# Design Requirements for AI-based Services Enriching Legacy Information Systems in Enterprises: A Managerial Perspective

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## Completed research paper

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## Abstract

Information systems (IS) have been introduced in enterprises for decades to generate business value. Historically systems that are deeply integrated into business processes and not replaced remain vital assets, and thus become legacy IS (LISs). To secure the future success, enterprises invest in innovative technologies such as artificial intelligence-based services (AIBSs), enriching LISs and assisting employees in the execution of work-related tasks. This study develops design requirements from a managerial perspective by following a mixed-method approach. First, we conducted ten interviews to formulate requirements to design AIBSs. Second, we evaluated their business value using an online survey (N = 101). The results indicate that executives consider design requirements as relevant that create strategic advancements in the short term. With the help of our findings, researchers can better understand where further in-depth studies are needed to refine the requirements. Practitioners can learn how AIBSs generate business value when enriching LISs.

**Keywords** Artificial intelligence, AI-based services, legacy information systems, design requirements, enterprises

# 1 Introduction

Information systems (IS) have been used for decades to generate business value by gaining advantages over competitors in almost every part of organisational environments. Systems are used by individuals to process and produce data (Aram and Neumann 2015), to speed up business processes (Neumann et al. 2014), regulate the informational, material, and human resources as well as enhance efficiency, effectiveness and productivity (Xu and Topi 2017). Large parts of systems have been instituted over years in enterprises and thus can be described as legacy information systems (LISs). They are considered to be the *"backbone of an organisation's information flow and the main vehicle for consolidating business information"* (Bisbal et al. 1999). Ensuring the ongoing operation is therefore mandatory for organisations as LISs are strongly linked to the strategic business goals (Robertson 1997). However, enterprises still need to be able to exploit novel and innovative trends to secure their future success. The continuous development of technology paired with the lack of time to replace LISs (Hasselbring 2000) requires the adaptation of existing applications. A currently popular group of technologies that enhance LISs in organisations is artificial intelligence (AI) (Frick et al. 2019a).

The term AI is used to describe a wide range of technologies with self-learning abilities which are possibly able to achieve superior performance compared to humans (Coombs et al. 2020). AI can have strong economic potential and generate strategic business advancements as it can take over repetitive tasks and relieves employees from unwanted duties (Siau and Wang 2018). When AI is used to enrich LISs in enterprises, we use the term AI-based services (AIBSs), which are *"components enriching IS in organisations with the main objective of collaborating with employees and assisting in the execution of work-related tasks"* (Frick et al. 2019a). AIBSs are applied in enterprises to support employees in the decision-making process (Brachten et al. 2020), accelerate internal support processes (Frick et al. 2019b) or facilitate strategic decisions on an organisational level (Aversa et al. 2018).

Despite the fact that AIBSs are increasingly being used in businesses (Dwivedi et al. 2019), there is an urgent demand to formulate requirements that should be considered when designing systems enhancing LISs. Most existing AIBSs adapted to business processes are considered to be narrowed down to a specified task (Batin et al. 2017), where the majority focuses on the short-term creation of added value while less attention is paid to design aspects. Research here needs to generate theoretical guidance to *"create ideal AI systems for human decision makers"* (Duan et al. 2019) in contrast with current literature that mainly targets technological aspects (Mikalef et al. 2018). Addressing the pressing need to do more research in this area, this study aims at proposing suitable recommendations and is thus guided by the following research question:

**RQ1:** What are the requirements that need to be considered to design AI-based services enriching legacy information systems in enterprises?

**RQ2:** To what extent do the identified design requirements for AI-based services enriching legacy information systems contribute to business value in enterprises?

This study makes a first foray into the examination of AIBSs from a business perspective following a mixed-method approach. We conducted semi-structured expert interviews with ten executives from multiple enterprises to derive design requirements. Preliminary results from these interviews were previously reported in a research-in-progress paper (Frick et al. 2019a). In this article, we additionally report on our quantitative evaluation of the findings using an online survey with N = 101 managers to verify which requirements create business value when enriching LISs.

Researchers and practitioners find the requirements helpful to consider important aspects before the actual introduction of AIBSs. From a theoretical perspective, this research gives an overview of design requirements when deploying AIBSs in enterprises and outlines an orientation for further in-depth research. From a practical point of view, practitioners can understand how AIBSs generate business value when enriching LISs. Hence, this article extends the IS literature by broadening our knowledge on how to design, implement and deploy AIBSs for enriching LISs. We believe this study is valuable to researchers and practitioners equally for understanding and overcoming difficulties when dealing with the introduction of AIBSs in enterprises.

# 2 Theoretical Background

Implementing IS in organisations aims to enhance business performance. IS ensure the effectiveness and efficiency of the organisation (Hevner et al. 2004) as well as supporting collaboration by fulfilling the role as a communication and coordination system (Aram and Neumann 2015). Within an

organisation, IS as support systems can be characterised by three central functions. First, supporting the company's business operations. Second, supporting managerial decision making. Third, supporting the achievement of strategic competitive advantages (Susanto and Meiryani 2019). Therefore, IS improving the organisation's business performance by ensuring these three functions can be considered as business IS (Aram and Neumann 2015) and is described as *"a collection of various information that has unity between one and the other aimed at business interests"* (Susanto and Meiryani 2019). IS in organisations consist of various information technologies (Orlikowski and Iacono 2001). These information technologies fulfil functions such as transmitting, processing, or storing information (Piccoli 2008). By doing this, IS in organisations help to process large amounts of information and to solve upcoming decision-making problems (Leavitt and Whisler 1958). Due to the generation of numerous benefits, organisations have been using IS to generate business value for decades. However, systems not coping with modern requirements or are not modifiable for business purposes (Robertson 1997) slowly turn into LISs but remain vital assets for organisations (Bianchi et al. 2003). The major problem with LISs is that they are deeply integrated into the running of a business (Robertson 1997) and that there is simply no rational reason for replacing them (Hasselbring 2000), thus organisations remain dependent (Robertson 1997). Nevertheless, enterprises are regularly required to invest in innovative technologies to generate or maintain advantages over competitors. Thereby, applications need to be adaptable to retain LISs as reasonably as possible (Bianchi et al. 2003) to enrich existing solutions and to assist employees in their daily work. Related to the dynamic development of new technologies, organisations need to consider ongoing improvements of LISs to ensure nascent business requirements, emphasizing the impact of information technologies on business operations (Bjerknes et al. 1991).

A concept which becomes increasingly relevant for the aligning organisational strategies is AI. There is no uniform definition, but AI can be considered as *"the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity"* (Rai et al. 2019). AI is believed to fundamentally change the future of business across industries, generating advantages over competitors and maximizing the market share (Benbya and Leidner 2018; Wang and Siau 2019). The potential benefits cannot be overlooked causing organisations to invest heavily (Schuetzler et al. 2018). When AI is applied as component enriching existing IS, it can be considered as AIBS (Frick et al. 2019a). They are typically implemented using machine learning algorithms (Kersting 2018) and are turning into a key element for enterprises (Dwivedi et al. 2019). In a recent study (Frick et al. 2019b) we demonstrated that AIBSs can be integrated into existing internal support workflows. The authors indicated that the categorisation and distribution of incoming customer inquiries are heavily accelerated. Another example (Pessach et al. 2020) evaluated the application of an AIBS to support human resource employees with the recruitment and placement of professionals. The results showed that insights might have been overlooked by internal recruiters who were using conventional methods. The examples illustrate that AIBSs promise great potential for organisations, including those which still rely on a multitude of LISs. Although AIBSs are becoming more ubiquitous within LISs, there are no properly validated requirements that need to be considered to design services enriching existing IS in enterprises.

# 3 Research Design

In order to examine which requirements need to be considered to design AIBSs enriching legacy IS in enterprises and likewise generate business value, we selected a mixed-method approach. This design strategy equips researchers with an effective technique in dealing with evolving situations and complex improvements while being able to achieve contributions for theory and practice (Venkatesh et al. 2013). Mixed-methods are capable of simultaneously addressing confirmatory and exploratory issues, provide greater insights compared to single methods and help to analyse divergent and/or complementary findings (Teddlie and Tashakkori 2003, 2009). The approach at hand is an exploratory sequential procedure combining qualitative and quantitative research to validate whether assumptions based on a small sample size can be generalized for a larger population (Creswell and Creswell 2018). We conduct qualitative research to identify core issues and obtain knowledge within a less explored domain (Kelle 2006), and use the subsequent quantitative phase to validate our findings with a larger population (Creswell and Creswell 2018).

## 3.1 Expert Interviews

Expert interviews established themselves and grown in popularity as an efficient and concentrated method to collect relevant data (Bogner et al. 2009). We chose this method to 1) give the interviewees

enough space to elaborate on issues, 2) provide selective assistance by the researchers and, 3) ensure capturing all relevant aspects to generate comparable responses to simplify the subsequent coding process. The term expert describes an individual with advanced knowledge in the investigated field of research (Meuser and Nagel 2009). In this study (see also Frick et al. 2019a), the experts are employees working at management level. Furthermore, experts needed to be familiar with AI and have knowledge of where AIBSs can be applied to improve business performance and further they needed to have a minimum of three years of experience to be well acquainted with the company and the sector. We also defined that the companies in which the experts worked should have applied AIBSs to enrich LISs and be planning future adoptions. In terms of sample size, we follow Creswell and Creswell (2018) who recommend using between three and ten individuals. Based on these factors, a large German retail holding organisation was selected which owns equity interests in further companies. Here, we chose companies focusing on various areas within the holding organisation: agricultural trade (C1), animal husbandry advisory (C2), energy product consulting (C3), animal feed advisory (C4), construction services (C5), wholesale e-commerce (C6) and agricultural machinery distribution (C7). We acquired two project managers (E1/C2 [male, 28 years old, tenure of 8 years], E2/C1 [f, 25, 8]), three managing directors (E3/C3 [m, 35, 10], E7/C6 [m, 40, 21], E8/C1 [m, 43, 19]), three heads of divisions (E4/C4 [f, 40, 9], E9/C3 [f, 30, 4], E10/C5 [m, 43, 18]), and finally two managers (E5/C7 [m, 57, 5], E6/C7 [m, 47, 15]). The interviews were conducted in person at the workplace of the interviewees. Participants were 39 years old on average, with three female and seven male experts and a mean tenure at the company of 11.7 years.

Conducting semi-structured expert interviews implies creating *"questioning guided by identified themes in a consistent and systematic manner"* (Qu and Dumay 2011). Therefore, a guideline with central questions on AI, AIBSs, LISs and business value was developed in advance, divided into the following 9 parts: 1) Introduction of the interviewer and brief summary of the purpose of the research, as the participants had already received relevant information when they were recruited. 2) Self-introduction of the interviewee, including career development, current responsibilities in the company as well as demographic data. 3) Definition of AIBSs and prior experience, followed by the authors' explanation of AIBSs to ensure the same level of knowledge among all participants. 4) Areas in which AIBSs are applied in organisations and which (L)IS are enriched. 5) Adoption and acceptance of AIBSs and which barriers might arise when enriching (L)IS with AIBSs. 6) Advantages, disadvantages and dangers when using AIBSs in (L)IS. 7) How AIBSs need to be developed to use them daily in (L)IS. 8) Responsibility for an implementation and what an introduction looks like. 9) Conclusion of the interview: Possibility for the interviewee to ask further inquiries followed by a debriefing.

Interpreting what respondents mean in their answers to questions assumes that researchers have extensive knowledge in the subject matter (Campbell et al. 2013). Following this requirement, the authors have a strong background on IS, LIS, AI and AIBSs as well as its utilization in enterprises. We used content analysis as the most precise method to analyse qualitatively collected material (Mayring 2014). The research data was coded according to certain, empirically and theoretically reasonable points, enabling a structured description of the material (Mayring 2014). Codes represent words or short phrases for attributes of language-based or visual data (Saldaña 2009) aiming at reducing the intricacy of vocabulary and identifying core categories. The coding was collaboratively done by two researchers to distribute the effort of the coding process and to get different perspectives on the qualitative data. A list of general codes was created coding two interviews in front and collected inside a codebook. One of the researchers maintained the codebook as editor and was responsible for updating, revising and maintaining the list of codes during the research process (Guest and MacQueen 2008). Respecting the codes-to-theory model (Saldaña 2009), the analytic process is not linear but rather cyclical. It is divided into two cycles: an initial coding of the data, followed by pattern coding for the categorization of coded data. The first cycle was used to structure the data and assigning codes. In the second cycle, categories were created. In summary, we created 379 codes with 10 categories using MAXQDA (version 18). We finally validated the intercoder reliability using Krippendorff's alpha, resulting in a value of .823 which is above the threshold of .800 (Hayes and Krippendorff 2007).

## 3.2 Online survey

To validate the design requirements, we conducted an online survey. As a precondition for participation in our study, participants had to speak English or German fluently, as the survey was designed in both languages. In addition, individuals had to work in a company within the management level to ensure an understanding of the business perspective. Various German organisations were approached directly by the researchers, plus, participants were recruited via Prolific, a platform designed to acquire subjects for surveys (Palan and Schitter 2018). The study started with a standardised briefing about anonymization and research purposes, followed by a detailed explanation

about AIBSs, why they are already introduced in organisations and what they are capable of. To verify each design requirement, we adopted and modified constructs from previously validated instruments to ensure the accuracy of the measurements. However, since the results provide new insights, we were not able to identify items for every design requirement, resulting in the development of own constructs. We used a combination of already existing as well as self-developed items which were validated as part of the evaluation. Besides items for the design requirements, we further measured the business value when using AIBSs to enrich LISs in enterprises. All items were measured on a 10-point numeric scale and questions starting with the phrase "how relevant are the following aspects/statements regarding AI-based services". Example items are "the utilization of AI-based services is a good idea" or "the strategy regarding the utilization of AI-based services is congruent with the business strategy of organisations". Participants had to answer 74 questions in total, excluding information about their demographic data. To ensure that the attendees were aware of the definition of AIBSs throughout the survey, they had to answer 2 questions with "yes" or "no" about the main intention as the last step: 1) "The main objective of AIBSs is to collaborate with employees and assist them in their daily tasks" and 2) "The purpose of this survey is to evaluate requirements to develop AIBSs". The survey was designed using LimeSurvey and took about 15 minutes to complete, the analysis was conducted using jamovi (version 1.1.9.0).

# 4 Results

## 4.1 Requirements

The **Strategic Orientation** of an enterprise controls the actual use of AIBSs within an organisation. However, AIBSs must not be implemented in a sweeping way but rather specifically to enhance distinct functions. This may reduce costs and the need for resources of an organisation, which is a key aspect of common strategic orientations (Cao 2002; Johnson 2018). One expert explained *"The management and executive board have to support that. We have to achieve additional benefits for ourselves as well as for our customers"*[1] (E8). Furthermore, an activity within an organisation has a strategic value when it contributes to the organisational success (Barney 1991). Likewise, the deployment of services such as AIBSs needs to align along the strategic orientation of the organisation in order to fulfil the overarching organisational strategy and vice versa (Henderson and Venkatraman 1999). In this context, such services have to provide concrete advantages with respect to employees and customers of the organisation (Luse et al. 2013).

**Process Organisation** describes the actual process of coherent and individual operations. This step aims to support the existing IT processes in order to improve their velocity by reducing non automated work steps. One respondent emphasised *"This is a whole process, fast, effective and customer-friendly. The system thinks and acts in a processual way"* (E2). Organisations supporting new technology investments such as new business models and new business processes will get superior returns comparing to other competitors that do not invest (Susanto and Meiryani 2019). Therefore, the process organisation is integrally tied to the Strategic Organisation. Enriching LISs with AIBSs enables the organisation to digitize the individual processes and functions (Luse et al. 2013).

Before the actual and continual interaction with the system, the **Acceptance and Adoption** of AIBSs by users must be achieved. Experts point out that new technology in general has an acceptance problem in organisations. However, to interact with it at all, perceived usefulness and perceived ease are the major aspects that must be taken into account. One participant pointed out that *"AIBSs should not dictate how to act in specific situations, that would only create unnecessary barriers"* (E2). *"User acceptance and confidence are crucial for the development of any new technology"* (Taherdoost 2017). With the growing interest in AIBSs, organisations need to investigate the challenges referring to adoption (Alsheibani et al. 2018). Research has developed various models explaining individual technology adoption (Venkatesh et al. 2003) which have been continuously revised especially in an organisational context. However, adoption is not only an important issue for technology in general but also for AIBSs.

**Authenticity, Trust and Transparency** describes that the interaction with an AIBSs should preferably be perceived as authentic. In addition, trust in AIBSs and their transparency has to be as high as possible. One respondent stated *"[Understanding the outcome is] very important! On the one hand, users can understand how the system came up with the decision, on the other hand, the users' level of knowledge is adjusted"* (E1). The decision-making process has to be as transparent as possible,

[1] Excerpts from the German interviews have been translated into English for the reader's convenience.

given that transparency is identified as crucial for trust building (Wünderlich et al. 2013) and leading to an increase of authenticity as well as use intention. *"The perception of authenticity is critical for a user's evaluation of the service as valuable and satisfactory and for establishing trust"* (Wünderlich and Paluch 2017). In addition, the interaction quality leads to trust and to usage intention (Nasirian et al. 2017).

A frequently mentioned topic in the interviews was the experts' concerns about **Security, Privacy and Ethics** during the interaction process. In the opinion of the experts, it is most important to clarify which (personal) data is processed, where, how and by whom and that no ethically reprehensible decisions are made. One interviewee said *"so, there will be a lot of scepticism, because everyone is afraid that personal data will be published. So, everyone has quite a bit of respect"* (E7). Another underlined that *"[The artificial intelligence system] may ask for things that may not be relevant in the context. Also, sensitive topics, there is a lot of sensitive [personal] data which the user does not want to reveal"* (E9). Informational self-determination refers to *"the right or ability of individuals to exercise personal control over the collection, use and disclosure of their personal data by others"* (Cavoukian 2008). The interviewees indicated that adequate communication had to take place before the introduction of AIBSs and that the legal basis had to be clarified in advance. AIBSs are trained by developers and thus might contain considerable human bias (Rothenberger et al. 2019). Ethical concerns are a major challenge (Duan et al. 2019), thus AIBSs must be implemented with caution (Wang and Siau 2018).

An often mention requirement for AIBSs can be summarised as **Task Support and Service Features**. Experts point out that interaction with AIBSs has the main goal to support employees in their daily work in order to fulfil tasks more quickly and thus save time and therefore money, summarised as increased effectiveness and efficiency. AIBSs can particularly adopt repetitive tasks for which no cognitive abilities are needed. One expert specified AIBSs as *"An expedient"* and further *"A way that it makes my work easier and I can take care of what I enjoy"* (E3). Service Features can be seen as a comparison between what the employee feels should be offered and what is provided, in other words, the discrepancy between perceptions and expectations (Pitt et al. 1995). In this case, users should have the overall opinion that AIBSs increase the effectiveness and efficiency at work.

A major aspect when designing AIBSs are **System Characteristics**. This requirement essentially describes the technical characteristics of the system. Experts point out that AIBSs have to be user-friendly, reliable and extensible as well as provide a quick response. Combined, the ease of use and learnability of AIBSs must be guaranteed. One expert depicted *"It has to be simple and practicable and it has to deliver additional benefits right from the start"* and more *"It has to be easy to use"* (E6). Technology needs to be understandable and usable, delightful and enjoyable, with the goal to actually fulfil human needs (Norman 2013). In addition to paying attention on engineering, manufacturing and ergonomics, aesthetics of form and the quality of interaction must be taken into account (Norman 2004). The system acceptability must always be guaranteed in order to be utilised by users.

The requirement of **Implementation and Deployment** describes how systems are developed and how they are introduced within the organisation and to employees. The development of systems should not only be done by IT experts but integrate users who provide functional know-how. An introduction needs to involve affected employees to minimize the resistance against AIBSs. Furthermore, introduced systems should be reviewed regularly to ensure their functionality. One respondent explains that *"I need someone who is able to exploit the possibilities together with me in order to reach maximal benefits"* (E5). Barki and Hartwick (Barki and Hartwick 1989) describe participation as *"the behaviours and activities that users or their representatives perform in the system development process"* with the overall responsibility as a key dimension (Hartwick and Barki 1994). In the development of IS, it is considered an important factor for achieving system success and is commonly mentioned in research (Mann and Watson 1984).

Another significant point that has been mentioned are concerns about the **Connectivity and Collaboration** of AIBSs. On the one hand, enriching LIS with AIBSs means systems being interconnected and complementing each other and employees. On the other hand, through the collaboration with AIBSs, communication between departments and locations as well as between employees will be promoted. One attendee said that *"As an advantage I see the fact, that AIBSs can generally promote collaboration between centralised and decentralised units"* (E2). Systems can be designed to serve as knowledgeable collaborators of employees, helping to accomplish goals while ensuring to remain in control (Xu and Topi 2017), thus the collaboration is becoming a partner relationship (Oberquelle 1984; Oberquelle et al. 1983). AIBSs greatly enhance collaboration of people and resources in organisations (Tang and Sivaramakrishnan 2003). By using AIBSs, employees are

able to process all available and relevant data to mitigate unintentional bias in human decisions (Elson et al. 2018). In addition, systems can be joined into groups working together.

Another requirement for AIBSs is that users should learn through the interaction with such systems. Through the interaction with AIBSs users can, for example, prepare better for upcoming appointments and pay attention to matters they have previously disregarded. Therefore, **Enhanced User Performance and Service Training** means enhancing people's (cognitive) performances by learning from AIBSs as well as challenging employees' cognitive abilities. One interviewee clarified that *"It is also increasingly important that I as a user quickly have a value. I think this factor should not be underestimated"* (E7). Learning from AIBSs and thereby enhancing the performance of employees should have a positive effect on the organisation: the technology should be an instrument to enhance people's performance. Interaction with AIBSs helps to boost performance at work (Siddike et al. 2018) and helps to overcome human limitations and enhance human abilities (Rouse et al. 2009).

## 4.2 Validation

In total, 150 participants took part in the study, 124 of whom completed it. After excluding data sets with a short completion time (below 5 minutes) and answers with significant similarities as well as analysing the two validation questions as the last step of the survey, we resulted in N = 101 participants. In terms of gender, 48 (47,5%) were female, 53 (52,5%) were male with a minimum age of 22 and a maximum of 64 (M = 37, SD = 9.79). Regarding the level of education, 12 (11,9%) have an apprenticeship, 8 (7,9%) a secondary school degree, 15 (14,7%) a high school degree, 60 (59,5%) a university degree and final 6 participants have a PhD (6%). Participants live in a variety of different countries, with the majority in the United Kingdom (35/34,7%) and Germany (26/25,8%), working in full-time employment (75/74,3%), part-time employment (18/17,8%), self-employed (6/5,9%), mainly in companies of a size between 1 and 49 employees (21/20,8%), 5.000 and 9.999 employees (22/21,7%) and 1.000 and 4.999 employees (18/17,82%). In terms of industries, most participants work in IT (23/22,8%), consumer goods (12/11,9%) and energy (12/11,9%). 34 companies (33,7%) are using AI and 67 (66,3%) are not. For validating which design requirements are relevant for enriching LISs, we assessed the correlation coefficient of the constructs using the Pearson correlation (Zhou et al. 2016). We found significant correlations between design requirements and business value (cf. Table 1): 1) Acceptance and Adoption ($r = .324$, $p < .001$), 2) Task Support and Service Features ($r = .353$, $p < .001$), 3) System Characteristics ($r = .329$, $p < .001$) and finally 4) Enhanced User Performance and Training ($r = .477$, $p < .001$).

| Requirement | Pearson's r | p |
|---|---|---|
| Strategic Orientation | .079 | .434 |
| Process Organisation | .146 | .145 |
| Acceptance and Adoption | .324*** | < .001 |
| Authenticity, Trust and Transparency | .172 | .086 |
| Security, Privacy and Ethics | .085 | .397 |
| Task Support and Service Features | .353*** | < .001 |
| System Characteristics | .329*** | < .001 |
| Implementation and Deployment | .156 | .120 |
| Connectivity and Collaboration | .154 | .125 |
| Enhanced User Performance and Training | .477*** | < .001 |

*Table 1. Pearson's r between requirements and business value (*** significant at < 0.001 (2-tailed))*

# 5 Discussion and Implications

IS used in organisations to improve business performance (Neumann et al. 2014), regulate resources and enhance efficiency, effectiveness and productivity (Xu and Topi 2017). However, the steady progression in improving technologies and the need of securing future success of organisations lead to new requirements especially for LISs, systems that have been used for decades but are not easy to replace (Hasselbring 2000) and remain vital assets for organisations (Bianchi et al. 2003). Thereby, the integration of AIBSs enriching LISs provides great potential for organisations. The goal of this

study was to identify design requirements from a business perspective that need to be considered to design AIBSs. Overall, managers assess 4 of 10 requirements as vital to generate business value (cf. Figure 1).

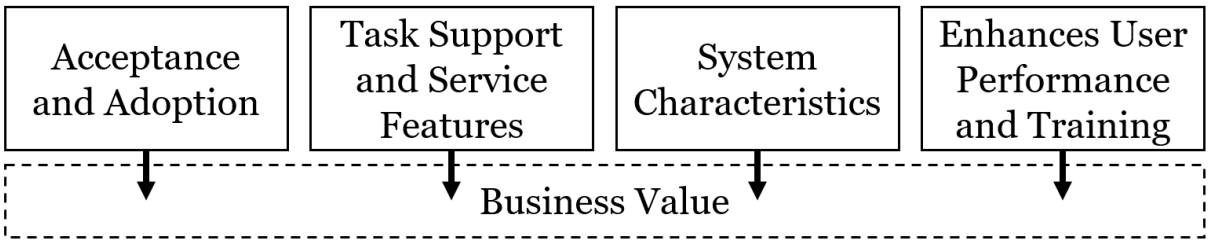


*Figure 1. Significant requirements generating business value for AIBSs enriching LIS in enterprises*

Acceptance and Adoption is considered significant. This goes in line with earlier research identifying acceptance as crucial for any technological advancement (Taherdoost 2017). We interpret this to the mean that managers have a great interest in employees accepting AIBSs in order to really use them in the workplace. Furthermore, Task Support and Service Features assists employees in their daily work to perform tasks more efficiently, thus saving time and money. Our results show that managers consider this to be relevant for the future success of enterprises. We understand that the introduction of AIBSs enriching LISs must always create benefits for the applying organisation. The same might be valid for Enhanced User Performance and Training. Previous research explains that AIBSs can boost performance at work (Siddike et al. 2018) and enhance human capabilities (Rouse et al. 2009). We argue that manager might perceive AIBSs as a suitable method to educate employees and train them faster for a certain task. By improving the skills of employees, the organisational revenue might be increased. System Characteristics, as the last significant requirement, explains that the ease of use and learnability of AIBSs must be guaranteed. This was confirmed by previous research (Norman 2013). We thus state that managers sense quick values for enterprises when AIBSs are easier to use.

Surprisingly, according to the survey of managers, many of the requirements were not significantly related to business value. In case of Strategic Orientation and Process Organisation, we appreciate that LISs are probably not necessarily aligned with the overall business strategy but rather have an end of life. Therefore, AIBSs enhancing existing systems temporarily are less aligned with the strategy or new processes and are thus intended to create benefits in the short term. We interpret the missing correlation of Authenticity, Trust and Transparency that managers may not care whether employees understand the results of AIBSs. Even though the decision-making process needs to be transparent for trust building (Wünderlich et al. 2013) it is not necessarily essential if employees are forced to use a system. This might also apply for Security, Privacy and Ethics and further, doubtful decisions are not in the spotlight of the industry but profit maximisation. Regarding Implementation and Deployment, managers might simply not be interested in how services are developed but focus on the overall strategic outcome. Finally, Connectivity and Collaboration might miss any correlation as managers do not exactly know what AIBSs are capable of. This this is also shown by our study as only 34 companies (33,7%) are using AI, thus the application in enterprises is not yet very widespread.

This research is not free of limitations. First, we derive design requirements from a limited group of ten experts. Although a number of experts was involved, they can each only cover their own perspective. In addition, interviews were conducted in just one holding organisation, although the experts represent very different departments. We describe results from on online survey which is based on a sample size of N = 101. Although the spread of AIBSs in organisations is increasing (Dwivedi et al. 2019), it was still difficult to acquire more participants from the management level who were already familiar with AI. Last, our design requirements do not cover personal user characteristics and innovativeness as major moderating effects on the intention to use such systems (Rzepka and Berger 2018).

The contribution of this paper is interesting for researchers and practitioners equally to design, implement and deploy AIBSs in enterprises to enrich LISs. From a theoretical point of view, this paper gives an overview of requirements to design AIBSs and provide insights for areas where future in-depth research is needed. IS researchers can better understand AIBSs' targeted characteristics which are fruitful to positively influence business value in enterprises. From a practical point of view, organisations appreciate the business value which can be generated by using our requirements. Enterprises following the recommendations are more likely to generate advantages over competitors. Practitioners further understand which design requirements are relevant for existing IS. Future

research should dive deeper into the design requirements as many of the requirements are rather broad. Therefore, studies need to conduct in-depth research working out the individual conditions for each requirement. In addition, IS scholars might also be interested in using the requirements to design an AIBS and evaluate a prototype in a real-world scenario possibly refining the design requirements.

# 6 Conclusion

Enterprises have been using IS for decades, however, many of those slowly became LISs. Nevertheless, organisations still need to adapt to ongoing technological advancements such as AIBSs. In this study, we have presented and discussed requirements for AIBSs from a managerial perspective. It became clear that executives consider design requirements as relevant that create business value in the short term. However, we argue that our requirements are still valid for AIBSs enriching IS in general. Admittedly, the picture painted by our research is far from clear as the requirements might have been formulated to broad. Researcher and practitioners need to watch future developments closely to understand how enterprises create and maintain business value using AIBSs.

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