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Artificial Intelligence robots in social groups: an extension of the AIDUA model

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Framing of the research. *The ageing population has grown significantly over the last thirty years. In 2019, the number of individuals who are 65 years old or older has surpassed 700 million and it is expected to double by 2050 (United Nations, 2019). The quantitative growth of ageing population also corresponds to changes in the needs of elderly, in demographic and economic profiles determining different behavioral patterns (Guido et al., 2020). This is what Barusch (2013) defines as "grey tsunami" indicating, with this metaphor, the dispute with the classic stereotypes that conceive the elderly as static, sick and unwilling to spend instead of people asking for wider life expectancy and wellbeing. These requests constitute the practical needs to satisfy. In this context, senior living facilities offering health, clinical, social, daily routines services (Figure 1) should be able to differentiate themselves from competitors enabling end users to live a real and positive experience (Johs-Artisensi et al., 2021).*

Fig. 1: Senior living facilities services

Services	Author/s
Clinical services	Clinical screening (Gnanasambantham et al, 2020) Fall risk screen (Norman et al, 2020) Infenction prevention (Shaban et al, 2020) Management of agitation (Watson and Hatcher, 2020)
Daily routines support services	Eating (Maluf et al, 2020) Medication support (Sluggett et al, 2020) Sit-to-stand activity (Kagwa et al, 2020) Oral Hygiene support (Steinmassl et al. 2020)
Healthcare services	Rehabilitation (Mitchell et al, 2020; Simonov and Delconte, 2015; Muhm et al, 2016) Treatment management (Kurch-Bek et al, 2018) End-of-life care (Kong et al, 2017) Avoidance hospital (Shepperd et al, 2016) Mental illness support (Bousa et al, 2016) Disease prevention (MacIntyre et al, 2016)
Social services	Spiritual services (Suchomelova, 2018) Social Vulnerability (Khaksar et al, 2016) Loneliness and Life Satisfaction (Bergefurt et al, 2019; Gmage et al, 2018) Social interaction and relationships (Thomas et al, 2013; Yu et al, 2019)

Purpose of the paper. *The aim of this paper is to investigate the potentiality of the use of Artificial Intelligence (AI) robots in social groups and specifically the antecedents that impact on either senior citizens' willingness or objection to use Artificial Intelligence robots. Knowledge about elderly needs may help to find solutions satisfying the most disparate requests in healthcare. These solutions have to be affordable for everyone. Indeed, accessibility in terms of price, availability and easy-to-use is of fundamental importance to offer equal opportunity (Wang et al., 2010). However, due to the presence of some barriers, healthcare services and products have represented and, in some cases, still represent a mismatch between supply and demand. This is a significant challenge for managers of senior living facilities. Managers are facing problems like labor shortages and increasing cost of labor in healthcare. Firstly, labor shortage of doctors and nurses is a global issue. High turnover level (Tao and McRoy, 2015), constant retirement of*

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medical staff and fewer entrance (Omachonu, and Einspruch, 2010) lower availability of skilled workers in specialized fields of healthcare (Scheffler et al., 2009) represent the main critical points of labor shortage. Secondly, there is the payroll growth of high labor cost of human resources (Cooke and Bartram, 2015), whose work is high knowledge and experience-based and whose outcomes are measured through the performance of care as well as the satisfaction of the elderly patients and the staff members. Thirdly, what appears to be common across countries are the strategies of restraint in the field of public healthcare. This has led to alternative models that marked the transition from a more state-sponsored to a customer satisfaction-oriented model where orientation is towards market (Cooke and Bartram, 2015). They represent the real challenges in this sector and at the same time the impetuous for innovation. The approach on satisfaction-oriented model puts the elderly in a central position and the patient experience assumes a key role. The terms hospitality and experience (Johs-Artisensi et al., 2021) constitute an axiom in the actual context of senior living facilities. Managers today have to solve dilemmas about cost of labor while focusing on the elderly satisfaction. Consistent with the expansion of ageing population and the high costs in healthcare, growing attention has been paid to AI in the last two decades (Yang et al., 2020), due to the awareness of healthy lives and well-being at all ages (United Nations, 2019) and to the digital transformation in this field. AI in healthcare has found its attention by the researchers of medical community in order to find real-life implementation and consequent benefits for older population. For example, the humanoid robot NAO (58 cm tall) interacts with seniors, speaking, singing, and dancing since it recognizes subjects and shapes (Pino et al., 2020). Zora, another humanoid robot, has two speakers, several microphones, and a camera to scan and identify shapes and it is able of many things, from demonstrating gymnastic exercises to sing elderly's favorite songs (Melkas et al., 2020). They are supportive for memory-training programs (Pino et al., 2020), for rehabilitation (Melkas et al., 2020. Nowadays, the use of AI in the field of healthcare covers different domains, such as daily physical, cognitive, psychological, and social activities that are expressions of specific elderly's needs from eating and medicine administration to cognitive exercises and mood (Vercelli et al., 2018). Existing literature on the topic of AI in healthcare for aging people (Pino et al., 2020) has been explored according to different perspectives. Given the variety not only of the actors (doctors, caregivers, nurses, family members, elderly, etc.) but also of the scenarios (hospitals, nursing homes, specialized centers, residential aged, etc.), this paper focuses on senior living facilities and retirement communities. Within these contexts, literature has paid the attention on the role of nursing in supporting elderly in using smart technologies (Fritz and Dermody, 2019), on the importance of the phase of diagnosis and treatment making (Graham et al., 2020). Another important focus is on the phase of monitoring since AI tools allow to observe if there are changes in physical or cognitive state and, consequently, to directly act according to the status of health. Indeed, literature covers the union between AI technologies and different actors of the process right from the beginning (i.e., analysis, diagnosis making, etc.) till the end when the older person uses the AI robots. It is at this step and, precisely, in what precedes the use or rejection that our paper focuses on. This clear cornerstone relates to the belief that there is room for improvements linked not so much to the willingness to use but rather to the antecedents that lead to rejection. Paradoxically it is all this focus on the technological component, either conceived as barrier or competence, that represents the real gap in literature. Indeed, the premises at the base of AI are of easy-to-use and versatility (Hansen et al., 2020) and smart features, such as hands free, mark these robots (McLean and Osei-Frimpon, 2019). This means that although these works explore user acceptance within AI context, the used variables relate to older technologies. To fill this research gap, we aim to investigate what can be the antecedents that can have impact on either willingness or objection to use of AI robots. Starting from the above-mentioned assumptions, the following research questions come out:

1) *What are the antecedents of elderly acceptance of AI robots in the context of senior living facilities?*
2) *What are the antecedents that inhibit the use and, therefore, act on the rejection of AI robots in the context of senior living facilities?*
3) *What role does each antecedent play in accepting or rejecting AI robots in the context of senior living facilities?*

Methodology. *The topic of willingness to accept the use of AI has been analyzed in literature using different theoretical models, such as norm activation model, planned behavior theory model, innovation diffusion theory model, technology acceptance model, reasoned action theory model, and Unified Theory of Acceptance and Use of Technology Model (Cimperman et al., 2018). Among these, technology acceptance model (TAM) and its expanded versions are the most used in literature. Although they have been used in healthcare studies, these models show several limits. Firstly, they have been originated and implemented in the context of self-service technologies rather than of smart technologies (Gursoy et al., 2019). Hence, they are difficult to apply because they do not capture a series of aspects concerning both the technology per se and the physical, cognitive, and emotional world of the person who will use the technology. Secondly, these models assume that human behaviors are rational without considering any kind of irrational (Zhou et al., 2020) and emotional choices as well as non-utilitarian aims in the decision-making process. Thirdly, the succession of models and related variables has not given sufficient stability to these models (Zhou et al., 2020). In the context of AI and, especially, in healthcare for elderly, a first evaluation concerns the necessity to satisfy a certain need and the following analysis concerning a comparison between human resources and AI devices in terms of who and how it provides the better service (Lu et al., 2019). To date, some studies (Lu et al., 2019) starting from the debate that exists in literature, have developed the model of AI Device Use Acceptance (AIDUA) - (Gursoy et al., 2019), encompassing six predictors (performance efficacy, hedonic motivation, anthropomorphism, social influence, facilitating condition, and emotion) of behavioral intention that can take to two dichotomous ways: willingness to accept the use or rejection to the use of AI technology. This paper also adds social gratification belonging to Uses and Gratification theory. This model has been applied to the hospitality industry (McLean and Osei-Frimpon, 2019; Gursoy et al., 2019), overlapping* *both Cognitive Appraisal Theory (CAT) - (Lazarus, 1991) and the Cognitive Dissonance Theory (Festinger, 1962) and explains the process from which comes the willingness to accept or not the use of AI. Conceived in the psychological field, CAT has been applied in different service settings (Liu et al., 2019). This theory explains the antecedents of consumption emotions since it offers a series of evaluation criteria that require the involvement of cognitive functions. According to this theory (Lazarus, 1991) there is a clear relationship between cognitive appraisal and the associated emotion. The Cognitive Dissonance Theory (Festinger, 1962) has been conceived in the social psychological field and it explains the existence of discordant thoughts (Harmon-Jones and Mills, 2019). In addition, this paper adopts the Uses and Gratification theory (U&G) - (Severin and Tankard, 1997), initially belonging to mass communication literature, since it links the satisfaction of needs with the willingness to use a specific medium. The topic of gratification is particularly important in elderly healthcare. Actually, according to some authors (Gursoy et al., 2019) the acceptance is part of the decision-making process shaped by three stages: primary appraisal, secondary appraisal, and outcome stage.*

Based on the literature review, 21 research hypotheses have been formulated:

Hp1: Social influence positively influences the performance expectancy of AI robots in the context of senior living facilities.

Hp2: Social influence positively influences elderly effort expectancy of AI robots in the context of senior living facilities.

Hp3: Social influence positively influences trust in AI robots in the context of senior living facilities.

Hp4: The hedonic motivations have a positive influence on performance expectancy of AI robots in the context of senior living facilities.

Hp5: The hedonic motivations have a positive influence on effort expectancy of AI robots.

Hp6: The hedonic motivations have a positive influence on positive emotions towards AI robots.

Hp7: The hedonic motivations have a positive influence on trust towards AI robots.

Hp8: Social gratification has a positive impact on performance expectancy of AI robots.

Hp9: Social gratification has a positive impact on social gratification has a positive impact on effort expectancy of AI robots.

Hp10: Social gratification has a positive impact on trust in AI robots.

Hp11: Anthropomorphism is positively related to performance expectancy of AI robots in the context of senior living facilities.

Hp12: Anthropomorphism is positively related to effort expectancy of AI robots in the context of senior living facilities.

Hp13: Anthropomorphism has a positive impact on trust AI robots in the context of senior living facilities.

Hp14: Symbolic gratification is positively related to performance expectancy of AI robots.

Hp15: Symbolic gratification is positively related to effort expectancy of AI robots.

Hp16: Anthropomorphism has a positive impact on trust AI robots.

Hp17: Performance expectancy positively influences the generation of positive emotions toward the use of AI robots.

Hp18: Effort expectancy negatively influence the generation of positive emotions toward the use of AI devices.

Hp19: Trust positively influences the generation of positive emotions toward the use of AI robots.

Hp20: Elderly emotions have a negative impact on willingness to use AI robots.

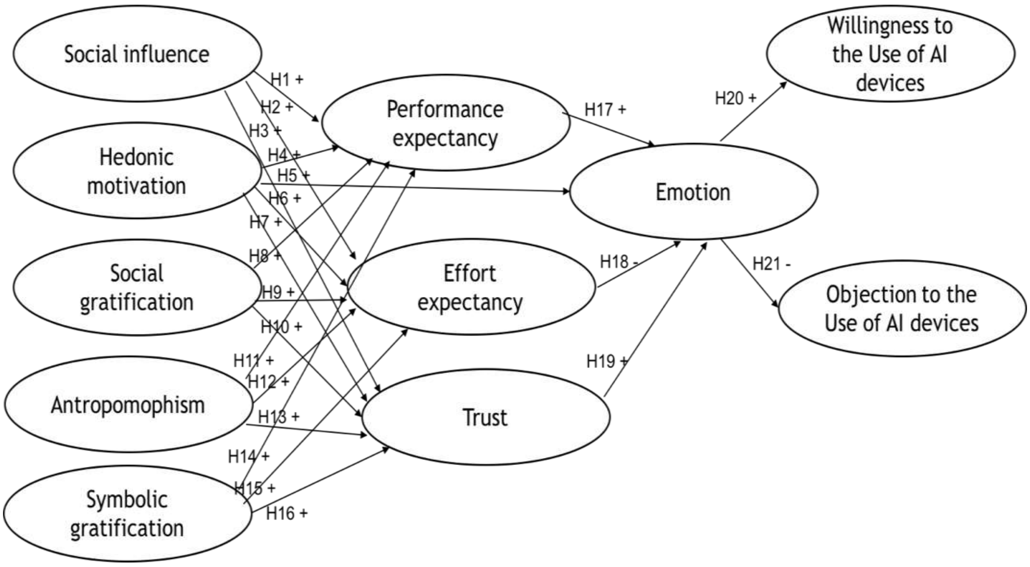
Hp21: Elderly emotions positively influence the objection to use AI robots.

Results. *The quality of the model (Table I) is evaluated by considering: the coefficient of determination (R^2) and the goodness of fit (GoF) statistics. R^2 values indicate how much of the variance in the endogenous latent variables is accounted for by their independent latent variables. More specifically, the model explained 54% of the variance in Performance expectancy, 20% of the variance in Effort expectancy 46% of the variance in Trust, 42% of the variance in Emotion, and 41% of variance in Willingness to accept the use of AI devices; and 21% of the variance in Objective the use of AI devices (Table 1). A GoF index has also been proposed as a solution for the global fit of the PLS-SEM. It is an index of prediction power for the entire model (Tenenhaus et al., 2004; 2005) and it is 0.47 for the whole model. The bootstrap results are useful for assessing the significance of the parameters of the inner and outer model and it is essential to check whether the constructed interval with the percentile bootstrap contains or not zero. As regards the significance of the path coefficients, Table 2 shows that all the links are significant, except for the impact of Social influence on trust; Symbolic gratification on Effort expectancy; Trust on Emotion. In this case, the path coefficients have an interval with negative and positive values. This study found that social influence was positively related to performance expectancy, Effort (β = .12, β = .25), respectively. Hedonic motivation was positively related to performance expectancy and trust (β = .36; β = .30) and negatively related to effort expectancy (β = −.17). Social gratification was positively related to performance expectancy and trust (β = .14; β = .18) and negatively related to effort expectancy (β = −.14). Anthropomorphism was positively related to effort expectancy, Effort and trust (β = .075, β = .33, β = .082).*

Performance expectancy was negatively related to emotion (β = -.43) and the effort expectancy was positively related to emotion (β = −.18, $p < .001$). In addition, emotion was negatively associated with willingness to accept the use of AI devices (β = -.63) and positively associated with objection to using AI devices (β = 0.46). However, findings indicated a non-significant positive relationship between social influence and Trust (β =.10); Symbolic gratification on

Effort expectancy (β =.08); and a non-significant negative relationship between Trust on Emotion (β = −.17). The results show important implications. From a theoretical point of view, the proposed model overcomes the current gaps of existing acceptance models and takes into consideration new items that are strictly related to the specific target of senior citizens and the related needs. From a managerial point of view, the paper deepens possible solutions as a response to the lack of available human resources, as well as how and to what extent robots can be exploited; also, the trade-off costs-benefits in adopting AI technologies and the possible options of usage for the customers are investigated. Moreover, it is important for senior living facilities' managers to look at AI as an opportunity or a threat, depending on users' willingness or objection to the use of AI technologies. It is useful for companies to look at AI through the lens of business capabilities, considering that AI technologies can support three important business needs: automating business processes, gaining insight through data analysis and engaging with customers and employees (Davenport and Ronanki, 2018).

Fig. 2: The proposed model



Tab. 1: R^2 value

	Original	Mean Boot	Std. Error	Perc.025	Perc.975
Performance expectancy	0.523*	0.526	0.0275	0.477	0.579
Effort expectancy	0.203*	0.216	0.0258	0.166	0.266
Trust	0.460*	0.465	0.0348	0.406	0.539
Emotion	0.414*	0.419	0.0352	0.358	0.485
Willingness	0.407*	0.398	0.0777	0.164	0.492
Objective	0.211*	0.217	0.0546	0.113	0.327

*significant at 5%

Specifically, AI can support the understanding of end-users' choices, by obtaining descriptive models to be used in optimization scheme (Laínez et al., 2009). The greater proximity to consumers enabled by new technologies makes the relationship between a business and its consumer deeper and more robust. In addition, data play a key role in offering personalized services by means of AI-based interface of their level of propensity in supporting strategies that entail extra-sensory experiences and automation.

Research limitations. *The study is not exempt from some limitations. In particular, the analysis has been conducted only within the Italian context. Further research should perform a cross country comparative analysis. Furthermore, the second limitation concerns the sample. Too small samples reduce the power of the study and increase the margin of error. Thus, authors suggest to perform the analysis using a large sample.*

Managerial implications. *The paper shows important theoretical implications as well as for the decision makers of elderly care and for the whole society. From a theoretical point of view the AIDUA model overcome the classical limits of TAM models considering the smart component of these technologies. As regards the managerial implications, this paper suggests how and to what extent elderly would use or not AI devices.*

Tab. 2: Significant links

	Original	Mean Boot	Std. Error	Perc.025	Perc.975
soc.inf -> perf	0.1190	0.1246	0.0515	0.0298	0.2105
soc.inf -> Eff	0.2483	0.2458	0.0633	0.1142	0.3517
soc.inf -> tru	0.1008	0.0998	0.0566	-0.0107	0.2158
hed -> perf	0.3584	0.3552	0.0342	0.2762	0.4169
hed -> Eff	-0.1719	-0.1733	0.0439	-0.2577	-0.0851
hed -> tru	0.3048	0.2964	0.0427	0.2174	0.3932
soc.grat -> perf	0.1446	0.1409	0.0494	0.0523	0.2420
soc.grat -> Eff	-0.1422	-0.1384	0.0524	-0.2321	-0.0533
soc.grat -> tru	0.1807	0.1815	0.0576	0.0753	0.2873
ant -> perf	0.0749	0.0823	0.0310	0.0254	0.1362
ant -> Eff	0.3300	0.3357	0.0494	0.2394	0.4292
ant -> tru	0.0822	0.0956	0.0415	0.0199	0.1808
sym -> perf	0.2301	0.2254	0.0536	0.1144	0.3195
sym -> Eff	0.0884	0.0923	0.0626	-0.0102	0.2073
sym -> tru	0.1969	0.1936	0.0552	0.0771	0.2963
perf -> emo	-0.4263	-0.4247	0.0822	-0.5264	-0.2000
Eff -> emo	0.3529	0.3588	0.0655	0.2355	0.4907
tru -> emo	-0.1771	-0.1558	0.0888	-0.2880	0.0640
emo -> will	-0.6378	-0.6097	0.1630	-0.7012	-0.0942
emo -> obj	0.4589	0.4623	0.0602	0.3359	0.5715

Originality of the paper. *To explore what are the antecedents of senior citizens' acceptance or rejection towards the use of AI robots in the context of senior living facilities, this paper proposes a revisited Technology Acceptance Model. The model is analyzed using SEM to test the hypotheses and to check the loading of each factor.*

Keywords: *artificial intelligence; TAM; SEM*

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