Defining Bots in an Enterprise Context

Short Paper

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Abstract

Bots, Virtual Assistants and Virtual Agents are well known in a personal environment. Technologies like “Apple Siri” or “Amazon Alexa” serve as digital assistants to enhance both accessibility and productivity. Yet, these technologies have to play with different rules in the enterprise context. Workflows within a digital workplace are different from what consumers are used to in a private surrounding. This concludes into the need for a definition for Enterprise Bots. In this short paper, we aim to provide insights in the current state of literature in this area and derive a definition for Enterprise Bots that is reusable by scholars and practitioners. Furthermore, we propose a research model based on the decomposed Theory of Planned Behavior, that both validates this definition and allows further insights into the topic of Enterprise Bots. Finally, we conclude by testing this model in a survey at a multi-national company and find that 10 of 12 used constructs are highly reliable.

Keywords: enterprise bots, virtual assistants, virtual agents, social bots, digital workplace

Introduction

Social media platforms have become an inherent part of everyday life for most people in the western world. As it is now possible to reach a wide audience beyond one’s own acquaintance and as there is money to be made (say as an influencer on Twitter or Instagram), there are now incentives in generating a huge following and extending one’s reach. One outlet of these tendencies is the use of automation on social media accounts so that a message can be spread on more channels simultaneously with the aim of pushing the possibility of being heard. So called social bots, automated accounts on social media platforms which post messages that at first glance cannot be distinguished from human messages, are a possible way to increase the reach on social media platforms. Amongst others, mainly due to the possible interference in the outcome of elections (presumably by influencing the voters’ opinions) the research on social bots has seen a rise in the recent years (Stiegitz et al. 2017). Research has shown that under certain circumstances those accounts do have the potential to influence the behavior of people (Munger 2017). However, while many of this research concentrated on negative effects of bots, there are also those fields of application in which automated communications can be potential helpful to humans (Stiegitz et al. 2017). There are utilizations such as the Woebot which offers a simple form of talk therapy via a web interface. Furthermore, there are whole ecosystems built around automated communication such as Amazon’s Alexa or Apple’s Siri. However, the
latter can rather be seen as virtual assistants and in contrast to social bots, are mostly used for 1:1 communication. As the term assistant indicates these oftentimes voice controlled applications can be used to assist its users with everyday tasks be it setting a timer or dictating messages which can then be send.

While these examples stem from the private sector, it is easy to see how the overall acceptance of and familiarity with such technologies holds potential for enterprises and slowly migrates into it. Following years of organizational transformation research with the support of information systems (Orlikowski 1996), the Digital Transformation at the workplace bears a high complexity, companies drive large initiatives to move in this direction (Matt et al. 2015). Employees need to get more productive, more efficient and they eventually need to reduce the use of paper within their working environment (Mock 2017). Most companies follow this trend (Dery et al. 2017) which eventually leads to an omnipresent automation in both services and processes as well as in the personal professional environment (Egeli 2016). In order to make this workplace automation accessible for a broad mass of users, natural language interfaces and conversational access are being added to recent software solutions. This leads to the unavoidable need of process knowledge for a user about manifold points of entry in order to satisfy various needs that arise during everyday work life.

Given these developments in both private and enterprise environments, we can see a trend towards the automation in both domains. There have been several approaches of joining both in the past years – most of them being unsuccessful. Probably the most prominent example is Clippy, a digital assistant that served as the single-point-of-entry for several processes that could be executed with Microsoft Office Products. While the intention was obvious, it was often described as the “most hated character” (Geller 2014) of the Microsoft Office suite.

As bots bring a benefit for private life that eases the little things, this effect might as well be applicable to the enterprise domain. Current work mostly focuses on possible harmful influence either of growing automation in the enterprise context or on social bots in the private domain. Nevertheless, we believe that the assumptions can be validated within an enterprise context and Enterprise Bots (in the following referred to as EB) can support companies to automate processes and provide the users a service that makes them more efficient around the digital workplace, though the literature is rare to non-existing in this regard.

Thus, we structure the short paper as follows. At first, we will present the related work with a focus on the public bot domain. We further seek for literature in relation to bots in an enterprise context and join the outcome of both into the derivation of an initial definition of EB (refer to RQ1 below) that we base our subsequent study on. We believe to be the first to define EB, which is why we initially test our definition in a pre-study with students. In conjunction with the results from both private and corporate domains, we will derive hypothesis that let us assume the comparability of both domains. We further aim to propose a research model, that will let us answer these overall research questions:

- **RQ1** How can Enterprise Bots be defined?
- **RQ2** What influences the intention-to-use of Enterprise Bots for users?
- **RQ3** How strong is the influence of the employees’ trust towards Enterprise Bots in the usage intention?

Our model is based on the decomposed Theory of Planned Behavior by Taylor and Todd 1995. We further aim to design a survey that we conduct at a large European manufacturing company with almost 100,000 employees, in order to validate our model and contribute to the findings in the area of EB. We conclude by reporting first reliability scores for our proposed model constructs and the outlook on further steps of our research.

**Theoretical Background and Related Work**

**A World of Difference: Public and Enterprise Bots**

While the foundation for human computer interaction in a natural way is artificial intelligence (AI), a term which stems from Alan Turing in the 1950s (Turing 1950), the topic garnered more widespread attention amongst others, due to supercomputers like IBM Watson and in the end user area by Siri, the virtual assistant (VA) which Apple introduced in 2011 with the iPhone 4s (Guzman 2017). Through this and similar
assistants of competitors which have been preinstalled on smartphones since then, such programs penetrated into everyday life and made people familiar with their use. Another point of contact with (seemingly) intelligent machines which has received more attention especially in the recent past are social bots (Stieglitz et al. 2017). This term describes artificial social media accounts that try to hide their artificial nature by behaving as human-like as possible in order to be taken fully by other social media users. Social Bots are postulated to try to bring certain issues into the public perception and to simulate broader support for these issues than is actually the case (Stieglitz et al. 2017).

Although similarities exist, social bots should not be confused with virtual assistants. As Guzman points out, “both [vocal social agent]s and socialbots are forms of AI and share a technological lineage. While agents can function across platforms, socialbots are autonomous programs operating in social media networks” (2017, p.70). This example shows that for technologies that communicate with humans in a human-like-manner the terms used to describe those phenomena are used interchangeably even though different aspects are described. Accordingly, Strohmann et al. point out, that e.g. “there are various synonyms for VAs [...] [and] similar to the variety of names there is also no single definition, but several definition approaches [...] tasks and characteristics.” (2018, p.3). For example, while Quarteroni sees both, chatbots and virtual agents, as subclass of conversational agents (2018), Io and Lee equate chatbots and conversational agents (2018). Klopfenstein et al. call Siri and the likes public voice-enabled Virtual Private Assistant in the field of conversational interfaces (2017), Io and Lee call Siri chatbot (2018) and Siri itself states that it is a personal assistant (Guzman 2017). To obviate confusion in the course of this paper, we will use the term virtual assistant (VA) when referring to software programs, that can be addressed via voice or text and that can respond to the users input (i.e. assist) with sought after information or carry out certain actions (like playing a certain song or generating a reminder, cf. Strohmann et al., 2018, Quarteroni, 2018). When talking about social bots, we refer to autonomous bot accounts operating on social media platforms (hence the term ’social’, cf. Stieglitz, Brachten, et al. 2017, Guzman 2017). Nevertheless, the debate over social bots and the associated research interest in the phenomenon has brought insights that could apply to VAs. In particular, the potential for influencing people is of interest to researchers, as it is an integral part of most of the underlying effects of social bots. Accordingly, some publications use the Computer are Social Actors Framework, which - based a series of experiments from the 1990s - postulates that humans perceive computers as social entities, even when it is known that the other person is a computer (Nass and Moon 2000). People in the experiments behaved to computers the same way as other people would behave in social situations. Based on these results, recent studies have shown that people perceive social bots in a similar way to other people (Edwards et al. 2014). Furthermore, it could be shown that under certain circumstances social bots were able to change people's behavior (Munger 2017). While VAs in general do not aim to change the behavior of their users (and thus exercise power / authority over them) the results can't be carried over to virtual assistants in their entirety – instead, with VAs the aspect of "serving" and subordination plays a greater role (Guzman 2017). Still, the findings described indicate important aspects of the relationship between humans and machines, showing that interactions are not per se considered 'artificial' and suggest that there is some acceptance in dealing with VA.

These findings refer to private, non-work related aspects of VAs. Nevertheless, the topic is also of interest to enterprises. Besides AI and machine learning which are their own fields of research and offer great potential in the analysis and optimization of business processes (or open completely new business fields), the use of VAs is of interest to companies as well. On the one hand, there is the aspect of external communication with customers, where e.g. the workload of call centers can be reduced by using VAs to intercept certain customer requests or users can be specifically addressed without having to employ additional staff (McTear et al. 2016). In addition, VAs also have potential for use within a company to also relieve service centers or enable employees to work more efficiently, as natural language requests can be quickly made and processed without the need for additional overhead, which has limited presence and capacity for processing such requests. Still, while there are potentials and uses for such VAs, research in enterprise contexts has rarely been concerned with them. A thorough literature search with various terms ("enterprise bot", "enterprise social bot", "virtual enterprise assistant" or "enterprise chatbot") hardly yielded results – if any. The papers that were at least partially fitting mostly researched said applications in a healthcare context or as a means to get in contact with potential customers but not to primarily reduce the workload within the company. As the latter is an essential part of discussions around organizational transformation (Besson and Rowe 2012), agility and flexibility have to be fostered. These dogmas prevail in modern organizations and lead to initiatives towards digital workplaces (Dery et al. 2017; Köffer 2015). As
productivity increase and user adoption are hot topics within the digital transformation, concepts like
digital nudging become attractive for corporations (Kissmer et al. 2018). At the same time, companies need
to manage a heterogenous workforce that has different needs based on their demographic profile (Meske et al. 2016). But given the impact of social bots or VA in private life (e.g. Apple Siri), this familiarity and prior findings could be carried over to the enterprise area (Quarteroni 2018). It becomes obvious, that in order
to support digital transformation initiatives within companies, concepts like EB have to be looked into –
which to our knowledge hasn’t happened so far. As we did not find existing literature on the subject of EB
and because of the confusion on the terminology surrounding VAs, we do see the need to delimit the virtual assistants used in the private sector (like Amazons Alexa or Apples Siri) from similar automated systems in
an enterprise context. In the following we thus establish the definition for Enterprise Bots as a simpler,
clearer term with the simplicity and novelty possibly being useful when conducting surveys (as in our case)
and to present a label for the technology to the test subjects.

**Defining Enterprise Bots**

Based on the considerations mentioned above, we summarize the benefits and purpose of social bots,
organizational transformation and the tendencies towards digital workplaces in a definition. It is essential
to be able to fall back on a uniform terminology in the future as well as to have a common understanding
for the study. Hence, we define Virtual Assistants which are applied in an internal enterprise context,
labeled Enterprise Bots, as follows:

An Enterprise Bot is an automated user service that provides casual and conversational interactions with
complex enterprise systems and processes. Enterprise Bots can e.g. answer questions or perform smaller tasks. A user can interact with it by just typing or speaking a request in natural language. It can only act
in a passive way, meaning it must actively be triggered by the user.

This definition has been positively pre-tested with a group of 13 students. With this, we intend to ensure
the quality and a common understanding before launching a larger study within the case company.

**Hypothesis, Research Model and Study Approach**

As we found in the related work, bots are commonly used in private life – either actively (e.g. Amazon Alexa
or Apple Siri) or passively (e.g. social bots on twitter). We further found, that current trends (digital
transformation, digital workplace) lead towards new concepts, such as digital nudging. Amongst others
these concepts drive a company to an increased productivity. Thus, EB are potentially helpful to fulfill these
requirements, as they are currently placed to increase productivity in a personal environment. Since this is
a major goal of the digitization as mentioned, EB are assumed to be fostering these goals. In order to answer
the research questions, we aim to propose a model, that helps to understand both the applicability of bots
in an enterprise context and the applicability of the definition provided by us in the previous chapter. Based
on this model, we derive hypotheses and indicate first meta-results of our survey towards data integrity and
descriptive means.

As previously shown, there seems to be a degree of acceptance for the interaction with machines (Nass and
Moon 2000). However, as the findings stem mostly from the private sector in which people are normally
not paid by a third party to fulfill their tasks in an efficient manner, other requirements apply for the
enterprise use of virtual entities. Therefore, before companies make investments to implement any type of
systems, it is important to evaluate the acceptance and willingness of employees to use these systems. A
common model for studying the acceptance of technology has been the unified theory of acceptance and
use of technology (UTAUT), which is based on the theory of planned behavior (TPB). As per Taylor and
Todd (1995), several extensions of the TPB exist, such as the UTAUT. Furthermore, one of the most reliable
extension of the TPB is the Decomposed Theory of Planned Behavior (dTPB), which is particularly suitable
in the case of innovative subjects. It is based on constructs from the innovation literature and provides a
more complete understanding of the actual usage intention. It includes constructs towards the mutual
superior and peer influence (Taylor and Todd 1995). As we aim to contribute to the understanding of
Enterprise Bots and thus focus on the professional perception by users, we are especially interested in the
users’ perceived ability and the individual’s beliefs. By focusing on specific beliefs, the model enables us to
derive assumptions towards adoption and usage, adding managerial relevance. Hence, the decomposition
of the well-established TPB constructs directly benefits our study. As the dTPB has been proven to be highly
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reliable and tested several times (Sadaf et al. 2012; Shih and Fang 2004) we found it particularly suitable for our study.

Our research model is illustrated below in figure 1. All scale relations except Trust are based on the dTPB (Taylor and Todd 1995). To fit our research needs in the enterprise context and to address corresponding matters, we removed the variable Compatibility and added Trust based on Reid and Levy (2008) as an already well-tested construct relation. As compatibility referred to the actual system compatibility and since integration and compatibility is a natural requirement towards bots, we are not expecting a major benefit and a rather low contribution from the inclusion of this variable. On the other hand, Trust was of particular interest, since EB are fulfilling smaller tasks autonomously for the user which requires the user to trust the bots work. Since, as mentioned, Trust was non-existing in the original dTPB, we took the construct from the study of Reid and Levy (2008) who extended the Theory of Planned Behaviour towards the construct of Trust and positively tested the overall reliability and item integrity. This way, we are able to keep the model integrity towards the influence of Trust on both Perceived usefulness and Perceived ease-of-use.

We further added moderators for a more extensive insight. For one we chose to add a set of demographic questions, since demographic attributes of employees can result in different behaviors (Meske et al. 2016). Furthermore we included the personal innovativeness based on Agarwal and Prasad (1998) and the technology acceptance scale by Neyer et al. (2012), indicated as “System usage behavior” in figure 1. As EB are an innovative technology that can change or at least support the daily workflow, we want to see the impact of a respondent’s personal attitude towards technology and whether this impacts the usage intention for EB or not. We further removed the latent variable for peer and superior influence in order to make the direct influence onto the usage intention of each more visible. Since we can’t measure the actual usage, we keep usage intention as the terminating latent variable in our model and do not include the original “Usage Behavior” variable. An overview of all scales and adjustments is shown in table 1.

![Figure 1. Research Model](image-url)

Given this research model, we propose hypotheses based on the related work that was outlined earlier and with the aim to answer our research questions. We are planning to test these against the survey results once they are available. Based on prior findings we expect all constructs to positively correlate with the corresponding latent variable. We base this assumptions on prior validations of the dTPB model (e.g. Sadaf et al. 2012) which indicated for example a higher usage attitude if the perceived usefulness is high as well. A lower score in trust will on the other hand result in a lower attitude towards using and an increased perceived usefulness will lead to a higher attitude to use EB. This will help us to validate both the model and the definition. Thus, we hypothesize:
**H1**: *All model correlations are positively flagged.*

Disapproving this hypothesis would indicate that either the individual’s intention is not reasonable or our definition was not understood properly.

Based on several studies, we expect the demographic influence to be significant, as we measure a rather digital technology (cf. Meske et al. 2016, 2018). We thus hypothesize:

**H2**: *Latent variables are significantly influenced by demographic attributes of employees.*

In contrast to e.g. social bots that exist in private life, Enterprise Bots are used in a professional context, which differs significantly from the private context (e.g. due to different security measures, stricter hierarchies, etc.). Given a natural hierarchic influence in companies (Stieglitz et al. 2014), we expect the superior influence to be higher than the peer influence, allowing us to derive adoption strategies. Due to organizational hierarchies that prevail in almost all large companies, we expect both, *Superior and Peer Influence* to be positively correlated, reflecting the hierarchical and peer influence (ref. to H1 as well).

**H3**: *The latent variable “Superior Influence” has a greater influence on usage intention than “Peer Influence”*

As EBs in our definition are referred to as simplifying instruments that are made to facilitate work, we hypothesize a positive attitude of the respondents towards the latent variables. The positive attitude implicates an above median mean for these constructs. Nevertheless as skepticism is rather high in novel, digital working environments (Köffer 2015), we postulate that the *Trust in EB* initially is low, resulting in a lower mean.

**H4a**: *The mean for all connected constructs (except Trust) is higher than the median.*

**H4b**: *The mean for Trust is lower than the median.*

To test our definition and model, we conducted an online-survey at a large German headquartered multinational manufacturing company with over 160 subsidiaries in 50 countries globally. The company currently does not run any kind of application that would fit our definition of EB. Thus, we needed to establish a common understanding of the concept which we did by providing respondents with our definition of Enterprise Bots. The survey was structured according to our research model and the scales (ref. table 1) were taken from literature related to the dTPB. The preliminary findings should provide insights in the users’ intention towards using Enterprise Bots. The survey was sent out on March 5th 2018 to 183 employees at a Romanian location of the company, generating 64 responses in total over the course of two weeks. In the next section we present preliminary findings based on the responses with the focus on data and construct reliability.

### Construct Reliability and Implications

Among the 64 responses, 1 had to be excluded for missing data generating our final dataset of n=63. All scales used were captured on a 7-point Likert scale with 1 indicating a rejection of the statement and 7 an agreement. Table 1 outlines the constructs together with the scale(s) that were used to measure the constructs as well as Cronbach’s Alpha indicating the reliability of answers within our dataset. Further, the mean values are reported for all constructs.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Scale</th>
<th>Cronbach’s Alpha α</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attitude towards using</td>
<td>Shih and Fang 2004; Taylor and Todd 1995</td>
<td>.960</td>
<td>4.633</td>
</tr>
<tr>
<td>Perceived usefulness</td>
<td>Taylor and Todd 1995</td>
<td>.414</td>
<td>4.675</td>
</tr>
<tr>
<td>Perceived ease-of-use</td>
<td>Taylor and Todd 1995</td>
<td>.532</td>
<td>3.228</td>
</tr>
<tr>
<td>Trust</td>
<td>Reid and Levy 2008</td>
<td>.948</td>
<td>4.409</td>
</tr>
<tr>
<td>Perceived behavioral control</td>
<td>Taylor and Todd 1995</td>
<td>.918</td>
<td>4.850</td>
</tr>
</tbody>
</table>
### Table 1. Construct reliability with Cronbach’s Alpha

<table>
<thead>
<tr>
<th>Construct</th>
<th>Source(s)</th>
<th>α</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Facilitating Conditions</td>
<td>Lu et al. 2005; Taylor and Todd 1995</td>
<td>.823</td>
<td>4.903</td>
</tr>
<tr>
<td>Efficacy</td>
<td>Taylor and Todd 1995</td>
<td>.836</td>
<td>4.300</td>
</tr>
<tr>
<td>Superior influence</td>
<td>Taylor and Todd 1995</td>
<td>.928</td>
<td>4.733</td>
</tr>
<tr>
<td>Peer influence</td>
<td>Taylor and Todd 1995</td>
<td>.969</td>
<td>4.533</td>
</tr>
<tr>
<td>System usage behavior</td>
<td>(-)</td>
<td>(-)</td>
<td>(-)</td>
</tr>
<tr>
<td>Superior influence</td>
<td>Agarwal and Prasad 1998</td>
<td>.834</td>
<td>4.295</td>
</tr>
<tr>
<td>Technology Acceptance</td>
<td>Neyer et al. 2012</td>
<td>.965</td>
<td>4.835</td>
</tr>
<tr>
<td>Intention to use EB</td>
<td>Nicolaou and Mcknight 2006; Taylor and Todd 1995</td>
<td>.963</td>
<td>4.580</td>
</tr>
</tbody>
</table>

Summarizing the Personal Innovativeness and the Technology Acceptance, we calculated an α of .930 and a mean of 4.565. Almost all constructs yielded an excellent reliability with values of α between 0.8 and 0.9, indicating that most of our research model is highly reliably and hence consistent. Perceived usefulness and the Perceived ease-of-use were not reliable and did not show specifically flawed items that would increase the reliability when left out. As mentioned previously, EB were not present in the company at the time when the survey was run. We assume that this impacts the reliability of the constructs. Both scales are based on Taylor and Todd 1995 and were not altered. This is rather unexpected and unusual compared to findings from prior studies (Reid and Levy 2008; Sadaf et al. 2012). As an anonymous reviewer suggested, this might be due to an insufficient understanding of our definition by the test subjects as, like we mentioned before, the company we tested in does not run any application similar to what we examined as enterprise bots. We intent to include a deeper analysis in our complete research by conducting interviews to analyze the root cause and propose actions accordingly. We observed a mean above the median (4) for almost all values, indicating a slight positive mindset towards EB by the users’ which is also reflected by the mean of 4.580 for the intention to use EB.

The latter findings indicate that hypotheses H4a and H4b have to be rejected, as for H4a the Perceived ease-of-use mean is below the median and for H4b the mean of 4.409 for Trust is above the median. The latter finding indicates that trust towards EB is (pending further analysis of the data) not perceived as negative. However, these results need further statistical testing (e.g. variance and value deployment).

### Conclusion, Contribution and Further Research

In this short paper we introduced the term of Enterprise Bots (EB). By analyzing the current state of literature, we showed the lack of research on bots within the enterprise domain and furthermore pointed out key motivators for the existence of bots in the public environment. We introduced a first definition for EB and outlined the research model that is the base for a quantitative survey we conducted. Preliminary findings based on answers by 63 subjects indicate that the chosen scales are highly reliable in most cases. Just two constructs were showing a reliability below an acceptable threshold of 0.7, which will be followed up on in the full paper of this study.

However, limitations apply. The survey (and thus the existing scales) had to be customized to fit the future tense and hence match the non-existing system availability (EBs don’t exist at the moment in our case company). This is causing a slight deviation of words for few items but does not impact the overall reliability of the model, as all questions were altered (this approach was used by Shih and Fang (2004) as well and has proven to be valid). As mentioned earlier one important aspect that needs deeper investigation are the low reliability scores for Perceived usefulness and Perceived ease-of-use, two of the most frequently used constructs in usage intention research. As one anonymous reviewer proposed that the lack of understanding

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1 As System usage behavior is not a latent variable it was not included in our model and is and table 1 doesn’t show corresponding values.
of definition of EBs by the test subjects may be a reason (possibly caused by the non-existence of EBs in the company). We plan to follow up this suggestion by conducting interviews with test subjects in the full paper and possibly discuss adjustments to the definition, for example to put more emphasis on the business context. As a last limitation we see that rather young respondents returned the survey (remark: due to space limitations in this short paper, we did not include a table with a demographic overview) and hence there is a possibility to have a demographic based bias which has not been captured. We will examine this in the following study on this subject and evaluate the significance of the influence of age and other moderating factors towards the answers.

All in all our study contributes in a unique way to the current state of research around bots and virtual assistants. Neither did we find a fitting definition nor an enterprise-oriented usage intention survey. Companies currently examining these technologies and service providers offer solutions accordingly (e.g. Microsoft Cortana) that are still in a rather immature state. Although this field is proceeding fast, science has yet to catch up. We aim to partially contribute to closing this research gap with our study by providing a novel definition for EB and outlining the difference between public bots and EB. The previously stated additional research questions and hypotheses will be answered in a complete research paper, building upon this short paper.

We conclude by encouraging scholars to provide feedback on literature, definition and the used research model. With this research we aim to provide the basis for further, more extensive analysis in the area of EB, such as the need of a user adoption for EB or the actual usage compared to the usage intention we derived.

References

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