RESEARCH-ARTICLE

Why Would Professionals Choose to Use a Robot with Their Clients with Autism? Applying the Theory of Planned Behaviour to Determine Professionals' Intentions

LOUISE CHARPIOT, University of Luxembourg, Esch-sur-Alzette, Luxembourg

ANDREIA PINTO COSTA, University of Luxembourg, Esch-sur-Alzette, Luxembourg

GEORGES STEFFGEN, University of Luxembourg, Esch-sur-Alzette, Luxembourg

Open Access Support provided by:

University of Luxembourg

Published: 04 December 2024
Online AM: 30 September 2024
Accepted: 02 July 2024
Revised: 30 April 2024
Received: 03 February 2023

Why Would Professionals Choose to Use a Robot with Their Clients with Autism? Applying the Theory of Planned Behaviour to Determine Professionals' Intentions

LOUISE CHARPIOT, ANDREIA PINTO COSTA, and GEORGES STEFFGEN, Department of Behavioural and Cognitive Science, University of Luxembourg, Esch-sur-Alzette, Luxembourg

Robots are thought to be able to address some of society's challenges in autism care and education. Robots may extend services and provide them in personalised, repeated, and playful ways. However, it is still largely unknown to what extent professionals intend to use robots and what determines their intentions. Using the Theory of Planned Behaviour framework, we aimed to better understand the determinants behind professionals' intentions to use robots with their clients with autism. We conducted an online survey, to which 447 professionals (e.g., psychologists) working with people with autism answered. Our results indicate moderate and well-predicted intentions for the enquired professionals to use a robot with their clients with autism. We found that attitude and perceived social norms are the main predictors of their intentions. Our results also point to the significant and positive influence of moral norms on the attitudes of professionals. Additionally, our preliminary analysis of underlying beliefs to the assessed predictors of intention enables a better understanding on how professionals perceive the place of robots in their work. These results can inspire roboticists who want to build assistive robots for the real world and guide stakeholders when implementing such robots in the health and education sectors.

CCS Concepts: • Human-centered computing → HCI theory concepts and models; Empirical studies in HCI • Applied computing → Psychology • Social and professional topics → People with disabilities;

Additional Key Words and Phrases: Robots, Intention to use, Professionals, Health and education, Autism

ACM Reference format:
Louise Charpiot, Andreia Pinto Costa, and Georges Steffgen. 2024. Why Would Professionals Choose to Use a Robot with Their Clients with Autism? Applying the Theory of Planned Behaviour to Determine Professionals' Intentions. *ACM Trans. Hum.-Robot Interact.* 14, 1, Article 9 (December 2024), 23 pages.
https://doi.org/10.1145/3682073

Authors' Contact Information: Louise Charpiot (corresponding author), Department of Behavioural and Cognitive Science, University of Luxembourg, Esch-sur-Alzette, Luxembourg; e-mail: louisecharpiot@gmail.com; Andreia Pinto Costa, Department of Behavioural and Cognitive Science, University of Luxembourg, Esch-sur-Alzette, Luxembourg; e-mail: andreia.costa@uni.lu; Georges Steffgen, Department of Behavioural and Cognitive Science, University of Luxembourg, Esch-sur-Alzette, Luxembourg; e-mail: georges.steffgen@uni.lu.

ACM 2573-9522/2024/12-ART9
https://doi.org/10.1145/3682073

1 Introduction

1.1 Autism Diagnosis

Autism is generally characterised by difficulties in communication, social interaction, and restricted and repetitive behaviours and interests [1]. People with autism represent approximately 1% of the population [2]. The severity and nature of symptoms vary from one person to another but usually have a slight to severe impact on the social, occupational, and functional domains. Comorbidities such as intellectual disabilities, language impairment, and psychological or neuropsychological disorders (about 70% of cases) also add difficulties to autistic people [3]. Because of the uniqueness of needs that people with autism have, interventions are costly, not easily accessible, often insufficient, and not adequately administered [4].

1.2 Robots and Autism

One solution to these challenges could be to employ robots to make healthcare and education more accessible, standardising care while personalising it in a repeated and playful way. Indeed, past research using robots during interventions for children with autism has shown encouraging results on robots' efficacy in this field [5–11]. It appears that robots' characteristics, such as being rule-based and predictable, may help children feel more comfortable working with such a device and somehow increase their learning opportunities [5]. For example, autistic children who interact with robots exhibit behaviours such as joint attention that are useful in interventions and are not typically exhibited in traditional interventions not involving robots [6]. Children with autism also show better attention [7], cooperation [8], imitation [9], and communication [10] abilities when interacting with a robot in comparison with a person and increased performance in turn-taking and role-switching [11]. Furthermore, professionals can implement their exercises on robots so that the person with autism may receive the appropriate content with the necessary repetitions required to integrate the learning properly. Therefore, the possibility of using robots as augmented support to provide evidence-based practices, so that professionals and families can easily use them has become a field in quick expansion. To this end, many research projects received funding of several million Euros (e.g., DREAM, BABY robot, DE-ENIGMA, RABI, Kaspar Explains, MindBot, PEERbots, ENGAGEMENT) aiming to develop robotic applications to be used by professionals in the field of autism (e.g., psychologists, occupational therapists, etc.).

1.3 Professionals' Perception of Robot Uses for Autism

Although the use of robots is promising and generates enthusiasm in the fields of applied research and industry, studies surveying the specific opinions of professionals for whom this solution is intended tend to indicate that they are somewhat mixed [12–16]. On the one hand, the literature points out positive attitudes from professionals working in education and health care of autistic people. For instance, although experienced professionals working with children with autism mention fears of using a robot, they also mention positive expectations [12]. They mention that robots could help them reach their care goals, provide additional aid, and take on several roles (e.g., reinforcer, and diagnostic provider) [12]. Among other qualities, professionals also highlight the robot's customisation possibilities and repetitive implementation of actions [12, 13]. Additionally, robots could enable the recognition, analysis, and recording of children's actions, facilitate the monitoring of progress and the writing of reports, and improve the appropriateness of the therapy for each child [14]. On the other hand, studies also point to negative or weak professionals' perceptions or intentions towards using a robot despite the advantages mentioned above [15, 16]. Indeed, Conti and colleagues [15] investigated the perceptions, attitudes, and intentions of 55 undergraduate students (in education and psychology) and 25 experienced professionals (in the field of developmental disorders) regarding the use of a robot in their field. They showed that, while students tended to have a positive intention to use a robot in their future profession, their experienced colleagues did not, despite all participants' positive attitudes and perceived pleasure. Moreover, experienced professionals perceived the robots as expensive and limited tools [16]. In another study using a larger sample size (N = 245), and in line with Conti and al. [15] Kossewska and Kłosowska [16] demonstrated that specialised professionals in the field of developmental disorders had low overall intentions but positive attitudes towards using robots in their work. While Conti et al. [14] found that among the used predictors, only the perceived usefulness of using a robot in their (future) job predicted professionals' or students' intention, Kossewska and Kłosowska found that it was the attitude that weakly but significantly correlated to the intention to use a robot in the coming months among experienced professionals [16]. That attitude was in turn predicted by perceived usefulness (performance expectancy), effort expectancy, social influence self-efficacy, and facilitating conditions [16].

Therefore, key motivations behind professionals' intention to use a robot with their clients with autism remain unclear. Also, even if stakeholders in the fields of education and care of people with autism have generally positive attitudes towards robots [12–16], Kossewska and Kłosowska's [16] results point to a significant gap between the attitude and the intention to use a robot as an educational or therapeutic tool. As these intentions would be essential for the actual use of robots [17, 18] in health and education services, it is crucial to identify the determinants of professionals' intent that can act as barriers and facilitators and that can lead to successful implementations.

1.4 Theoretical Background

The quest for user acceptance of technology is a challenge in many areas besides autism education and health [19]. The models proposed in this field are very diverse and nuanced (e.g., set of acceptance determinants) depending on the type of technology and its specificity of use [20]. The Theory of Planned Behaviour (TPB) [18] is a socio-cognitive theory of behavioural change that has been widely used to help describe beliefs and psychological constructs that lead a person to behaviour [21, 22] including those related to the use of technology (e.g., [23–25]). It also has already been successfully used in the autism sector to predict the use of evidence-based practices by parents and teachers [26, 27].

According to the TPB [18], human behaviour would be predicted by a reduced number of predictors, which are intention and, to a lesser extent, the person's perceived behavioural control (as a proxy for actual behavioural control). Then, the intention would be, in turn, predicted by three general core factors: attitude, subjective norms (or social norms), and, again, perceived behavioural control, themselves underpinned by the person's beliefs (see Figure 1). In the TPB, attitude toward a given behaviour (here, the use of a robot) refers to the degree to which a person (the professional) has a favourable or unfavourable evaluation of this behaviour (here, the use of a robot with their client with autism). This attitude would reflect cognitive beliefs about the likely consequence of doing such a behaviour. Then, subjective norms refer to the perceived social pressure to perform such behaviour and the person's motivation to conform to these expectations. Social norms are strongly influenced by what the person believes important people to them (family, friends, colleagues, society in general) expect them to do. Finally, perceived behavioural control is a construct grounded in the theoretical framework of social cognitive theory and Bandura's concept of self-efficacy [28]. It refers to a person's belief that it can perform the given behaviour. Thus, the TPB assumes the existence of beliefs, which would be at the very origin of the core predictors of intention. Such beliefs would be context-dependent of different background factors such as age, gender, ethnicity, familiarity, media, and so on.

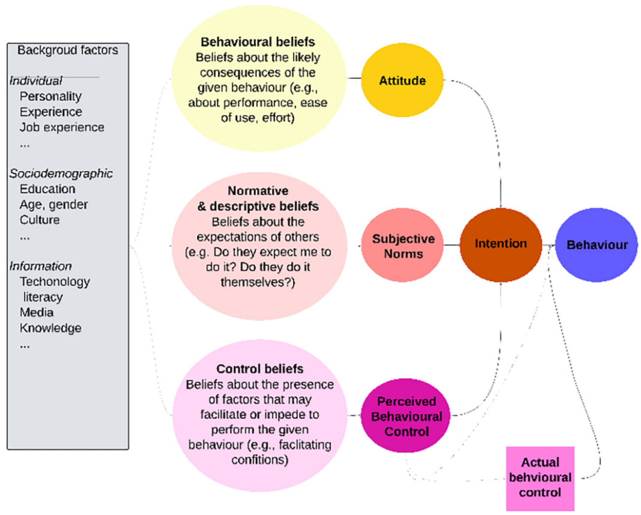

Fig. 1. Schematic representation of the original Theory of Planned Behaviour (TPB).

The context of using robots among clients with autism may lead professionals to have unique concerns and needs [12, 13, 29, 30]. These beliefs may depend on the diversity of the cases encountered (severity, comorbidities, etc.), on the care and interventions provided, or even the level of expectations of use and results. The TPB authors propose a rigorous and standardised methodology to elicit these specific beliefs in a pilot study [18]. They also offer the possibility to include these elicited beliefs in an adapted questionnaire and to measure them based on the expectancy-value model [18]. According to this method, we are considering not only the presence of certain beliefs (to what extent is this belief associated with the given behaviour) but also the strength of these beliefs (how important this belief is for the person) among the targeted group of users. Such a method would be essential to obtain more insight into how personal attitudes (advantages and disadvantages), subjective norms (social influence), and perceived behavioural control (perceived ability to use the technology effectively) influence the intention to use robots in specific interventions. This method allows us to gain more insight into how, through specific beliefs, constructs such as personal attitudes (advantages and disadvantages), subjective norms (social influence), and perceived behavioural control (perceived ability to use the technology effectively) influence the intention to use robots in specific interventions. Thus, by allowing the identification and measurement of such key beliefs among a particular population, the use of the TPB method makes it possible to take account of the specificity and complexity of the context surrounding the care of persons with autism. So far this has not been the case in studies that looked specifically at the acceptance of robots in this field. Using the TPB approach would therefore provide a more nuanced and tailored analysis and the individual motivations underlying professionals' intention to use a robot with autistic clients than what has been done in previous studies [15, 16] and provides essential information to design future interventions for robotic implementation (e.g., training, marketing).

Finally, the TPB model can be extended by including any additional and relevant variables allowing to refine the understanding of a behaviour in a specific situation. In the context of using robots with autistic clients, we decided to include three additional factors: emotion [31–33], moral norms [34], and professionals' self-efficacy [35–37], as they may also influence the intention to use new tools and methods, especially in new technology adoption.

Emotions refer to mood or affect and the somatic activation that is arousal [38], where attitude is often shown to reflect only people's cognitive beliefs and components [39, 40]. Emotion (also assimilated with anticipated affect) has been found on several occasions to be associated with the adoption of a new or innovative product [41–47]. For example, anxiety was found to negatively influence perceived ease of use beliefs regarding assistive social robots by elderly people, while perceived enjoyment was found to be a direct predictor of this intention [48, 49]. In the current context, we could imagine that a positive emotional state, such as enthusiasm could increase the propensity of a professional to perceive the benefits of using robots, leading to a stronger intention to use this technology. We could also imagine that a professional might feel a strong sense of confidence or emotional security at the idea of integrating a robot into its practice. This emotion would reflect an overall emotional response based on confidence in technology and the solutions developed by science, and could directly motivate the professional to intend to use the robot, independently of the specific attitudes formed by a rational evaluation of the advantages and disadvantages.

Moral norms are defined as the sense of moral duty to carry out a certain action or the perception of the moral correctness of performing a given behaviour [50]. Literature demonstrates that adding moral norms to the TPB variable would help to increase the explained variance of intention by 3%. This predictive validity would be true, especially for behaviour that has consequences for the welfare of others [51]. The use of robots designed to assist, mediate, or replace human caregivers in the practice of caring for vulnerable people such as those with autism, naturally raises philosophical questions of an ethical and moral nature [52]. We could therefore envisage that an educator or other practitioners, despite a negative attitude or feeling towards the robot, might try to use the robot out of a duty to optimise the patient's opportunities for success. Alternatively, a professional who recognises the potential benefits of using a robot—such as educational content, patient enjoyment and reduced workload - might nevertheless decide not to deploy it. The professional may feel that the robot, as a synthetic and limited agent, could further compromise the patient's social interactions, which are already impaired in autism, and therefore, reduce the quality of the care provided.) Additionally, if a behaviour is perceived as morally right, this could also influence the positive evaluation of the attitude towards that behaviour (and vice versa).

Finally, professionals' self-efficacy refers to the professionals' judgments of their capabilities to meet specific environmental demands [36], in the present case, being capable of caring successfully and educating people with autism. Teacher self-efficacy is linked to the adoption of specific classroom behaviour patterns (e.g., classroom organisation, and instruction) [53], and teacher self-efficacy is also shown to be directly linked to prospective information and communication technology integration into future teaching and learning practices [54]. In special education, teachers who have stronger beliefs in their ability to teach students show a greater willingness to try innovative techniques, new approaches, and materials to improve their teaching method [55]. Consequently, a professional with a high sense of professional self-efficacy would feel more competent in choosing professional methods. Thus, a healthcare professional might have a positive attitude towards the use of robots with autistic clients (recognising the benefits), perceive a favourable social norm (colleagues support the use of the technology), and have a good understanding of the technical challenges (perceived behavioural control). However, if the professional does not believe in the ability to effectively integrate this technology into practice, the professional may not intend to use it. It is the professional's specific belief in the ability to effectively integrate this technology into practice (professional self-efficacy) that directly determines the intention to use it. The professional believes that thanks to the owned skills and expertise, it is possible to overcome the potential challenges of using the robot and maximise its potential benefits.

Thus, the flexibility of the TPB can be useful for exploring how specific additional factors such as emotions, moral norms, and professionals' self-efficacy influence intention and behaviour. By integrating these additional factors as determinants of intention as well as beliefs more specifically related to the context, the use of TPB could allow us to better account for the nuances and specificities related to the use of robots in this domain of specific interventions.

To the best of our knowledge, few studies have explored the intention to use a robot in professionals with their autistic clients, and none used the TPB framework to explore it. Therefore, the aims of this study are threefold. First, to verify the suitability of the TPB to explain professionals' intention to use robots in the autism field. Second, to explore to which extent additional factors (emotions, moral norms, and perceived professionals' self-efficacy) contribute to improve the fitness of the original model. Third, to identify the fundamental beliefs held by professionals regarding the use of robots in their work with people with autism, which underlie the different intention predictors that are found significant.

2 Methods

2.1 Participants

In total, 447 professionals aged between 18 and 64 took part in the online survey (M = 35.9; SE = 9.61). The frequency and percentage of participants' gender distribution, years of experience in their job related to autism, familiarity with robots for autism and recent experience with robots or technology with their client are reported in Table 1 and detailed in Section 2.3.2. We can see in Table 1 that although 86.8% of participants had used technology at least once in the past year with their customers, only 13.1% felt that they had a good understanding of the use of robots in their area of expertise with their customers, and 4.4% had used a robot the previous year in the context of their work with patients. Most of the participants worked in European countries (87.2%). The others worked in North America (11.2%) or Africa (1.6%). The sample was made up of a wide variety of professionals such as psychologists, occupational therapists, speech therapists, specialised educators or teachers, assistants to pupils with disabilities, social workers, heads of services, volunteers, and accompanying persons for disabled students. Most worked exclusively with children (53.4%), but some (17.5%) worked exclusively with adults, and others (29.1%) with both.

2.2 Recruitment

Participation was open to all French-speaking professionals working with persons with autism (e.g., psychologists, speech therapists, specialised teachers). Recruitment took place online through social networks (especially LinkedIn by applying the appropriate filter and contacting the participants individually). To thank the participants, they had the opportunity to enter their email and register for a lottery at the end of the questionnaire to win one of six Amazon vouchers for 30 each. The main study was reviewed and approved by the ethics committee of the [ethics entity and approval number to be indicated after peer review].

2.3 Procedure and Measures

2.3.1 Procedures. This study took place in the context of the early Covid-19 pandemic. Therefore, the study questionnaire was held online using LimeSurvey platform. It could therefore be completed from anywhere at the participant's convenience. The estimated time to complete the questionnaire was approximately 20 minutes. After clicking on the invitation link and before the study began, the participants were informed in the text about the course of the study, its purpose, and the nature of the data processing following ethical requirements and data protection. In this notice, participants

Table 1. Characteristics of the Study Sample

Variable	Frequency	%
Gender		
Female	392	87.7
Male	52	11.6
Not answered	3	0.7
Job experience		
1 year or less	44	9.8
1–3 years	93	20.8
3–6 years	94	21.0
6–9 years	67	15.0
More than 9 years	146	32.7
Missing	3	.7
Use of technology with their client the last year		
Never	57	12.8
Rarely	86	19.2
Sometimes	112	25.1
Often	110	24.6
Almost always	68	15.2
Missing	14	3.1
Familiarity degree with robots for autism		
Never heard of it	236	52.8
Does not really understand the use	136	30.4
Understands well the use	56	12.5
Missing	19	4.3
Use of a robot with their client the last year		
Never	390	87.2
Rarely	13	2.9
Sometimes	2	0.4
Often	2	0.4
Almost always	1	0.2
Missing	39	8.7

were informed that the study was voluntary and pseudonymised and that they could request to have their data deleted at any time. After participants confirmed that they had read the information notice, they were asked for their informed consent. The questionnaire was only accessible to those providing their consent. The questionnaire then started with questions on basic demographics and control questions, followed by questions about professionals' self-efficacy with a client with autism. Because many of these professionals may also work with people without autism, we asked that they think of an autistic client when responding to all items. Also, before going further with our questions and to make sure that participants had comparable references in mind, we provided participants with a short description of the possible uses of these robots in their practice with their clients (e.g., as a mediator, a teacher or assistant in the clinical or educational curriculum) and its implications (e.g., go to a workshop, read documentation, get trained, spend some time exploring the different possibilities of the robot). We gave them a short description of how robots can be used in interventions for people with autism (e.g., giving instruction) and in which manners they can do it (e.g., as a mediator). We also provided them with some pictures of the leading specialised robots used in these interventions to ensure that the mention of a robot in this sector evoked the same kind of images for all participants (Leka, Pepper, Buddy, Nao, QTrobot, Kaspar, and Milo). This was followed by questions about professionals' intentions, attitudes, and related behavioural beliefs, perceived control and related beliefs, subjective norms and related beliefs, perceived morality, and perceived emotions felt regarding the use of a robot with a person with autism. Given that robots are still an innovative and not very accessible product, we specified this behaviour as being that of using a robot in the coming year with their clients if a loan or acquisition opportunity arose. We thus assessed all our variables by specifying beforehand and throughout the questionnaire this specific context. At the end of the procedure, they were invited to provide their contact information to be contacted for a field test study, if they wished so to participate (these data are beyond the scope of the present work and will be reported elsewhere).

Note that following Fishbein and Ajzen's guidelines [18] and Dean's recommendation [56], an initial elicitation study (N = 34) was conducted online a few months before the data collection with a different but similar sample. This prior study was essential to identify the salient beliefs underlying the TPB predictors of our targeted population's intention (i.e., attitude, perceived norms, and perceived behavioural control) as well as the emotions felt by this population regarding the behaviour investigated (the use of robots with clients with autism). This procedure allowed us to develop the TPB measures used in this study, mentioned above and described in Section 2.3.2. According to the authors' guidelines [18], we thus collected information about professionals' beliefs regarding the perceived advantages and disadvantages of using robots in their work with a person with autism. We also collected information regarding the important people who would approve or disapprove of such use of robots or who would use it themselves or not (subjective norms), as well as information regarding the perceived barriers and facilitators of such use (perceived behavioural control) [18, 57]. Finally, we used one other open-ended question to specifically raise and identify behaviour-related emotions felts as it has been successfully done by Dean et al. [56] regarding the idea of using a robot [18, 56, 57]. For all the open-ended questions, two researchers then extracted semantic units with a total proportion of agreement equal to .90. This extraction allowed us to identify the most salient beliefs and emotions felt by the professionals that were used to develop some of the measures described below. In this pilot study, the definition of the behaviour was the same, and equivalent precautions were taken to ensure that participants had a similar description of robot use in mind (i.e., robot photos, description of use cases, examples of associated behaviours).

2.3.2 Measures. The main questionnaire was therefore developed following Azjen and Fishebein's guidelines [18]. The scales to measure the constructs we added to the model were self-developed according to the literature [56, 58, 59, 67]. The belief composites of each belief-based measure (behavioural beliefs, normative and descriptive beliefs, and control beliefs) were obtained according to an expectancy-value model, in which the score for the likelihood of an outcome is multiplied by the score of its importance [18, 57]. For all other variables, each total score was averaged (intention, attitude, subjective norms, perceived control, professional' self-efficacy, and moral norms). Before proceeding in this way, we reversed the scores of the negatively worded items. For all the scales, the total score and its Cronbach alpha were calculated after factor analysis (see Table 3, in Section 3.3).

The demographic and control variables (background variables) included gender, age, education, years of experience working with people with autism, job title, and client's age. We also asked about participants' previous experience with technology (in general or with a robot for autism) and familiarity with robotic technology used in autism (see Table 1). Thus, we used two items to ask the professionals how often during the previous year and in their work with their clients (1) they used a technology or (2) they used a robot such as Nao, QTrobot, Kaspar, Milo, Leka. Those items were rated on a five-point scale (never = 1, rarely = 2, sometimes = 3, often = 4 and almost always = 5). Then, only after giving them the description of robot use in autism (see Section 2.3.1), we also asked them if they felt familiar with this type of robot. They could answer (1) 'No, I've never heard of this type of robot being developed for the autism sector before today', (2) 'I don't really understand what these robots developed for the autism sector are, but I had already heard about them', or (3), 'Yes, I know what these robots developed for the autism sector are'.

The intention to use a robot as a tool with a client with autism was assessed using the statement 'If you were given the financial opportunity to access this robot (loan or special budget) in the coming year...' followed by five items (1) 'I would be determined to try this type of robot', (2) 'I could incorporate this robot into my practice', (3) 'I would plan a time period for further information or training', (4) 'I would discuss its possible implementation with my superiors and colleagues', and (5) 'I would approach people offering me such an opportunity to gain access to the robot'. Participants had to answer using a five-point scale (1 = Strongly disagree, 2 = Somewhat disagree, 3 = Neither agree nor disagree, 4 = Somewhat agree, and 5 = Strongly agree). Participants' intentions were measured just after having given them a list of potential behaviours that could be implied using such a robot in their clinical practice (e.g., taking part in a workshop or visiting blogs and sharing with other professionals).

The *attitude* was measured using the statement 'For me, using a robot in my interactions with this person with autism over the next year would be ...' followed by six items (pleasant, tiring, exciting, strange, disturbing, and necessary). Participants answered on a five-point scale (1 = Not at all, 2 = Somewhat no, 3 = Neither yes nor no, 4 = Somewhat yes, and 5 = Yes, absolutely). The scores of negatively worded items were reversed before the overall average was calculated.

Attitudes to related behavioural beliefs were assessed by presenting a list of 22 potential beliefs about the outcomes of using a robot for autism care and education (e.g., 'The robot could make me less useful' or 'The robot would be reassuring for this person with autism because it would function a bit like her.'). Those beliefs were identified through the pilot study. First, participants had to rate the likelihood that using a robot for education and care would produce each outcome on a five-point scale (1 = Not at all, 2 = Somewhat no, 3 = Neither yes nor no, 4 = Somewhat yes, and 5 = Yes, absolutely). This list started with a statement: 'If I were to use a robot of this type in my interactions with this person with autism over the next year, I think the following things would occur...'. Then, they had to rate the importance of each outcome using the same five-point scale (1 = Not at all, 2 = Somewhat no, 3 = Neither yes nor no, 4 = Somewhat yes, and 5 = Yes, absolutely). This other list started with a statement: 'In my work, for me, the following things are important or not important ...'.

For the subjective norms, three items assessed injunctive norms: (1) 'The people who are important to me in my work would find it good if I tried or adopted the use of this type of robot in my work', (2) 'The authorities to whom I report would expect me to use this type of robot in my work', and (3) 'My peers in the same trade might consider it appropriate for me to use this type of robot in my work.'. Two items assessed descriptive norms: (1) 'The people who are important to me in my work could adopt the use of such a robot.', and (2) 'My peers in the same trade could adopt the use of such a robot.'. Subjective norms items were preceded by the statement 'In general, if an opportunity arose ...'. Participants rated the items on a five-point scale (1 = Not at all, 2 = Somewhat no, 3 = Neither yes nor no, 4 = Somewhat yes, and 5 = Yes, absolutely).

The normative beliefs were assessed by asking the participants to indicate to which extent they thought significant people (managers, colleagues, peers, partners, institutions, professional or client' friends & family, or authorities—these potentially important people had been previously identified thanks to the pilot study) would expect them to adopt a robot for autism care and education and whether they were motivated to comply with these expectations. Then, for the descriptive beliefs, participants were asked whether they thought these same significant people would adopt these behaviours next year and whether they considered these significant people to be behavioural role models. All items were rated on a five-point scale (1 = Not at all, 2 = Somewhat no, 3 = Neither yes nor no, 4 = Somewhat yes, and 5 = Yes, absolutely).

The perceived behavioural control was measured with three items: (1) 'Financially, it seems possible to incorporate the use of such a robot into our budget', (2) 'Even if I had the opportunity, it would take a lot of effort and organisation to use this robot in the coming year', and (3) 'If I had the opportunity, I would feel capable of using such a robot in the coming year', using the five-point scale (1 = Not at all, 2 = Somewhat no, 3 = Neither yes nor no, 4 = Somewhat yes, and 5 = Yes, absolutely).

The related control beliefs were assessed by presenting a list of 13 potential beliefs about control factors of using a robot for autism care and education (e.g., 'If I were to use such a robot over the next year in my interactions with people with autism, I think I would receive training in its use' or 'A robot would offer the possibility of personalising content and physical parameters.'). Participants rated the occurrence likelihood of each factor using similar statements for behavioural beliefs and its perceived facilitating value. Items were rated on a five-point scale (1 = Not at all, 2 = Somewhat no, 3 = Neither yes nor no, 4 = Somewhat yes, and 5 = Yes, absolutely).

The emotional items were developed like the traditional predictor items (e.g., attitude). Salient emotional beliefs extracted from the pilot study were assessed using the statement 'At the idea of possibly using a robot like that, I feel ...' followed by ten items, five positive elicited emotions (interested, confident, in harmony, indifferent, enthusiastic, and helped/supported) and five negative elicited emotions (suspicious, uncomfortable, shocked, distraught/frustrated, and indifferent). Participants rated the items on a five-point scale (1 = Not at all, 2 = Somewhat no, 3 = Neither yes nor no, 4 = Somewhat yes, and 5 = Yes, absolutely).

The moral norms were measured using the statement, 'How much do you agree with the following statements about using such a robot with any of the persons with autism with whom you work? In the coming year...' followed by eight items: (1) 'I would have the impression of doing something morally correct.', (2) 'I would demonstrate responsibility in my duties.', (3) 'I would show respect towards these people.', (4) 'I would act with my professional duty', (5) 'I believe I would feel a moral obligation to use it', (6) 'I would fulfil my moral duty towards these people', (7) 'I would feel I was doing something necessary', and (8) 'I think that, given the limited resources available to us to help these people, we feel a duty to try the alternatives open to us, such as the use of such a robot.'. The items were designed to appraise the positive self-evaluation stemming from the expected adherence to one's moral principles [50]. Participants answered using a five-point scale (1 = Strongly disagree, 2 = Somewhat disagree, 3 = Neither agree nor disagree, 4 = Somewhat agree, and 5 = Strongly agree).

Professional self-efficacy was assessed using a self-report test including eighteen items that were developed by us for this study. Items were designed to measure professionals' perceptions of their capability to carry out care or education tasks with people with autism. The items were inspired and adapted from existing self-efficacy scales specific to teaching, special education context, or autism [58, 59]. Items were developed following the six dimensions of teaching self-efficacy highlighted by Skaalvik and Skaalvik [60] but adapted for the professionals (instruction, adaptation of education/care (or care) to person's needs, motivating person, keeping discipline, cooperation with colleagues and families and coping with changes and challenges). Participants answered using a five-point scale (1 = Strongly disagree, 2 = Somewhat disagree, 3 = Neither agree nor disagree, 4 = Somewhat agree, and 5 = Strongly agree).

3 Results

3.1 Analysis

Structural Equation Modelling (SEM) analysis is a second-generation multivariate statistical technique. Using simultaneous regression equations, the SEM technique allows to study a set of

Table 2. Correlations between Expected Latent Variables

Construct	1	2	3	4	5	6	7
1. Intention	-	0.71	0.67	0.54	0.65	0.74	0.02
2. Attitude		-	0.61	0.60	0.69	0.85	0.05
3. Subjective norms			-	0.57	0.57	0.63	0.05
4. Perceived behavioural control				-	0.57	0.62	0.09
5. Moral norms					-	0.68	0.01
6. Emotions felt						-	0.07
7. Professionals' self-efficacy							-

unidirectional or bi-directional relationships between latent dependent (not directly observed) and independent variables [61]. Thus, we used it to analyse the data from our questionnaire, as it seems adequate to answer all our study's aims. We conducted the descriptive analysis using SPSS Statistics 28 and R 4.3.2, and the main analysis using Mplus 8.0 [62].

Since we included new predictors in the TPB, we first did an Exploratory Factor Analysis (EFA), as recommended in the literature [63] before conducted a Confirmatory Factor Analysis (CFA), on our main questionnaire. In addition to sufficient sample size ($N > 200$), the assumptions of factor analysis and SEM include multivariate normality and linearity. Therefore, we conducted several analyses to evaluate the psychometric properties of the different scales. We observed histograms and examined skewness and kurtosis. This first examination pointed to a lack of normality in our distributions. An additional examination of correlations (see Table 2) between latent constructs (intention, attitude, subjective norms, perceived behavioural control, moral norms, felt emotions, professionals' self-efficacy) revealed that attitude and positive emotions shared a high correlation coefficient ($r = 0.85$, $p < 0.001$). This would be an indicator of redundancy between both constructs [64]. Moreover, professionals' self-efficacy was not found to be correlated with any of the latent variables measured. Also, when looking at the point clouds between self-efficacy and each of the other variables in the presumed model, no pattern emerged. Therefore, there was no association between self-efficacy and the outcome variables. Finally, box plots indicated no unexplained univariate outliers. Note that for our analysis, all significance levels were fixed at $p < 0.05$.

Therefore, in light of this first exploration, we decided to conduct our EFA analyses using the Unweighted Least Squares (ULS) method and oblique rotation (promax) [65]. We then worked with maximum likelihood estimations with robust standard errors for our CFA and the SEM analyses (Maximum Likelihood with Robust standard errors; MLR) as it is more robust with the non-normal distribution of scores [66]. Given our lack of observed normality and the known oversensitivity of the chi-square to minor deviations from normality and minor model misspecifications, we also decided to consider the comparative fit index (CFI), the Tucker–Lewis index (TLI), and the RMSEA. According to the recommendations, RMSEA should not exceed 0.07. Furthermore, a CFI value exceeding 0.90 is necessary to discard poorly specified models, while a CFI value of 0.95 or higher suggests a good model fit (Hu and Bentler, 1999). Likewise, the TLI must reach a minimum of 0.90 for a model to be deemed acceptable (Hox and Bechger, 1998), while a TLI of 0.95 or greater signifies an excellent fit of the model (Hu and Bentler, 1999). Finally, as relying on global model fit only is not encouraged (e.g., Niemand and Mai, 2018), we also looked at our local model fit (e.g., Cronbach alpha, factor loading, the residual correlation matrix, modification indices) before accepting any models.

3.2 EFA

The Kaiser–Meyer–Olkin (KMO) indicated the adequation of our data for a factor analysis, KMO = 0.937. Bartlett's test of sphericity χ^2 (1,485) = 17,977.34, $p < 0.00$, confirmed the suitability of the

Table 3. Descriptive Statistics of the Final Scales

Construct	Nb. of Items	α	n	Mean	SD	Factor loading Range
1. Intention	5	0.95	327	3.68	1.07	0.81–0.93
2. Attitude	4	0.85	326	3.34	1.04	0.56–0.89
3. Subjective norms	4	0.90	320	3.20	0.94	0.79–0.88
4. Moral norms	4	0.92	327	3.56	1.09	0.75–0.91
5. Professionals' self-efficacy	14	0.93	447	3.99	0.59	0.61–0.77

correlation structure. Therefore, we ran a multiple-factor retention method to determine the number of factors explaining the correlation between our variables (ULS method and promax rotation). There was no obvious convergence between the methods. However, a partial consensus emerged around 4 to 6 factors (for the Kaiser–Guttman criterion and Parallel analysis). Driven by our hypotheses suggesting 7 factors and given that it would be preferable to keep one or two additional factors rather than extracting too few factors [69], we decided to explore the factorial structure of our extended TPB model by running a 6-factors model. The Chi-square test for this first 6-factors model yielded a value of χ^2 (1,170) = 2,362.37, with a p-value < 0.001, indicating a statistically significant discrepancy between the estimated model and the observed data. However, the RMSEA was 0.048, and the **Root Mean Square Residual (RMSR)** was 0.033. These initial results suggested that the proposed model could provide a satisfactory representation of the underlying structure of the analysed data. The exploration of the provided factor loadings (see Appendix A) indicated the factor's singularity independence of professional self-efficacy, morality, and subjective norms. The exploration also highlighted two sub-scales of attitude and emotions relative to their positive or negative polarity (reversed items). It also pointed out a redundancy of these two sub-scales of measurements between them (positive attitudes with positive emotions and negative attitudes with negative emotions). The sub-scale of positive attitudes and the sub-scale of positive emotions also shared high loadings with the intention factor. Moreover, the items intended to measure perceived control failed to represent a unique factor. Considering this initial analysis, we have decided to remove the items related to perceived control. Furthermore, following the principle of parsimony, we have chosen to retain only the attitudinal scale to remain faithful to the TPB. Finally, after having checked for the meaning of the items, we also excluded items from moral norms scale that did not load with the expected factors. This new and retained 5-factors model (including only intentions, attitudes, subjective norms, professionals' self-efficacy, and moral norms) still showed satisfactory fit indices (χ^2 (661) = 1,179.235, $p < 0.001$; RMSEA = 0.05; RMSR = 0.03). It also brought more clarity to the structure of the scale (see Appendix B).

3.3 CFA

Our first CFA on the previous 5 five-factors, model defined during our EFA analysis showed unsatisfactory fit indices (CFI = 0.91; TLI = 0.91; RMSEA = 0.04; **Akaike information criterion (AIC)** = 30947.017). Therefore, except for the behavioural attitudinal scale, we eliminated all items with factor loadings smaller than 0.6 (see Appendix C). For the attitudinal scale, we eliminated only the item below .5 (0.32) to maintain conceptual consistency within the measure. Then, we recalculated the factor loadings. The new model showed better and satisfactory fit indices (CFI = 0.94; TLI = 0.93; RMSEA = 0.04; AIC = 25,342.99). Table 3 presents the final scales' characteristics, including Cronbach's alpha (α) for each construct and the factor loadings range of the retained items.

3.4 Model's Examination

Here, we used SEM to test the suitability of the extended TPB to explain professionals' intention to use robots in the autism field. We compared the original TPB model (Model 1, see Figure 1) to our extended model (Model 2) in which we wanted to add professionals' self-efficacy, moral norms, and emotions as additional predictors of intention to the original model. However, because the manifest analysis pointed out that there exists no relationship (either linear or non-linear) between self-efficacy and the outcome variables, we decided not to include it within the SEM analysis. Also, given the conceptual similarity of emotions with attitude, indicated by a high correlation between the two constructs and confirmed during the EFA with factors loading superposition, and in favour of parsimony of constructs [64], we decided to discard emotions from Model 2. Thus, this alternative model retained included only the additional moral predictor.

For the first structural model (Model 1), we applied an SEM for the intention on attitude and perceived norms, themselves predicted by their associated beliefs composites. We have also specified the correlations between the latent variables in the model. This first model showed an acceptable fit to the data (CFI = 0.92; TLI = 0.91; RMSEA = 0.08; AIC = 18,716.84) and accounted for 69.8% of the variance in professionals' intentions. In this model, the effect of subjective norms on intention was moderate ($\beta = 0.35$, $p < 0.001$) and that of attitudes large ($\beta = 0.60$, $p < 0.001$). The effect of beliefs composites on their respective proxies were from moderate to large (β s between 0.34 and 0.83, $p < 0.001$). In an SEM analysis, it is possible to specify correlations between the measurement errors of the variables observed in the model, also known as common measurement errors. Indeed, observed indicators measuring the same latent variable (such as intention towards behaviour) may be subject to common measurement errors due to factors not captured by the model, such as the similarity of measurement items or systematic response biases. Thus, specifying these correlations makes it possible to consider the residual covariance between observed indicators of the same latent variable, thereby improving the precision and reliability of model parameter estimates. We used the index modifications suggested by the Mplus software to guide our item selection. After examining the suggestions, we reviewed our items to identify those who may share some residual variance due to common factors not captured by the model. We retained item 1 ('I will be determined to try this type of robot.') and item 2 ('I will be able to integrate this robot into my practice.') from the intentional scale, as they were conceptually close and clustered on a potential factor during exploratory data analysis (see Appendix C). We also retained the correlation between items 1 and 3 of attitude and the correlation between items 4 and 5 of attitude as they would reflect respectively positive and negative wording items. This specification led to an improvement in model fit (CFI = 0.95; TLI = 0.94; RMSEA = 0.06; AIC = 18,599.34). This specification in Model 1 leads to explain 69.3% of the variance in professionals' intention. The effect of subjective norms on intention was still moderate ($\beta = 0.34$, $p < 0.001$) and that of attitudes large ($\beta = 0.60$, $p < 0.001$). The effect of beliefs composites on their respective proxies was still from moderate to large (β s between 0.34 and 0.66, $p < 0.001$).

For the second structural model (Model 2), we added to the previous analysis moral norms as an additional direct and indirect predictor of intention. We observed that it improved the model as demonstrated by the model fit indices (CFI = 0.97; TLI = 0.96; RMSEA = 0.045; AIC = 21,811.301) and increased slightly the explained variance of intention (70.4%). Here, the effect of subjective norms on intention was moderate again ($\beta = 0.28$, $p < 0.001$), that of attitudes large ($\beta = 0.64$, $p < 0.001$), and there was no effect of moral norms on intention ($\beta = -0.01$, $p = 0.860$). However, we found a strong and significant positive relationship of moral norms on attitudes ($\beta = 1.03$, $p = 0.001$). The effect of beliefs composites on their respective proxies was smaller but significant (β s between 0.33 and 0.51, $p < 0.003$) except for attitudinal beliefs ($\beta = 0.19$, $p = 0.337$). Therefore, we retain the extended model (Model 2) presented in Figure 2.

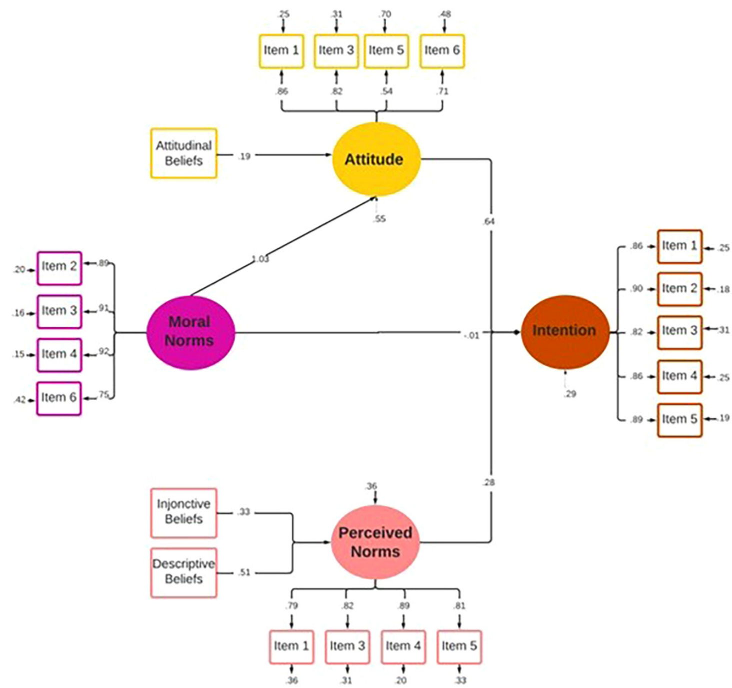

Fig. 2. Extended TPB model (Model 1) applied to the intention to use robots with clients with autism among professionals. Note that to avoid overloading the figure, we did not represent the relations between predictors nor between beliefs composites. Correlations between predictor variables were: .55 between attitude and subjective norms, −.56 between attitude and moral norms, and −.40 between perceived norms and moral norms. Also, correlations between belief composites scores were: .59 between attitudinal beliefs and injunctive beliefs, .58 between attitudinal beliefs and descriptive beliefs, and .75 between injunctive beliefs and descriptive beliefs. All correlations had a $p < .0001$.

Using a **Multiple-Indicator Multiple-Cause (MIMIC)** model [68], we finally controlled Model 2 by introducing simultaneous control variables. In the MIMIC model, one or more observed variables can be included as predictors of one or more latent variables. Here, we considered gender (1 = female, 2 = male), work experience in their job related to autism, previous usage of technology during intervention in the past year with patients with autism, and professional familiarity regarding the use of robots for autism. In past research, all these variables were shown to be linked to either use intention or attitude regarding technology [20, 37, 69, 70]. This model showed a good fit to the data (CFI = 0.96; TLI = 0.95; RMSEA = 0.04; AIC = 20,906.205). We did not find any of these variables to impact the professionals' intentions directly or attitudes.

3.5 Effect of Beliefs

As our results showed that the significant predictors of professional intention were attitudes and perceived norms, we decided to explore the professionals' beliefs (i.e., expectancy-value products) that significantly impacted these predictors. Using MIMIC models again, we found that 47.8% of the variance in professionals' attitudes toward using a robot if an opportunity was given to them was explained by their beliefs related to the perceived advantages and disadvantages of such use. These most significant beliefs are reported in Table 4. The regression model provided a satisfactory fit (CFI = 0.94; TLI = 0.92; RMSEA = 0.04, AIC = 3,261.812).

Table 4. Overview of the Significant Beliefs Explaining Professionals' Attitudes and Perceived Norms

Beliefs related to attitude	β	SE	p
Gender	−0.11	0.06	0.045
Female	−0.22	0.05	0.000
Male	−0.17	0.06	0.003
Not answered	0.28	0.07	0.000
Job experience	0.16	0.07	0.014
1 year or less	0.11	0.05	0.039
1–3 years	0.19	0.05	0.000
3–6 years	0.16	0.06	0.010
Beliefs related to norms			
I think that if they were in my shoes and had the opportunity, my manager would make use of this robot themselves in the next year.	−0.22	0.08	0.007
My relatives (friends & family) think that, given the opportunity, I should use, try out, or adopt a robot with the people with autism I work with over the next year.	0.16	0.07	0.019
I think that if they were in my shoes and had the opportunity, my peers in the same profession would make use of this robot themselves in the next year	0.26	0.08	0.001

Finally, when looking through the perceived norms, we found that descriptive and injunctive normative beliefs explained together only 15% of the variance. The regression model provided a good fit (CFI = 0.96; TLI = 0.94; RMSEA = 0.04; AIC = 3,022.446). The relevant normative beliefs are also available in Table 4.

4 Discussion

Our study proposed three main aims. The first was to verify, for the first time, the suitability of the TPB to explain professionals' intention to use robots in the autism field. The second purpose was to explore to which extent additional factors (emotions, moral norms, and perceived professionals' self-efficacy) contribute to improving the fitness of the original TPB model. Finally, the third aim was to identify the fundamental beliefs held by professionals regarding the use of robots in their work with people with autism, which underlie the different intention predictors that are found significant.

Overall, the study results confirm the utility of using the TPB as a framework to understand and explain professionals' intention to use a robot in the care and education of people with autism. Indeed, our results highlighted the important role of attitude and perceived norms as predictors of professionals' intentions to use a robot in the coming year if given the opportunity. They both explained a large proportion of the variance of professionals' intentions. Our result points to the importance of attitudes as a central construct in predicting intention. Therefore, similar to Kossewska et Kłosowska [16], our results contradict some of the prediction models used in the IT field in which attitudes are ignored [20, 37]. We, therefore, support the importance of attitude as a determinant of intention. Note that we failed to represent perceived control as an independent factor. However, the described context stipulated access to a robot (donation or loan), and therefore may have provided an indirect perceived control regarding price and accessibility. Also, using a robot for autism is still not that common, and our results are based on the limited knowledge regarding the potential of using robots with clients with autism of health and education professionals. Indeed, even if most of the participants used technology at least once during the previous year with their client with autism, they were few to report a good understanding of the use of robots in their area of expertise. Therefore, it would be interesting to replicate these measures after an (ideally prolonged) use of robots for autism. Actual use of this type of solution with a more precise measurement scale. Another limitation was that, although our sample population was diverse and concentrated at the European level, the cultural variable was not controlled. Yet, cultural influence that can interfere with professionals' attitudes and their considerations could have brought some nuance to our results as attitudes towards robots already shown to fluctuate according to culture [71, 72]. However, these preliminary results provide a solid foundation for the direction to be taken in terms of implementation effort and acceptance leverage.

Indeed, in this study, we also wanted to test the relevance of integrating three new predictors to the TPB (professionals' self-efficacy, moral norms, and emotions) in our model in the context of technology adoption in autism practice. Our results failed to demonstrate the value of adding professionals' self-efficacy, moral standards, and emotions as direct predictor of professionals' intentions, but they pointed to the important influence of perceived morality as an indirect factor of intention via attitudes. Indeed, our results showed that as moral considerations increase, there is a corresponding positive increase in positive attitudes towards the subject. The statistical significance of this relationship underscores the robustness of perceived moral norms as a predictor of attitude in our model. These results suggest that ethical and moral values indirectly influence intentions regarding professional practices. Thus, if the use of robots is perceived as morally justified and beneficial for autistic clients, professionals are likely to develop a positive attitude towards the practice, making its adoption and integration into regular practice more likely. Therefore, understanding the impact of perceived morality on attitudes is crucial to facilitating the adoption of innovative and potentially beneficial practices, such as the use of robots in the care of autistic clients. This could help to shape effective behavioural interventions to ensure that these interventions are ethically aligned with the values of the professionals involved. This could involve, for example, clarifying misunderstandings, providing evidence of benefits from research or experiments carried out by themselves, and engaging in open ethical dialogue. Our research findings are therefore consistent with the literature on robot ethics and philosophy by reinforcing the need to consider public moral perceptions and attitudes when developing and implementing robotic technologies (e.g., [73, 74]).

Finally, the foundation of the TPB has proved useful in highlighting the most significant beliefs professionals hold regarding using robots in their work. In this study, attitude had a substantial impact on intention. Examination of the specific attitudinal beliefs that impacted professionals' attitudes pointed to fundamental beliefs. Thus, for example, we can imagine that interventions should be designed to reassure professionals about the support quality, in terms of feedback, responsiveness, and adequacy of responses. Also, the communication should point out the benefits of using such a robot with children (e.g., attention and interest). It should also emphasise the different roles that the robot can take on. Eventually, new projects could also work on designing a robot or robotic applications that can be used in groups. In general, participants stressed the need to have diversified tools and methods. Such communication could foster the emergence of positive attitudes of professionals towards robots. Regarding the role of perceived norms, our findings show that beliefs about 'what others would do', especially management staff and peers, are more frequent than beliefs about what they would think. Thus, professionals may need examples to follow to motivate their intentions to use robots themselves with their autistic clients, especially when it was highlighted that around half had never heard about it, and one-third did not understand the use of robots for autism. A focus on concrete use cases and a generalisation of field trials and studies could be an impetus for the implementation of robots in the domain of care and education of people with autism. Those studies would also tell us whether these solutions in the field live up to their expectations in research about the expected results with autistic clients.

Overall, this study used the TPB framework for the first time to assess professionals' intention to use robots with autistic clients. In comparison to previous models used in the literature [15, 16], the TPB allowed us to better explain the variance of experienced professionals' intentions, in addition to specifying the underlying beliefs of its determinants. In this case, the TPB may be more appropriate to measure the intention regarding a tool unknown to the general public. Indeed, an important limitation of the present study is the almost total absence of such devices in the field. Thus, although we gave a standard description of the use and appearance of such robots before the data collection, participants had no opportunity to interact with real robots. All their perceptions and intentions were based on participants' conceptualisation skills and imagination. Results could therefore differ after real-world use. Future research could attempt to test whether this theory is still adequate in the 'real world', to what extent the highlighted determinants of intentions and associated beliefs would be similar to a real interaction with robots, and to what extent they would predict the actual use and the maintenance of professionals' intention.

5 Conclusions

To conclude, our results are encouraging toward the use of the methods of the TPB to determine the intention to use robots in autism. Our results provide essential information about the main determinants of professionals' intention to use a robot with their autistic clients, the beliefs associated with it, and how these can be exploited to better implement its promising solutions. Our results also point to further research needed to better define the limits of the use of the TPB model in the implementation of robots for autism.

References

[1] American Psychiatric Association. (2013). *Diagnostic and Statistical Manual of Mental Disorders* (5th ed.). American Psychiatric Association. Retrieved April 4, 2024 from https://www.hakjisa.co.kr/common_file/bbs_DSM-5_Update_October2018_NewMaster.pdf

[2] M. Elsabbagh, G. Divan, Y. J. Koh, Y. S. Kim, S. Kauchali, C. Marcín, C. Montiel-Nava, V. Patel, C. S.Paula, C. Wang, et al. (2012). Global prevalence of autism and other pervasive developmental disorders. *Autism Research* 5, 3 (2012), 160–179. DOI: https://doi.org/10.1002/aur.239

[3] E. Simonoff, A. Pickles, T. Charman, S. Chandler, T. Loucas, and G. Baird. (2008). Psychiatric disorders in children with autism spectrum disorders: Prevalence, comorbidity, and associated factors in a population-derived sample. *Journal of the American Academy of Child & Adolescent Psychiatry* 47, 8 (2008), 921–929. DOI: https://doi.org/10.1097/CHI.0b013e318179964f

[4] A. Gustavsson, M. Svensson, F. Jacobi, C. Allgulander, J. Alonso, E. Beghi, R. Dodel, M. Ekman, C. Faravelli, L. Fratiglioni, et al. (2011). Cost of disorders of the brain in Europe 2010. *European Neuropsychopharmacology* 21, 10 (2011), 718–779. https://doi.org/10.1016/j.euroneuro.2011.08.008

[5] A. P. Costa, L. Charpiot, F. R. Lera, P. Ziafati, A. Nazarikhorram, L. Van Der Torre, and G. Steffgen. (2018). More attention and less repetitive and stereotyped behaviors using a robot with children with autism. In *Proceedings of the 27th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*. IEEE, 534–539. DOI: https://doi.org/10.1109/ROMAN.2018.8525747

[6] D. J. Ricks and M. B. Colton. (2010). Trends and considerations in robot-assisted autism therapy. In *Proceedings of the IEEE International Conference on Robotics and Automation*. IEEE, 4354–4359. https://doi.org/10.1109/ROBOT.2010.5509327

[7] G. Bird, J. Leighton, C. Press, and C. Heyes. (2007). Intact automatic imitation of human and robot actions in autism spectrum disorders. *Proceedings: Biological Sciences* 274, 1628 (2007), 3027–3031. DOI: https://doi.org/10.1098/rspb.2007.1019

[8] J. Wainer, E. Ferrari, K. Dautenhahn, and B. Robins. (2010). The effectiveness of using a robotics class to foster collaboration among groups of children with autism in an exploratory study. *Personal and Ubiquitous Computing* 14, 5 (2010), 445–455. DOI: https://doi.org/10.1007/s00779-009-0266-z

[9] B. Robins, P. Dickerson, P. Stribling, and K. Dautenhahn. (2004). Robot-mediated joint attention in children with autism: A case study in robot-human interaction. *Interaction Studies* 5, 2 (2004), 161–198. DOI: https://doi.org/10.1075/is.5.2.02rob

[10] A. R. Taheri, M. Alemi, A. Meghdari, H. R. PourEtemad, and N. M. Basiri. (2014). Social robots as assistants for autism therapy in Iran: Research in progress. In *Proceedings of the 2nd RSI/ISM International Conference on Robotics and Mechatronics (ICRoM)* 760–766. DOI: https://doi.org/10.1109/ICRoM.2014.6990995

[11] B. Robins, K. Dautenhahn, R. Te Boekhorst, and A. Billard. (2005). Robotic assistants in therapy and education of children with autism: Can a small humanoid robot help encourage social interaction skills? *Universal Access in the Information Society* 4, 2 (2005), 105–120. DOI: https://doi.org/10.1007/s10209-005-0116-3

[12] C. A. Huijnen, M. A. Lexis, and L. P. de Witte. (2016). Matching robot KASPAR to autism spectrum disorder (ASD) therapy and educational goals. *International Journal of Social Robotics* 8, 4 (2016), 445–455. DOI: https://doi.org/10.1007/s12369-016-0369-4

[13] C. A. Huijnen, M. A. Lexis, R. Jansens, and L. P. de Witte. (2019). Roles, strengths, and challenges of using robots in interventions for children with autism spectrum disorder (ASD).*Journal of Autism and Developmental Disorders* 49, 1 (2019), 11–21. DOI: https://doi.org/10.1007/s10803-018-3683-x

[14] I. Zubrycki and G. Granosik. (2016). Understanding therapists' needs and attitudes towards robotic support: The Roboterapia project. *International Journal of Social Robotics* 8, 4 (2016), 553–563. DOI: https://doi.org/10.1007/s12369-016-0372-9

[15] D. Conti, S. Di Nuovo, S. Buono, and A. Di Nuovo. (2017). Robots in education and care of children with developmental disabilities: A study on acceptance by experienced and future professionals. *International Journal of Social Robotics* 9, 1 (2017), 51–62. DOI: https://doi.org/10.1007/s12369-016-0359-6

[16] J. Kossewska and J. Kosowska. (2020). Acceptance of robot-mediated teaching and therapy for children with atypical development by polish professionals. *Journal of Policy and Practice in Intellectual Disabilities* 17, 1 (2020), 21–30. DOI: https://doi.org/10.1111/jppi.12296

[17] I. Ajzen. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes* 50, 2 (1991), 179–211. DOI: https://doi.org/10.1016/0749-5978(91)90020-T

[18] M. Fishbein and I Ajzen. (2011). *Predicting and Changing Behavior: The Reasoned Action Approach.* Psychology Press. DOI: https://doi.org/10.4324/9780203838020.

[19] A. Schwarzand and W. Chin. (2007). Looking forward: Toward an understanding of the nature and definition of IT acceptance. *Journal of the Association for Information Systems* 8, 4 (2007), 230–243. Retrieved April 4, 2024 from https://uh-ir.tdl.org/server/api/core/bitstreams/cac3ea89-e0a9-4a9d-b961-1b2c192e5dab/content

[20] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly* 27, 3 (2003) 425–478. DOI: https://doi.org/10.2307/30036540

[21] G. Godin and G Kok. (1996). The theory of planned behavior: A review of its applications to health-related behaviors. *American Journal of Health Promotion* 11, 2 (1996), 87–98. DOI: https://doi.org/10.4278/0890-1171-11.2.87

[22] C. J. Armitage and M. Conner. (2001). Efficacy of the theory of planned behaviour: A meta-analytic review. *British Journal of Social Psychology* 40, 4 (2001), 471–499. DOI: https://doi.org/10.1348/014466601164939

[23] I. Ajzen. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies* 2, 4 (2020), 314–324. DOI: https://doi.org/10.1002/hbe2.195

[24] T. Teo and C. Beng Lee. (2010). Explaining the intention to use technology among student teachers: An application of the Theory of Planned Behavior (TPB). *Campus-Wide Information Systems* 27, 2 (2010), 60–67. DOI: https://doi.org/10.1108/10650741011033035

[25] J. Lee, F. A. Cerreto, and J Lee. (2010). Theory of planned behavior and teachers' decisions regarding use of educational technology. *Journal of Educational Technology & Society* 13, 1 (2010), 152–164. Retrieved April 4, 2024 from https://www.jstor.org/stable/jeductechsoci.13.1.152.

[26] J. Fishman, R. Beidas, E. Reisinger, and D. S. Mandell. (2018). The utility of measuring intentions to use best practices: A longitudinal study among teachers supporting students with autism. *Journal of School Health* 88, 5 (2018), 388–395. DOI: https://doi.org/10.1111/josh.12618

[27] B. Ingersoll, D. Straiton, K. Casagrande, and K. Pickard. (2018). Community providers' intentions to use a parent-mediated intervention for children with ASD following training: An application of the theory of planned behavior. *BMC Research Notes* 11, 1 (2018), 1–6. DOI: https://doi.org/10.1186/s13104-018-3879-3

[28] A. Bandura. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review* 84, 2 (1977), 191. DOI: https://doi.org/10.1037/0033-295X.84.2.191

[29] J. J. Diehl, L. M. Schmitt, M. Villano, and C. R. Crowell. (2012). The clinical use of robots for individuals with Autism Spectrum Disorders: A critical review. *Research in Autism Spectrum Disorders* 6, 1 (2012), 249–262. DOI: https://doi.org/10.1016/j.rasd.2011.05.006

[30] B. Robins, K. Dautenhahn, and P. Dickerson. (2009). From isolation to communication: A case study evaluation of robot assisted play for children with autism with a minimally expressive humanoid robot. *Advances in Computer-Human Interactions* 2009 (2009), 205–211. DOI: https://doi.org/10.1109/ACHI.2009.32

[31] E. Shih, and H. J. Schau. (2011). To justify or not to justify: The role of anticipated regret on consumers' decisions to upgrade technological innovations. *Journal of Retailing* 87, 2 (2011), 242–251. DOI: https://doi.org/10.1016/j.jretai.2011.01.006

[32] R. Q. Stafford, E. Broadbent, C. Jayawardena, U. Unger, I. H. Kuo, A. Igic, R. Wong, N. M. Kerse, C. I. Watson, and B. A. MacDonald. (2010). Improved robot attitudes and emotions at a retirement home after meeting a robot. In *Proceedings of the International Symposium in Robot and Human Interactive Communication*. IEEE, 82–87. DOI: https://doi.org/10.1109/ROMAN.2010.5598679

[33] M. M. De Graaf, and S. B. Allouch. (2013). Exploring influencing variables for the acceptance of social robots. *Robotics and Autonomous Systems* 61, 12 (2013), 1476–1486. DOI: https://doi.org/10.1016/j.robot.2013.07.007

[34] A. Rivis, P. Sheeran, and C. J. Armitage. (2009). Expanding the affective and normative components of the theory of planned behavior: A meta-analysis of anticipated affect and moral norms. *Journal of Applied Social Psychology* 39, 12 (2009), 2985–3019. DOI: https://doi.org/10.1111/j.1559-1816.2009.00558.x

[35] R. M. Allinder. (1994). The relationship between efficacy and the instructional practices of special education teachers and consultants. *Teacher Education and Special Education* 17, 2 (1994), 86–95. DOI: https://doi.org/10.1177/088840649401700203

[36] G. Sang, M. Valcke, J. Van Braak, and J. Tondeur. (2010). Student teachers' thinking processes and ICT integration: Predictors of prospective teaching behaviors with educational technology. *Computers & Education* 54, 1 (2010), 103–112. DOI: https://doi.org/10.1016/j.compedu.2009.07.010

[37] R. A. Vannatta, and F. Nancy. (2004). Teacher dispositions as predictors of classroom technology use. *Journal of Research on Technology in Education* 36, 3 (2004), 253–271. Retrieved April 4, 2024 from https://researchspace.auckland.ac.nz/bitstream/handle/2292/45028/whole.pdf?sequence=2

[38] N. Schwarz and G. L. Clore. (1983). Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states. *Journal of Personality and Social Psychology* 45, 3 (1983), 513. DOI: https://doi.org/10.1037/0022-3514.45.3.513

[39] R. P. Bagozzi. (1989). An investigation of the role of affect and moral evaluations in the purposive behaviour model of attitude. *British Journal of Social Psychology* 25 (1989), 95–107. DOI: https://doi.org/10.1111/j.2044-8309.1989.tb00851.x

[40] I. Ajzen and B. L. Driver. (1991). Prediction of leisure participation from behavioral, normative, and control beliefs: An application of the Theory of Planned Behavior. *Leisure Sciences* 13 (1991), 185–204. DOI: https://doi.org/10.1080/01490409109513137

[41] M. L. Richins. (1997). Measuring emotions in the consumption experience. *Journal of Consumer Research* 24, 2 (1997), 127–146. DOI: https://doi.org/10.1086/209499

[42] R. P. Bagozzi and K. H Lee. (1999). Consumer resistance to, and acceptance of, innovations. *Advances in Consumer Research* 26, 1 (1999). Retrieved April 4, 20242 from https://openurl.ebsco.com/EPDB%3Agcd%3A10%3A6972938/detailv2?sid=ebsco%3Aplink%3Ascholar{&}id=ebsco%3Agcd%3A83144281{&}crl=c

[43] E. Shih and H. J. Schau. (2011). To justify or not to justify: The role of anticipated regret on consumers' decisions to upgrade technological innovations. *Journal of Retailing* 87, 2 (2011), 242–251. DOI: https://doi.org/10.1016/j.jretai.2011.01.006

[44] C. P. Kirk, S. D. Swain, and J. E. Gaskin. (2015). I'm proud of it: Consumer technology appropriation and psychological ownership. *Journal of Marketing Theory and Practice* 23, 2 (2015), 166–184. DOI: https://doi.org/10.1080/10696679.2015.1002335.

[45] L. Watson and M. T. Spence. (2007). Causes and consequences of emotions on consumer behaviour: A review and integrative cognitive appraisal theory. *European Journal of Marketing* 41, 5/6 (2007), 487–511. DOI: https://doi.org/10.1108/03090560710737570

[46] A. A. Anderson. (1996). Predictors of computer anxiety and performance in information systems. *Computers in Human Behavior* 12, 1 (1996), 61–77. Retrieved April 4, 2024 from https://eric.ed.gov/?id=EJ518424

[47] J. W. Kotrlik and D. H. Redmann. (2009). Technology adoption for use in instruction by secondary technology education teachers. *Journal of Technology Education* 21, 1 (2009), 44–59. Retrieved April 4, 2024 https://scholar.lib.vt.edu/ejournals/JTE/v21n1/pdf/kotrlik.pdf.

[48] M. Heerink, B. Kröse, V. Evers, and B. Wielinga. (2010). Assessing acceptance of assistive social agent technology by older adults: The Almere model. *International Journal of Social Robotics* 2, 4 (2010), 361–375. DOI: https://doi.org/10.1007/s12369-010-0068-5.

[49] M. Heerink, B. Kröse, V. Evers, and B. Wielinga. (2010). Relating conversational expressiveness to social presence and acceptance of an assistive social robot. *Virtual Reality* 14 (2010), 77–84. DOI: https://doi.org/10.1007/s10055-009-0142-1

[50] S. H. Schwartz and J. A Howard. (1981). A normative decision-making model of altruism. In *Altruism and Helping Behavior: Social, Personality, and Developmental Perspectives*. P. J. Rushton and R. M. Sorrentino (Eds.), Lawrence Erlbaum, Hillsdale, 91.

[51] A. Rivis, P. Sheeran, and C. J. Armitage. (2009). Expanding the affective and normative components of the theory of planned behavior: A meta-analysis of anticipated affect and moral norms. *Journal of Applied Social Psychology* 39, 12 (2009), 2985–3019. DOI: https://doi.org/10.1111/j.1559-1816.2009.00558.x
[52] S. Vallor. (2020). Carebots and caregivers: Sustaining the ethical ideal of care in the twenty-first century. In *Machine Ethics and Robot Ethics*. Routledge, 137–154. DOI: http://doi.org/10.1007/s13347-011-0015-x.
[53] M. H. Dembo, and S. Gibson. (1985). Teachers' sense of efficacy: An important factor in school improvement. *The Elementary School Journal* 86, 2 (1985), 173–184. DOI: https://doi.org/10.1086/461441
[54] G. Sang, M. Valcke, J. Van Braak, and J. Tondeur. (2010). Student teachers' thinking processes and ICT integration: Predictors of prospective teaching behaviors with educational technology. *Computers & Education* 54, 1 (2010), 103–112. DOI: https://doi.org/10.1016/j.compedu.2009.07.010
[55] R. M. Allinder. (1995). An examination of the relationship between teacher efficacy and curriculum-based measurement and student achievement. *Remedial and Special Education* 16, 4 (1995), 247–254. DOI: https://doi.org/10.1177/074193259501600408
[56] M. Dean, A. Arvola, M. Vassallo, L. Lähteenmäki, M. M. Raats, A. Saba, and R. Shepherd. (2006). Comparison of elicitation methods for moral and affective beliefs in the theory of planned behaviour. *Appetite* 47, 2 (2006), 244–252. DOI: https://doi.org/10.1016/j.appet.2006.04.005
[57] J. Francis, M. P. Eccles, M. Johnston, A. E. Walker, J. M. Grimshaw, R. Foy, E. F. S. Kaner, L. Smith, and Bonetti. (2004). *Constructing Questionnaires Based on the Theory of Planned Behaviour: A Manual for Health Services Researchers*. Centre for Health Services Research. Retrieved April 4, 2024 from https://openaccess.city.ac.uk/id/eprint/1735/1/
[58] A. M. Love, M. D. Toland, E. L. Usher, J. M. Campbell, and A. D. Spriggs. (2019). Can I teach students with autism spectrum disorder?: Investigating teacher self-efficacy with an emerging population of students. *Research in Developmental Disabilities* 89 (2019), 41–50. DOI: https://doi.org/10.1016/j.ridd.2019.02.005
[59] L. A. Ruble, M. D. Toland, J. L. Birdwhistell, J. H. McGrew, and E. L. Usher. (2013). Preliminary study of the autism self-efficacy scale for teachers (ASSET). *Research in Autism Spectrum Disorders* 7, 9 (2013), 1151–1159. DOI: https://doi.org/10.1016/j.rasd.2013.06.006
[60] E. M. Skaalvik, and S. Skaalvik. (2007). Dimensions of teacher self-efficacy and relations with strain factors, perceived collective teacher efficacy, and teacher burnout. *Journal of Educational Psychology* 99, 3 (2007), 611. DOI: https://doi.org/10.1037/0022-0663.99.3.611
[61] L. Klem. (2000). Structural equation modelling. In *Reading and Understanding More Multivariate Statistics*. L. G. Grimm and P. R. Yarnold (Eds.), American Psychological Association, 227–260.
[62] L. K. Muthén and B. O. Muthén. (1998–2010). *Mplus User'S Guide* (6th ed.). Muthén & Muthén, Los Angeles, CA.
[63] S. Vallor. (2020). Carebots and caregivers: Sustaining the ethical ideal of care in the twenty-first century. In *Machine Ethics and Robot Ethics*. Routledge, 137–154.
[64] H. Le, F. L. Schmidt, J. K. Harter, and K. J. Lauver. (2010). The problem of empirical redundancy of constructs in organizational research: An empirical investigation. *Organizational Behavior and Human Decision Processes* 112, 2 (2010), 112–125. DOI: https://doi.org/10.1016/j.obhdp.2010.02.003
[65] Jean-Louis Berger. (2021). *Analyse Factorielle Exploratoire et Analyse en Composantes Principales: Guide Pratique*. hal-03436771v2 Retrieved April 30, 2024 from https://hal.science/hal-03436771/document
[66] J. F. Hair, W. C. Black, B. J. Babin, and R. E Anderson. (2010). *Multivariate Data Analysis*. Prentice Hall, Upper Saddle River, NJ.
[67] R. L. Gorsuch. (1997). Exploratory factor analysis: Its role in item analysis. *Journal of Personality Assessment* 68, 3 (1997), 532–560. DOI: https://doi.org/10.1207/s15327752jpa6803_5
[68] K. G. Jöreskog and A. S. Goldberger. (1975). Estimation of a model with multiple indicators and multiple causes of a single latent variable. *Journal of the American Statistical Association* 70 (1975), 631–639. DOI: https://doi.org/10.2307/2285946
[69] S. Carlson and C. T. Gadio. (2002). Teacher professional development in the use of technology. In *Technologies for Education: Potentials, Parameters, and Prospects*. W.D. Haddad and A. Draxler (Eds.), UNESCO and the Academy for Educational Development, 118–132. Retrieved April 4, 2024 from https://www.researchgate.net/profile/GudmundHernes/publication/44828882_Emerging_trends_in_ICT_and_challenges_to_educational_planning/links/54415fee0cf2a76a3cc7e389/Emerging-trends-in-ICT-and-challenges-to-educational-planning.pdf#page=124
[70] C. K. Blackwell, A. R. Lauricella, and E. Wartella. (2014). Factors influencing digital technology use in early childhood education. *Computers & Education* 77 (2014), 82–90. Retrieved April 4, 2024 from https://cmhd.northwestern.edu/wp-content/uploads/2011/06/Blackwell.Lauricella.Wartella.2014.Factors-influencing-digital-tech-use-in-early-education.pdf
[71] D. Conti, A. Cattani, S. Di Nuovo, and A Di Nuovo. (2019). Are future psychologists willing to accept and use a humanoid robot in their practice? Italian and English students' perspective. *Frontiers in Psychology* 10 (2019), 2138. DOI: https://doi.org/10.3389/fpsyg.2019.02138

[72] C. Bartneck, T. Nomura, T. Kanda, T. Suzuki, and K. Kato. (2005). Cultural differences in attitudes towards robots. In *Proceedings of the AISB Symposium on Robot Companions: Hard Problems and Open Challenges in Human-Robot Interaction*, 1–4. DOI: https://doi.org/10.13140/RG.2.2.22507.34085

[73] S. Vallor. (2016). *Technology and the Virtues: A Philosophical Guide to a Future Worth Wanting*. Oxford University Press.

[74] W. Wallach and C. Allen. (2008). *Moral Machines: Teaching Robots Right from Wrong*. Oxford University Press.

Appendices

Appendix A

Questionnaire items to elicit professionals' beliefs about the use of a robot for the education and care of children with autism.

Behavioural beliefs
1. If you had the opportunity, for which reason you be interested in using a robot? What positive aspects or benefits would you see in using a robot (for you or for children with ASD)? 2. If you had the opportunity, for which reason you not be interested in using a robot? What negative or disadvantages do you see in using a robot (for you or for children with ASD)?
Normative and descriptive beliefs
3. There may be people, or groups of people, around you who, in this context (if you had an opportunity), could encourage you to adopt the use of a robot or to try it out. a. Please list the people or groups who would approve or think that you should use a robot with children with ASD if you had the opportunity. b. Please list the people or groups who would disapprove or think you should not use a robot with children with ASD if you had the opportunity. 4. Sometimes, when we are not sure what to do, we look to see what others will do in the same situation. a. Please list the people or groups who, if given the opportunity, would be most likely to use this type of robot with children with ASD. b. Please list the people or groups who, if given the opportunity, would be least likely to use this type of robot with children with ASD
Control beliefs
5. Please list any factors or circumstances that would make it easier or more convenient for you to use a robot with children with ASD, if you had the opportunity. 6. Please list any factors or circumstances that would make it difficult or impossible for you to use a robot with children with ASD if you had the opportunity.
Emotion felts beliefs
What feelings, affects or emotions do you have about the use of a robot in your work with children with ASD? Describe as much as necessary in simple words or short sentences

Appendix B

Dispersion of Belief Categories among Respondents depending on TPB Constructs (%) and their description (Number of professionals having evoked this category of beliefs out of the total number of individuals having answered each of the questions.)					
	Advantages ($n = 31$)	Inconvenient ($n = 29$)	Facilitators ($n = 30$)	Barriers ($n = 28$)	Description
Product	32.3	41.4	43.3	35.71	Includes topics such as the robustness of the robot, its possible customisation, its design, its interactivity, its reliability (safety & operation), its AI level and anything else directly or indirectly related to the use of its software or hardware.
• Other	32.3	6.9	23.3	17.9	
• Fragility	-	20.7	6.7	14.3	
• Ease of use	-	24.13	20.0	17.9	
Child' well-being	19.4	13.8	-	-	Aggregated the concerns of professional to best meet the needs of their clients and includes topics such as addiction, distraction, sensory stimulation, the pleasure of the child, the reassuring aspect of the robot.
Tools and practices diversification	22.6	10.3	-	-	Focus on the need or not for alternative and complementary practice tools.
Accessibility	19.4	31.0	50.0	35.7	Gathers cost and time for the professional and access to care for the client
• Other	-	24.1	43.3	32.1	
• Cost	-	10.3	6.7	3.6	
• Time	19.4	-	3.3	3.6	
Skill development	41.9	31.0	3.3	7.1	Integrated the potential areas of use of the robot such as learning space, autonomy, relationship to error, social interaction, emotions, motor skills, etc.
User experience	19.4	-	-	-	Gathers themes related to the user experience, for example, the innovative perception of the robot, its novelty effect, or its playfulness.
Interaction quality	38.7	20.7	-	7.1	Emphasises the attractive quality of the robot for the child with ASD and its positive and negative consequences on the interaction between the user and his 'client'. Thus, for example, the robot could be seen as a means to enter into an exchange, to arouse curiosity, to promote or support social interaction.
Use specification	22.3	10.3	10.0	25.0	Includes beliefs about the specifics of use on the one hand about where it would be more appropriate to use a robot (e.g., home, school, medical institute), and on the other hand about the size of the group suitable for such use (individual, small group, large group).
Roles	22.6	10.3	6.7	-	Highlights the specific roles that can be assigned to the robot during interactions. Thus, it could be seen as an assistant, a reinforcer, a pairing object, a mediator, an extinguisher of defiant behaviour by not reacting, or even a friend. It could also be used to recall tasks, or even to cut tasks in series, code information (e.g., movement or scores).
Work Quality	19.4	13.8	6.7	-	Compiled the positive or negative consequences of using a robot on work efficiency (e.g., work progress recording, progress measurements, permanent availability, material management, assistance and support, time-saving and general efficiency complexity of use).
Support	-	-	43.3	42.9	Refers to the various aids to be put in place to use the product and evaluate it (e.g., training, technical support, accompaniment, presence of a local suitable for its use) as well as the support and acceptance of others (from the team, hierarchy, families, etc.).
• Social			13.3	21.4	
• Implementations			36.7	28.6	

Appendix C

Factor loadings[a] for Promax Rotated Six-Factor Solution (N = 447)

	Factor Loading						Expected Dimensions
	F1	F2	F3	F4	F5	F6	
SE.1					.656		
SE.2					.582		
SE.3					.643		
SE.4					.730		
SE.5					.699		
SE.6					.704		
SE.7					.643		
SE.8					.653		
SE.9					.575		Professional' Self-Efficacy
SE.10					.719		
SE.11					.697		
SE.12					.635		
SE.13					.658		
SE.14					.784		
SE.15					.755		
SE.16					.694		
SE.17					.596		
SE.18					.547		
I.1	.645		.466				
I.2	.657		.440				
I.3	.424		.628				Intention
I.4	.435		.611				
I.5	.571		.548				
E.1						.632	
E.2						.746	
E.3	.862						Emotions
E.4	.823					.688	
E.5						.747	
E.6							
E.7	.789					.063	
E.8							
E.9	.922						
E.10	.869						
M.1							
M.2				.734			
M.3				.827			Moral
M.4				.747			
M.5							
M.6				.659			
M.7	.579						
M.8	.486						
Att.1	.680						
Att.2						.459	
Att.3	.703						Attitude
Att.4						.555	
Att.5						.582	
Att.6	.597						
Ctl.							
Ctl.							Perceived Control
Ctl.	.453						
SN.1		.627					
SN.2		.590					
SN.3		.654					Subjective Norms
SN.4		.794					
SN.5		.684					

[a]Factor loadings sup to .4

Received 3 February 2023; revised 30 April 2024; accepted 2 July 2024