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Research Article

Improving Decision Quality for Business Users Based on Cloud-Based Self-Service Business Intelligence Tools

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Abstract: The ever-growing volume of data promotes data-driven decision-making in more cases and more areas than before. The development of user-friendly self-service business intelligence (SSBI) tools enable business users to autonomously execute tasks in the area of business intelligence (BI), statistical analysis, or data science. Cloud computing offers the opportunity to provide SSBI as services as well. This paper focusses on cloud-based SSBI tools and their support for data-driven decisionmaking by business users. This paper aims to identify the influence of a deeper understanding of business informatics on (a) the handling of the cloud-based SSBI tools and (b) the data-driven decision making performance. An experimental setting was used to collect empirical data. Two groups with equal knowledge in business administration, but different backgrounds in business informatics have been defined. Based on different backgrounds in business informatics, the results show no significant difference in handling the cloudbased SSBI tool but reveal significant differences in decision-making performance.

Keywords: self-service business intelligence, cloud computing, data-driven decision making, business informatics, empirical research

1. Introduction

The enormous volume of data created inside and outside an organization can be leveraged to improve decisionmaking processes to gain a competitive advantage. Various studies report that BI is an enabler for value creation [1, 2].

Data-driven decision making using BI requires skilled people being able to collect and analyze data, interpret and present the derived results, on time, and on-demand [3, 4]. In the past, companies analyzed their data with rigid, costly, and time-intensive BI tools, which were mainly managed by IT departments. In recent years, a new kind of tools has been provided, which are more flexible, less expensive, and much faster than the traditional systems.

As the business landscape is continuously evolving due to technologies like cloud computing as well as the generation of Big Data streams, the BI technology has to be adapted continuously [3].

The internet and especially cloud computing plays a crucial role in these developments. These tools are called SSBI tools and can also be used by non-IT-experts [5-7] and follow a similar idea as NoCode/LowCode Applications [7].

A literature review on BI and SSBI proves that there is a high demand for sophisticated and user-friendly tools [8].

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Based on the specific characteristics of cloud computing, these tools can be accessed anytime and anywhere, leading to a competitive advantage [9].

The usage requires basic knowledge of data modeling and statistics to be able to select and use the right techniques and interpret the outcome of the analysis correctly [5, 6, 10].

Recent studies show that there is a lack of people with those skills, and this situation will not change shortly [11]. This lack of people is supported by another study, which indicates that only 22% of potential business users can use some form of SSBI in their jobs [12].

The World Economic Forum reports that “data science roles and skills form a relatively small part of the workforce, recent trends indicate that these are currently among the highest in-demand roles in the labor market” [13].

Companies have to enable their employees to use SSBI tools correctly and efficiently in their daily routines. A high degree of user-friendliness is a prerequisite to make SSBI tools available for a large group of business users. Furthermore, it can be assumed that different backgrounds in business informatics vary among SSBI users, and this, in turn, influences the data-driven decision making performance. The knowledge of SSBI users has to be upgraded accordingly, and this further education should be as individual as possible.

This research tries to find empirical evidence if SSBI tools are perceived as user-friendly, independent from the user’s background in business informatics.

With an experimental setting, skill gaps of SSBI users should be identified. These gaps can be used as a basis to develop individual pieces of training and plans for further education to enable users to apply SSBI tools more effectively.

The conceptual framework of the paper is displayed in Figure 1 and will be described as follows. The basic concept of the research is the cloud-based SSBI tools and their usage for different user groups: Group A with more in-depth knowledge in Business Informatics and Group B without knowledge in Business Informatics. The empirical was conducted to find out if there is a difference between the user groups regarding the perceived usefulness (UF) and their decision making performance (DMP) according to the given Hypotheses in section 4.

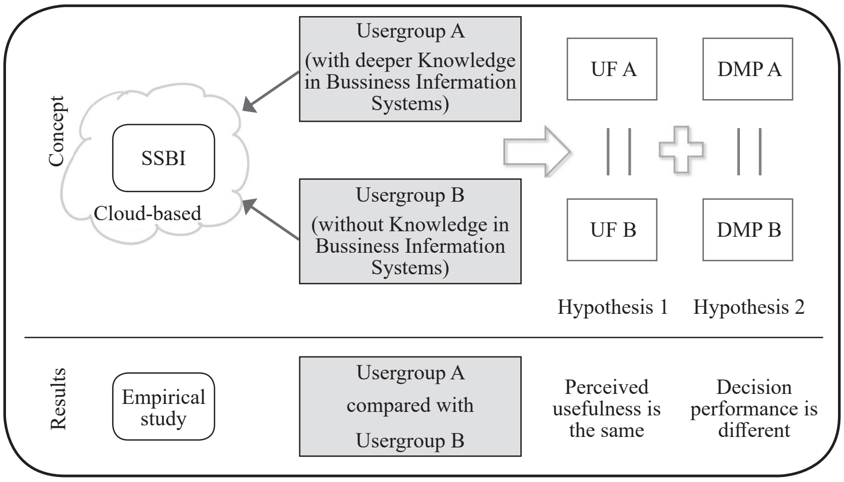

Figure 1. The conceptual framework

The structure of this paper is as follows: The first section presents the theoretical basis for business intelligence and cloud computing and the concept of SSBI. Based on the literature review, the conceptual model of empirical research is derived, and the hypotheses are established. All collected data are described; the hypotheses are validated and discussed. SPSS is used for all statistical analyses. Finally, the results are summarized, and a conclusion is made. The paper ends with limitations and potential directions for further research.

2. Business intelligence

Even though researchers introduced the term “Intelligence” in Artificial Intelligence already in the 1950s, it took around 40 years until it became popular in business communities.

With the advent of the Big Data movement and developments in fields like cloud computing or the Internet of Things, the introduction of BI and applications for data analytics is getting more critical [14].

According to Watson and Wixom, BI is defined as a process concerning two primary activities. The first activity implies getting data into a data warehouse [15]. This step is followed by a second activity, which gets the data out of the warehouse, to perform analyses, or to use them for reporting purposes. BI is a collection of various technologies enabling a user to make faster and better decisions [14].

Duan and Xu claim that “BI is the process of transforming raw data into useful information for more effective strategic, operational insights, and decision-making purposes so that it yields real business benefits” [16].

BI represents a set of hardware infrastructure and software tools to provide solutions for enterprises to gather, store, and analyze data to improve decision-making. The following Figure 2 gives an overview of the evolution of BI tools.

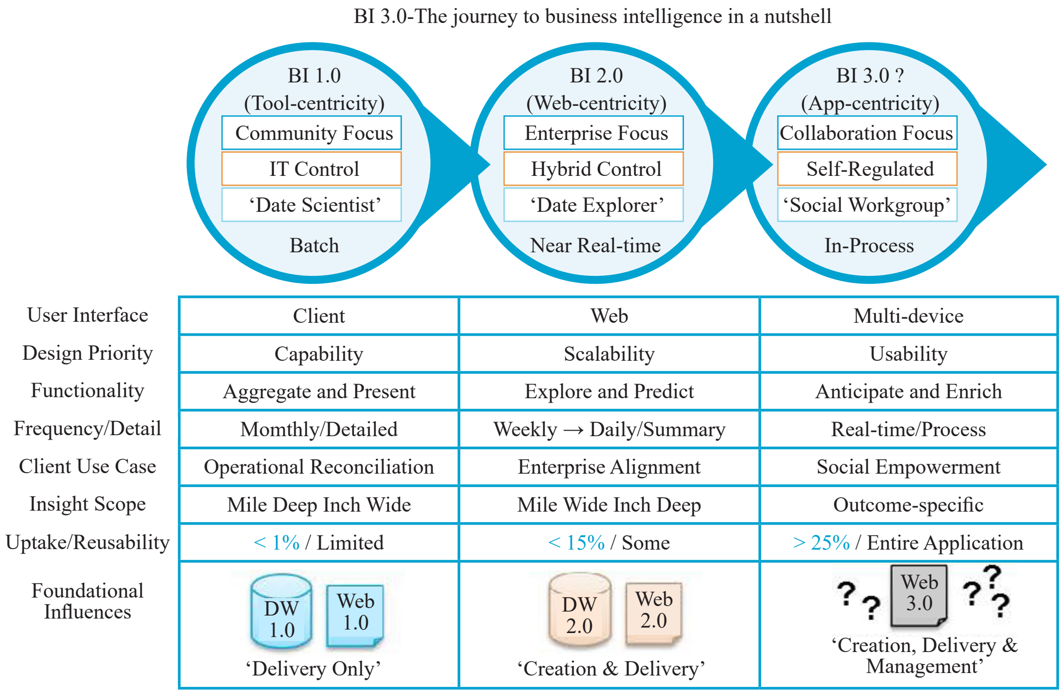

Figure 2. The evolution of business intelligence [17]

2.1 *BI 1.0*

BI 1.0 could be termed as the traditional BI based on data warehousing and data management. In this stage, data are collected by organizations coming from several independent IT systems. These primarily structured data are usually stored in relational database management systems [3].

The concept of extract, transform, load (ETL), and online analytical processing (OLAP) is the basis for analyzing and exploring relevant data [18]. These systems and the related processes are usually controlled by IT departments and are empowered by data scientists [17]. As BI 1.0 is rather rigid and costly, it is mostly adopted by large enterprises [9].

2.2 *BI 2.0*

With the rise of the internet and the exponential growth of data, BI tools had to evolve from rigid BI 1.0 to faster BI 2.0 tools [3]. These tools are web-focused and allow near real-time data processing. These systems provide more power and scalability, as well as increased flexibility and simplicity for the system developers. However, the BI 2.0 approach still misses extended visual analysis and exploration capabilities for business users. Similar to BI 1.0, BI 2.0 is still characterized by operational silos and tool-centricity [17].

2.3 *BI 3.0*

BI 3.0 tools can be utilized on different devices, like smartphones, tablets, or notebooks. They are user-friendly and enable collaborative work. According to Gratton, "BI 3.0 will focus on collaborative workgroups which are selfregulated (…) and, which focus on information outcomes within the confines of core business interactions with customers, employees, regulators, and third-parties" [17].

Instead of generating monthly, weekly, or daily reports, which are usually based on the ETL process BI 3.0 can be used to generate ad-hoc reports that can easily be adjusted to current and changing requirements by business users.

Based on this flexibility, BI 3.0 can be used in different business departments and application fields, e.g., warehousing, accounting, sales, and marketing [19, 20].

Cloud computing, especially the SaaS service model (is explained later on), is a trigger for the evolution of BI 3.0. BI 3.0 solutions can be implemented and deployed quickly, flexibly, and cost-effectively [9].

3. Cloud-based SSBI

The combination of BI 3.0 and cloud computing is referred to as cloud-based SSBI tools, which is a fast developing application area [21].

3.1 *Cloud computing*

Cloud computing turns computing power and storage space into a commodity that is purchased when required and scaled up when necessary [22].

Cloud computing can be characterized as on-demand self-service, broad network access, resource pooling, rapid elasticity and measured service, and pay-per-use [23].

According to the client's needs, cloud providers offer different service models typically called infrastructure as a service (IaaS), platform as a service (PaaS) and software as a service (SaaS) as well as four different deployment models Private, Public, Community, and Hybrid [22].

SaaS is a web-based software delivery model hosted by a service provider who offers software tools with the related IT-infrastructure. Typically, customers have to pay a subscription fee to get access to this service. An advantage of this solution is that customers do not have to worry about any maintenance, hardware or software topics as these are the responsibilities of the SaaS provider [24].

Concerns about using cloud services are often related to security, privacy, compliance, and legal risks, which have to be mitigated by the management of the enterprise and the cloud provider [24, 25].

3.2 *Self-service business intelligence*

SSBI enables decision-makers to detect current and subtle changes in their environments. Hence, business users can analyze data without waiting for support from IT experts [5].

Imhoff and White define SSBI as "the facilities within the BI environment that enable BI users to become more self-reliant and less dependent on the IT organization." Furthermore, they stress the following key objectives of SSBI tools [6]:

a. Provide easy access to different data sources;

b. Easy to use with customizable user interfaces;

c. Support enhanced reporting and data analysis features;

d. Can be quickly deployed and are easy to manage.

3.2.1 *SSBI provide easy access to source data*

Accessing different data sources has always been an effort in BI as data had to be stored in data warehouses, which is time-consuming and expensive [18]. However, with SSBI, not all required data need to be stored in a data warehouse. They are readily available and can be analyzed by the business users, without assistance from IT departments.

Therefore, the SSBI infrastructure has to permit free access to data from different sources, inside or outside the organization. This is a prerequisite to guarantee the optimal performance of SSBI usage [6].

3.2.2 *SSBI is easy to use with customizable user interfaces*

A significant factor for the success of SSBI tools is their user-friendly interface. As a result, business users who are new to BI should be able to select and design personal reports and conduct the required analyses. Business users with a better understanding of the related technologies can use these tools in a faster and more efficient way [6].

Although SSBI tools have achieved a high level of user-friendliness and user support within the system, SSBI users should further be classified in "power" and "casual" users Alpar and Schulz [5]. While power users are either IT experts or experienced BI users, unexperienced casual users merely have a minimum knowledge of these tools. Power users can create more complicated analyses and provide them with casual users [26].

3.2.3 *SSBI support enhanced reporting and data analysis features*

In contrast to traditional BI, SSBI provides a platform that allows business users to discover, access autonomously, and share data and information, as well as reports or dashboards. All that promotes faster and better decision-making.

Technical features, such as visualization, also play a significant role in SSBI as it allows its users to recognize patterns in their data much more quickly. It has been proven effective for not only presenting vital information of enormous amounts of data, but also for conducting complex analyses [8, 27].

Finally, SSBI tools are easily accessible across multiple devices like tablets, phones, and computers, and some more. Thanks to its collaboration focus, it is ideal for social workgroups [17]. Especially cloud-based SSBI services promote these features.

3.2.4 *SSBI can be quickly deployed and are easy to manage*

The cloud technology and especially SaaS have had a significant impact on its deployment [9].

As a result, business users can autonomously implement applications and tailor them to their specific needs [28]. Furthermore, SSBI tools provide excellent performance as well as scalability for simple to complex tasks and substantial data volumes [5, 9, 29].

In addition to that, SSBI supports companies and their users with simple administration and enhancement of the BI environment in time. User satisfaction can be increased significantly when they can autonomously create, adapt, manage, or deploy individual reports and analyses [6].

3.3 *Levels of SSBI*

Alpar and Schulz propose three levels to classify SSBI tools, based on system support and self-reliance shown in Figure 3. They distinguish between the usage of information, the creation of information, and the creation of information resources [5].

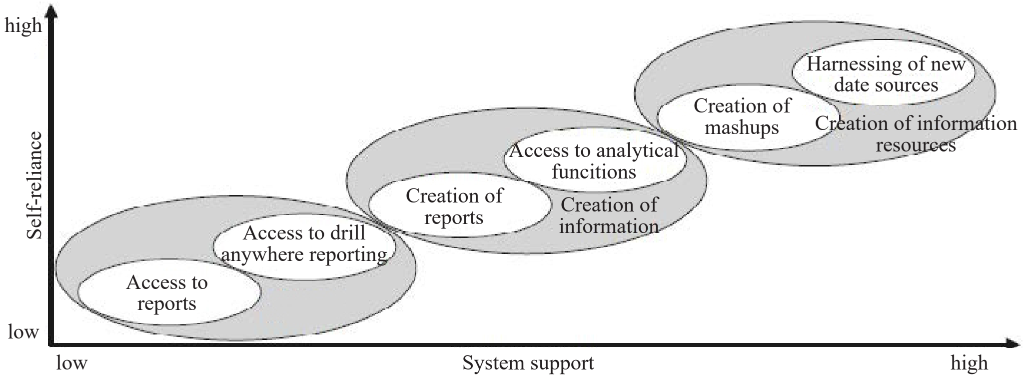

Figure 3. The levels of SSBI [5]

3.3.1 *Usage of information*

In the first level, "usage of information", users have access to prepared reports that can be adjusted to current requirements by changing settings or other parameters that define the report. Data, which are needed for reports, are usually prepared for the reports by IT experts or power users. Users can add new reports and dashboards on existing data or add new data with rather simple data structures.

3.3.2 *Creation of information*

At the second stage, "creation of information", users have access to already available data sets at a low disaggregated level to create new individual reports and analyses.

Data required for reports and dashboards have to be prepared partly by the user. Due to the considerable amount or great variety of data and the complexity of data structures, users might not be able to consider all potential problems and data requirements. Due to incomplete data understanding, incorrect data or aggregates might be used, which leads to wrong analysis [10].

As some analytical functions provided by the SSBI tools are quite complex, the support of power users is needed to avoid incorrect results [5], and the validation of the used algorithms has to be secured [4].

At both stages, data from various sources are combined and can be reused by users as stationary data, which are mainly controlled by IT departments [18].

3.3.3 *Creation of information resources*

In the third level, "creation of information resources," users have to include and combine data from multiple sources, which are not pre-processed by the IT department. The result of this combination and integration results in new data and information sources [30].

Different statistical and analytical functionalities have to be combined by using shared components that have to be prepared by IT departments or business experts. Hence, this stage has the highest need for support by IT professionals or users with sophisticated knowledge in data modeling, statistics, and data science.

The concept of SSBI seems to be appealing to foster data-driven decision-making in all areas of an organization. As a response to these developments, SSBI tools should be provided across the company [6].

4. Research outline and hypotheses

Based on the characteristics of SSBI tools, they are supposed to be "easy-to-use" and should provide "improved support for data analysis" with "simpler and customizable end-user interfaces".

These qualities must be provided for every type of user, especially independent from their knowledge in business informatics. Business informatics is a scientific discipline that integrates mainly business administration, information technology, and elements of computer science. The IT-related topics have a strong focus on business and economics.

The central aim of this research is twofold:

1. Since SSBI tools are supposed to be user-friendly, the first aim was to find out if SSBI tools are perceived as easyto-use by business users independent from their knowledge in business informatics.

2. The second aim was to explore how a more in-depth knowledge of business informatics influences the decisionmaking performance of business users.

The central aim is supported by scientific contributions, which state that SSBI tools should be intuitively and easy to use, independent of the user's background and knowledge in information technologies [5, 6, 8, 26].

To validate the hypotheses, two user groups have to be defined, one group with more in-depth knowledge of business informatics and a second group with standard knowledge in business informatics.

To ensure valid results between both groups, all other skills of the participants should be on a similar level. As a consequence, business students with or without further education in business informatics are the target group for this study. Group A consists of students with further education in business informatics, whereas Group B does not.

If SSBI tools are easy to use, there should be no difference in being able to use the tool between Group A and B. This leads to the following hypothesis:

H1: Participants from both groups are generally able to handle the essential functions of the cloud-based SSBI tool accurately.

To find out if a more in-depth knowledge of business informatics influences decision-making performance, the following hypothesis can be established:

H2: Participants from Group A should perform better in data-driven decision-making with cloud-based SSBI tools than participants from Group B.

5. Methodology and design of the empirical research

An experimental approach was selected to collect data and finally validate the hypotheses. The research team evaluated every participant individually within 30 minutes.

The participants had to go through the following steps:

1. Present a fictional data set in Microsoft Excel from the US-stock market;

2. Answer part one of the questionnaire (general questions on the participant, demographics, backgrounds in business informatics, mathematics, statistics);

3. Register for the cloud-based SSBI tool;

4. Load the data set;

5. Analyze the data and make decisions on these analyses;

6. Answer part two of the questionnaire (user-friendliness of the tool, the ability to make data-driven decisions, detecting positive aspects and problems during the analysis, and more);

7. In the meantime, the researchers evaluated the data-driven decision-making performance of the participant.

All items had to be rated on a Likert scale from 1 to 7. Finally, all collected data were analyzed with the statistical software platform SPSS.

The decision-making performance was measured on a 7-step Likert scale (1 = not able at all, 7 = very able), whereas the following items were rated by the research team. Were the participants able to

a. identify patterns hidden in the data;

b. identify trends hidden in the data;

c. analyze the data correctly;

d. derive meaningful insights from the analyses.

5.1 *Selection of the cloud-based SSBI tool*

Reddy et al. give an overview of multiple vendors in the SSBI sector [31].

For this research, Qlik sense cloud (https://www.qlikcloud.com/) was selected for the experiment. Qlik sense cloud is less of a traditional dashboarding tool, but more of a visual analytics and data exploration application builder.

Therefore, a lot of indicators and functionalities are provided to support the analysis of data sets or tools to slice and dice the data.

5.2 *Data collection*

Besides the data from the experiment, a questionnaire and an observation protocol were used for data collection.

According to Langer, the structuring of an observation is based on an observation scheme analogous to the procedure of a fully structured interview. The observation scheme is a type of questionnaire that is intended to fulfill the three following purposes [32].

a. Verbal control of the observation;

b. Content-related control of the observation;

c. Facilitation of recording and documentation of the observation.

5.3 *Description of the participants*

As already mentioned, the skills of both groups should be similar except their backgrounds in business informatics. Since the right sample is crucial for this study, business students from the same university with different backgrounds in business informatics were selected. Typical sample methods are purposive sampling, quota sampling, convenience sampling, or snowball sampling. In this particular experiment, a quota sampling approach has been chosen, which is a sampling method that gathers data from homogenous groups [33, 34].

Group A comprises participants with a more in-depth knowledge of business informatics. Participants with a standard of knowledge in business informatics are associated with Group B.

To be assigned to Group A, students had to pass at least three courses in business informatics and BI, whereas students in Group B were not allowed to have a single course on these topics.

Based on the division of users by Alpar and Schulz in "power" and "casual" user, Group A represents power users, whereas Group B can be seen as "casual" users.

5.4 *Descriptive statistics of the participants*

The average age of the participants is 23 years, with the youngest being 19 and the oldest being 29 years old. The distribution of gender shows that 60% of the participants are male (n = 60), and 40% female (n = 40). Both groups (A and B) have 50 participants. The knowledge level of all participants was fixed by a grade less than 1.5 for all three lectures in IT topics group A had to fulfill.

A total of 100 experiments were conducted and subsequently evaluated. The fastest experiment was conducted within 12 minutes, and the slowest took 22 minutes. The average duration was approximately 15 minutes.

While participants from Group A had an average duration of almost 14 minutes, participants from Group B had an average duration of around 17 minutes. Hence, Group A performed slightly faster than Group B. Nevertheless, all participants were able to finalize the experiment within the given period, which was limited to 30 minutes.

6. Results of the empirical research

This section presents the results of the hypotheses validation as well as further in-depth analyses of the decisionmaking performance.

H1: Participants from both groups are generally able to handle the essential functions of the cloud-based SSBI tool accurately.

To test H1, the respective arithmetic means of the variable "Sum_toolhandling" for both groups were calculated first. The higher the arithmetic means, the higher the students' accuracy of handling the tool.

Then, a Shapiro-Wilk test has to be carried out to check what kind of distribution exists for the two groups. For both groups, the output indicates $p = 0.000$, and therefore, the data is not typically distributed, since $p < 0.05$. Hence, a nonparametric test is conducted [35]. The Mann-Whitney U-test (also called Wilcoxon-Mann-Whitney test) is a ranked, nonparametric test. It determines differences between two groups that refer to a nominally or ordinally scaled dependent variable. Since this experiment contains two groups, and the variable is ordinally scaled, the Mann-Whitney U-Test is used.

Table 1 shows the arithmetic means and results of the Mann-Whitney U-Test:

Table 1. Arithmetic means and mean ranks of the variables "Group" and "Sum_toolhandling"

	Group	*N*	Arithmetic mean	Mean rank
Sum_toolhandling:	Group A	50	39.16	54.44
(Index for tool handling & properties)	Group B	50	38.28	46.56
Test size	$Z = -1.372$	Asymp. Sig. (2-tailed); $p = 0.170$		

Given that the maximum arithmetic means of "Sum_toolhandling" for both groups is 42 (6 items multiplied by 7-step Likert scale), the arithmetic means of both groups (Group A = 39.16; Group B = 38.28) indicate a rather straightforward tool handling.

To examine whether this result is statistically significant, the Z and p values of the test statistics have to be evaluated. For the Mann-Whitney U-test, if $p < 0.05$, the difference in the mean ranks between the analyzed groups is statistically significant. If $p > 0.05$, no statistically significant difference between the analyzed groups are detected. As shown in the Mann-Whitney U-Test, the mean rank of Group A is 54.44, whereas the mean rank of Group B is 46.56. Finally, the test statistics show $p = 0.170$, meaning $p > 0.05$ and $Z = -1.372$, which indicates that the Mann-Whitney U-test, which was conducted to determine differences between Group A and B, has no statistical significance

These results are consistent with the previously analyzed studies which state that SSBI tools should be intuitively and easy to use, independent of the user's background and knowledge in math and statistics [5, 8, 26].

Since the arithmetic means of both groups are generally rather high (39.16 vs. 38.28 out of maximum 42), this indicates that the tool handling is considered to be rather easy. Furthermore, the Mann-Whitney U-Test shows that there is no statistically significant difference in handling the tool between these two groups.

Thus, H1 "Participants from both groups are generally able to handle the basic functions of the cloud-based SSBI tool accurately", can be supported.

The H2 "Participants from Group A should perform better in data-driven decision-making with cloud-based SSBI tools than participants from Group B" has to be evaluated.

As the hypotheses suggest, it is assumed, that Group A has a better decision-making performance than Group B.

The arithmetic means of the variable "Sum_dependent_variable" of both groups are compared. This variable represents an index of the participants' decision-making performance. The higher the arithmetic means, the better the participants' data-driven decision-making performance.

To check the distribution of the variables, the Shapiro-Wilk's test shows $p = 0.000$ for both groups. The data is therefore not normally distributed, which in turn requires conducting the non-parametric Mann-Whitney U-test to reveal differences between the two groups. The following table depicts the results of this test (Table 2).

Table 2. Arithmetic means and mean ranks of the variables "Group" and "Sum_dependent_variable"

	Group	*N*	Arithmetic mean	Mean rank
Sum_dependent_variable:	Group A	50	22.94	62.89
(dependent variable)	Group B	50	19.14	38.11
Test size	$Z = -4.286$	Asymp. Sig. (2-tailed); $p = 0.000$		

As the maximum arithmetic means of “Sum_dependent_variable” for both groups is 28 (4 items multiplied by 7-step Likert scale), the scores of both groups (Group A = 22.94; Group B = 19.14) show a notable difference in the data-driven decision-making performance in favor of Group A.

The different mean rank values from the Mann-Whitney U-Test for Group A and B are 62.89 and 38.11.

Nevertheless, to make sure whether these values are statistically significant, the Z- and the p-value of the test variable has to be checked ($Z = -4.286$; $p = 0.000$). The test statistics show $p = 0.000$, thus $p < 0.05$, which means that Group A significantly outperforms Group B.

Consequently, the hypotheses H2 “Participants from Group A should perform better in data-driven decision-making with cloud-based SSBI tools than participants from Group B” can be supported.

Users who are inexperienced in statistics and mathematics significantly made more errors in their analyses than experienced candidates. Additionally, depending on the level of SSBI, also some proper skills in data modeling are necessary [36].

It can be assumed that IT-savvy participants have a better knowledge of statistics and mathematics because IT is closely related to math. In the questionnaire, participants were asked to rate their skills in statistics and mathematics. The analysis revealed no significant difference between both groups for this item.

The overall decision-making performance consists of four dimensions. To get deeper insights into the two groups, further analysis is required. Since each item is measured on a 7-step Likert scale, the respective arithmetic means and medians between the two groups can be compared.

Table 3. Comparison between performance arithmetic mean and median of both groups

Performance dimension	Group	Mean	Median
Identify patterns and trends	Group A	6.02	6.00
	Group B	5.46	5.50
Analyze data correctly	Group A	6.12	6.00
	Group B	5.22	5.00
Making data-driven decisions	Group A	5.34	5.00
	Group B	4.50	4.00
Work on more complex data set	Group A	5.46	5.50
	Group B	3.96	4.00

The comparison of the performance dimensions differences between the two groups can be found.

The items “Identify patterns and trends” (mean Group A/B: 6.02/5.46; median Group A/B: 6.00/5.50), “Analyze data correctly” (mean Group A/B: 6.12/5.22; median Group A/B: 6.00/5.00), “Making data-driven decisions” (mean Group A/B: 5.34/4.50; median Group A/B: 5.00/4.00) and “Work on more complex data set” (mean Group A vs. B: 5.46 vs. 3.96; median Group A/B: 5.50/4.00) all show a higher rating for Group A.

The most significant difference can be observed in the last item, “Work on a more complex data set”, which supports the statement that the higher the complexity of the data set, the more difficult it gets for Group B participants to understand the data set and make a correct decision.

7. Summary and conclusion

As already presented above, the central aim of this research is twofold:

Since SSBI tools are supposed to be user-friendly, the first aim was to find out if SSBI tools are perceived as easy-touse by business users independent from their knowledge in business informatics.

The second aim was to explore how a more in-depth knowledge of information technologies influence the decisionmaking performance of business users.

Prior studies have revealed that better knowledge in statistics and mathematics improve data-driven decision making. The study at hand shows that a deeper understanding of information technologies improve data-driven decision making as well.

Further analysis of the decision-making performance shows in which performance dimensions business informaticssavvy users outperform users with a standard knowledge of business informatics. The most significant difference refers to the complexity of the data and data structures that have to be analyzed and interpreted. It can be concluded, the more complex the data, the better the performance of business informatics-savvy users.

As a consequence, courses in related fields, like courses in business intelligence and business analytics, data science, cloud computing, statistics, and mathematics should be part of the education and should be incorporated in every curriculum of business and management studies.

8. Limitations and further research

The sample size of the empirical experiment is limited to two groups, with 50 participants in each group. The experiment was conducted with students from one university. This approach ensures that the participants have a homogenous and comparable background besides their knowledge in business informatics.

As this experiment has been designed on the lowest level of SSBI, "usage of information", the results are limited to this level and cannot be extended to the other levels.

According to Alpar and Schulz, there are three different levels of SSBI: "usage of information", "creation of information," and "creation of information resources". In this particular experiment, the participants had to load the data set into the cloud-based SSBI tool. The data set was provided by the researchers in an excel sheet, which was prepared beforehand.

Hence, the participants received access to data, which had already been created and only required setting some basic parameters before they further analyzed it. Due to the well-prepared data set, it was not necessary to clean up the data. Only some simple settings had to be made before data analysis. However, this approach is not flexible enough for a deeper understanding of underlying data and data structures. This approach is uniquely well suited for casual business users who neither have a deeper understanding of data structures nor special tool skills.

Therefore, an experiment on the level of "creation of information" and "creation of information resources" would provide more profound insights.

A further option to obtain a deeper understanding of BI-related topics would be to conduct a qualitative research study on different levels of SSBI. Conducting those experiments with business users from the field with different demographics could help to get insights into the application of SSBI tools in everyday business. By doing so, it could be possible to reveal in detail which SSBI level causes what kind of challenges.

For this research, only one SSBI tool was used. Applying the same research setting on different SSBI tools would get more comprehensive insights and would lead to better generalizable results.

Conflict of interest

There is no conflict of interest for this study.

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