleagues (2021) used transcripts and recordings of English-speaking of older adults to identify MCI and AD from verbal utterances. Their results showed that individuals with MCI tended to go out of the context of describing the Cookie Theft picture, and individuals with AD lost context in the middle of their talking. The results of the research questions 1.1. and 1.2. showed that older adults living with dementia demonstrated the voiced utterance (E-VAU) behaviours (not using real words) 30% of the time compared with older adults without dementia (less than 1% of the time intervals). In addition, the E-VAU behaviour was statistically significantly different (*$p<0.001$*) between the two groups. Therefore, the results of the present study provided insights that older adults living with dementia tended to use voiced utterance behaviours more than older adults without dementia while playing. Therefore, high use of voiced utterances seems to be a good indicator in older adults with dementia.

The fifth behaviour was face pouting (E-FPO), which was related to the lip behaviours of older adults living with dementia. This behaviour is described as pouting, pursing lips, biting lips, and mouthing words. Although the study participants played individually and were not asked to talk, they played in a group session. In addition, the results showed that older adults living with dementia had higher frequencies in lip behaviour (59% of the time intervals) in contrast to older adults without dementia (32% of the time intervals) and the difference was statistically significant ($p<0.001$). These results suggest that facial expressions related to lip behaviours might indicate dementia. This result might be explained by previous research findings that indicate that older adults living with dementia tended to pull their lips back and up when smiling as per facial electromyography recordings–(Burton & Kaszniak, 2006). As mentioned before, Rajagopal et al. (2022) found that older adults living with dementia demonstrated behaviours including whispering to themselves, lips movement with no vocalization, grunting, coughing, and other non-words behaviours when they had social interaction with each other.

The sixth and seventh important engagement-related behaviours were related to concentration, i.e., concentration with no distraction (E-CND), and concentration while doing something else (E-CAS). The results from research questions 1.1. and 1.2. showed that older adults without dementia concentrated on the games without any distractions 100% of the time while older adults living with dementia were totally concentrated less time (74% of time intervals), and the difference in frequencies was statistically significant ($p<0.001$) between the two groups. It was also noticeable that older adults living with dementia could be easily distracted when playing the game (E-CAS) (e.g., playing games while doing something else, picking up something that fell). Older adults living with dementia were distracted 26% of the time interval compared with older adults without dementia (less than 1% of time interval). The results of the study showed that this behaviour was statistically significantly different ($p<0.001$) in the two groups. According to Hookham and Nesbitt (2019), the concept of engagement consists of behavioural, cognitive, and affective dimensions, and attention belongs to the cognitive dimension of engagement. Dementia is a progressive neurodegenerative condition that impairs concentration and changes cognition (Scott, Kugelman, & Tulloch, 2019). Similar to the results of the present project, previous research has found that older adults living with severe dementia had difficulty in maintaining their attention behaviours when interacting with a robot toy (Jøranson, et al., 2016).

5.1. Clinical implications

Literature on engagement-related behaviours of older adults in some activities such as playing with a robot asserts that older adults living with dementia demonstrate some unique engagement-related behaviours (Jøranson, et al., 2016; Perugia, et al., 2018). Results of the present project show that older adults living with dementia can demonstrate distinct patterns of engagement-related behaviours while they are engaged in playing mobile games. For instance, they showed different behaviours such as sitting upright (E-TUP), voice utterances (E-VAU), face pouting (E-FPO), and concentrating while doing something else (E-CAS) more frequently compared to older adults without dementia. These results can be used by clinicians to help them recognize these engagement-related behaviours while older adults are engaged in a game. The indication of engagement-related behaviours can help health-care professionals understand the signs of dementia by observing older adults playing mobile games. The identified engagement-related behaviours may help to recognize the signs of dementia simply and quickly, which could potentially be used along with cognitive screening tools. For example, using the cognitive screening tools such as MoCA or MMSE need trained personnel, and they cannot be administered frequently due to the learning effect. In addition, health professionals can observe behaviours while older adults play mobile games, which can provide valuable information. Also, the health-care professionals may train caregivers, who are taking care of older adults, or older adults' families to identify the engagement-related behaviours of older adults when they play mobile games at home. This may help older adults who are living in rural areas or low-income families to recognize the signs of dementia while playing mobile games. Mobile games can be played regularly and is a safe activity. Thus, it is unlikely that playing generates anxiety compared to the administration of cognitive screening tools. In addition, it is possible to observe engagement-related behaviours remotely. This could be helpful for future pandemic scenarios like the one we are experiencing with the COVID-19 pandemic, which requires isolation. For instance, older adults' cognition could be monitored remotely by observing their behaviours via teleconferencing and identifying the cognitive impairment based on their engagement-related behaviours while clients play mobile games.

Using ICT could be a useful method to identify and monitor dementia in older adults because older adults are increasingly using these technologies (Macedo, 2017). Interestingly, this study shows that all the included participants were using at least one or two technologies, and 50% were using computers, tablets, and smartphones in their lives. Engagement in playful activities may reduce the risk of the progression of dementia (Dartigues, et al., 2013). The literature suggests that computer-based training interventions may have some benefits on older adults living with MCI or dementia, including improvements in learning and short-term memory, as well as behavioural symptoms (Klimova & Maresova, 2017). In addition, computerized cognitive training indicated significant improvements in the cognitive domains of older adults with MCI with attention, processing speed, visuospatial memory, and self-reported measures of everyday function (Gates, et al., 2019), and the large effect of the cognitive training program was related to the attention of older adults with MCI and dementia (Hill, et al., 2017). Therefore, playing mobile games seems to be beneficial and accessible for older adults living with dementia.

5.2. Limitations

This study has some limitations. First, the sample size used to create the dataset was 15 older adults, five living with dementia and ten without dementia. For future studies, there is a need to increase the sample size and include more older adults living with dementia to generalize the engagement-related behaviours for identifying the presence or progression of this disease. ML models require large amounts of data (Qiu, Wu, Ding, Xu, & Feng, 2016), and future studies need to include more da to present more accurate predictions. Also, different biases can influence ML predictions. For example, sample bias (Gu & Oelke, 2019). Sample bias is defined as the samples of a stochastic variable collected to determine its distribution are incorrectly selected and do not represent the true distribution (Panzeri, Magri, & Carraro, 2015). In this study, the dataset contained only five individuals with dementia compared with ten older adults without dementia. This may reduce the accuracy of the ML models for older adults living with dementia. In addition, overlooking different races could be included in sample bias. For example, in the present study, the engagement-related behaviours were demonstrated only by white older adults from North America, which could limit the findings' generalizability. In addition, the study of engagement-related behaviours of older adults would need to include different ethnicities and cultural backgrounds, which may improve the generalizability of behaviours from other countries for identifying the behaviours related to dementia.

Second, the focus of this study was on mild to moderate dementia only. Although older adults living with mild or moderate dementia demonstrated various engagement-related behaviours, it is important to include older adults living with severe dementia to demonstrate if their engagement-related behaviours are different from mild to moderated cognitive impairment older adults.

Lastly, the game setup can influence the engagement-related behaviours of older adults. For example, some older adults put the tablet on the table horizontally, while some older adults use tablet stands to angle the tablet screen. These changes may affect the engagement-related behaviours, for example, torso behaviours of older adults.

5.3. Future research

Based on the results of the present study, some research questions emerge that can be answered in future studies. Engagement-related behaviours could be used to identify the most common behaviours demonstrated by older adults with dementia based on the severity of the disease. Jøranson et al. (2016) showed that older adults living with severe dementia had difficulty in maintaining attention toward the robot toy, Paro, compared with older adults living with mild to moderate dementia. Thus, it is important to consider older adults living with severe dementia and compare their engagement-related behaviours with older adults living with mild/moderate dementia while playing games.

Also, this study identified only the engagement-related behaviours of older adults. For future study, it would be important to identify the level of the older adult's engagement while doing activities, e.g., playing mobile games. The level of engagement of older adults could vary due to the severity of their cognitive impairment and the type of game they play. For example, older adults living with mild to moderate dementia may have higher engagement compared with older adults living with severe dementia while playing mobile games. This could help the health-care professionals to recognize the level of engagement of older adults and identify the relationship to the severity of dementia. In addition, by playing those serious cognitive games, it might be noticeable which games are more engaging for older adults living with MCI or dementia to mitigate the progression of this disease.

In addition, there is a need to focus on different routine home activities, e.g., walking, cycling, cleaning etc., and each activity needs its unique ethogram to identify the engagement-related behaviours demonstrated by older adults with dementia. After analyzing the results of the present study in light of previous research, it was found that the engagement-related behaviours of older adults living with dementia while playing mobile games are different from those playing other activities, e.g., playing with a robot or playing board games, and each activity may need its own ethogram to identify engagement-related behaviours of older adults with dementia from those without dementia.

The next step of this research could rely on deep learning methods, a subset of ML, to identify the engagement-related behaviours of older adults using their recorded videos while playing games. This project took six months for occupational therapists to watch the videos of older adults every 15 seconds and annotate their behaviours using the ethogram. This method could be costly and time-consuming (e.g., hiring different occupational therapists to annotate the behaviours). Thus, using deep learning methods will help generate some unique patterns of engagement-related behaviours that can be used to identify older adults with dementia from those without dementia by using video recordings. This method will be more cost-effective and less time-consuming.

6. Conclusion

This study focused on understanding the most common frequencies of engagement-related behaviours of older adults with dementia while playing mobile games. This research showed that older adults living with dementia exhibited some common engagement-related behaviours compared with older adults without dementia. The most frequent engagement-related behaviours demonstrated by older adults were related to gaze, eyes, head, face, gameplay, and concentration. The statistically significant different behaviours ($p<0.001$) were leaning forward to the game (E-TLF), upright posture (E-TUP), voice utterance (E-VAU), concentration with no distraction (E-CND), and concentration while doing something else (E-CAS), voiceless utterance (E-VMW), eyebrow movement (E-FEM), face pouting (E-FPO), rhythmic breathing (E-BRB), head leaning toward game (E-HLT), saccadic eye movements (E-ESM), non-play hand at the mouth (E-LNM), between older adults living with dementia vs. those without dementia.

The best ML model to identify engagement-related behaviours of older adults with dementia from those without dementia was the one that used engagement-related behaviours along with personal characteristics, environmental disturbance, and technical issues features, which achieved the highest accuracy compared to the other models. In addition, personal characteristics had a great influence on recognizing older adults with dementia when added to the engagement-related behaviours, achieving the second-highest accuracy.

The most relevant behaviours to understand the person may have dementia were related to the *torso*, upright posture (E-TUP) and leaning forward to the game (E-TLF), *voice,* voice utterance (E-VAU), *face*, face pouting (E-FPO), *concentration,* concentration with no distraction (E-CND) and concentration while doing something else (E-CAS) behaviours and age. This method may be an accessible way to identify and monitor older adults with dementia along with the cognitive screening tools. Also, playing mobile games could be a safe and inexpensive activity that can be accessed and performed by many older adults.

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