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Research article

From data to decisions: Exploring common challenges faced in behavioural monitoring programmes

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Abstract

Many accredited zoos and aquariums aspire to provide evidence-based animal care. Systematically recording animal behaviour, the most direct and practical form of evidence for evaluating animal welfare, can be a valuable tool for this. However, challenges in using behaviour data to inform decisions may limit the potential impact of these efforts and has not yet been explored in zoos and aquariums. In this pilot study, three independent surveys investigated the challenges zoo professionals face in developing behaviour monitoring programmes and successfully utilising the resulting data. This included a survey of staff at zoos and aquariums accredited by the Association of Zoos and Aquariums (AZA) and two surveys of users of a behaviour-recording app. The survey of AZA-accredited organisations revealed that roughly half conducted formal behaviour observations and for those organisations, general behaviour monitoring was one of the most commo22n processes for recording animal behaviour. The surveys highlighted a general pattern with later phases of analysing data, informing actions and evaluating actions ranking as relatively more challenging than earlier phases of designing projects, training observers and recording data. In considering various factors that could contribute to these challenges, such as staff motivation and skills, evidence of past successes, equipment availability and trust in data, this study found all factors were challenging to some organisations. This confirms the inherent challenges many organisations face in using data which are likely not unique to zoos and aquariums; there may be insights to be gained from research in other industries. To maximise the impact of their behaviour monitoring efforts in enhancing animal wellbeing, zoos and aquariums are encouraged to pay greater attention to the challenges associated with using data.

Introduction

Data is an essential component of any modern organisation. Hailed as the "new oil" (Arthur 2013), data has been viewed as a raw material driving innovation and success in today's companies. For modern accredited zoos and aquariums, the transition to science-based organisations has placed an emphasis on data in guiding evidence-based practices in care and welfare (Brereton and Rose 2022; Melfi 2009; Miranda et al. 2023). Although the potential value of data is hard to overstate, the effective use of data to inform decision-making is challenging for many organisations (Gartner 2023; Henrion 2019). Here, data arising from ongoing behaviour monitoring programmes is examined, considering the potential obstacles to putting data into action.

As the terminology around what constitutes data can differ, considering the meaning of 'data' from a formal perspective may be helpful to start. In epistemological traditions, data is viewed as the foundation of knowing. This is most explicitly represented in the data-information-knowledge-wisdom (DIKW) pyramid (Rowley 2007). In this model, visualised similarly to Maslow's hierarchy of needs, data is situated as the base of a pyramid with subsequent tiers representing increasing levels of understanding: data as unstructured, raw facts; information as the processing of data to extract value; knowledge as the activation of information to guide decisions; and wisdom as the accumulation of knowledge to generate broader understanding. Although in this view the plural of anecdote is indeed data (the oft-repeated "the plural of anecdote is not data" is actually a misquote of an original statement to the contrary that was meant to highlight the value of anecdotes in guiding objective inquiries; Polsby 1993), western scientific traditions place greater emphasis on empirical, objective sources of data and this usage of 'data' is adopted hereafter. Thus, as the DIKW pyramid illustrates, a robust data collection practice can provide a strong foundation for knowledge but does not by itself guarantee insight.

In zoos and aquariums, changes to accreditation standards have made assessing animal welfare a priority and in response many organisations have begun to initiate behaviour monitoring programmes. Animal behaviour can provide zoo and aquarium practitioners a direct perspective on the welfare of an individual, unlike traditional approaches that inferred welfare from a review of the environment, and has been shown to be the most commonly used indicator in animal welfare research (Binding et al. 2020). Although the size and scope of a behaviour monitoring programme will likely differ between organisations, it typically seeks to record animal behaviour data in a systematic fashion to provide an ongoing source of knowledge that can be used by husbandry managers to inform decisions. This process is in contrast to the hypothesis-driven, research-oriented data collection of zoos and aquariums and shares many features with the operational use of data in business contexts (Wark 2022). Ongoing behaviour monitoring offers exciting potential for understanding baseline behaviour patterns of individuals and identifying if these behavioural norms change over time or in response to unexpected changes, which may indicate a shift in welfare status (Wark et al. 2019; Watters et al. 2009). However, to fully realise this potential value of behavioural monitoring programmes, there needs to be success at every stage in the process from data to decisions (Wolfensohn et al. 2018).

In this study, zoo professionals and users of a common behaviour monitoring app were surveyed on their behavioural monitoring practices. There were two primary aims in this investigation: 1) describe the current state of behaviour monitoring efforts across Association of Zoos and Aquariums (AZA)-accredited organisations and 2) identify common challenges to developing successful behaviour monitoring programmes. The steps of the behaviour monitoring process, from designing projects to using data to inform decisions were evaluated. In addition, we assessed what aspects, from an organisational perspective, created difficulty. Three separate surveys were conducted that targeted different audiences and the results were opportunistically combined to provide a pilot, exploratory examination of these topics. To the author's knowledge, this is the first study to explore the challenges in behavioural monitoring programmes. Building a better understanding of these challenges will help zoos and aquariums develop successful monitoring programmes that effectively use data to inform decisions that enhance animal welfare.

Methods

Survey procedure

Three separate surveys were conducted that included questions on the challenges faced by organisations in using data from behaviour observations to guide decisions. As part of the strategic planning process of AZA's Behaviour Scientific Advisory Group, institutional representatives of AZA-accredited zoos and aquariums were surveyed in February 2022. This survey contained 29 questions that asked respondents' views on a diverse range of behaviour-related topics and focused mostly on aspects of behavioural husbandry. Questions relating to data use were included near the end of the survey and the respondents were not required to complete the questions.

Questions relating to behaviour monitoring challenges were included in the 2021 annual satisfaction survey of general users of the ZooMonitor behaviour recording app (Wark et al. 2019). ZooMonitor was created by Lincoln Park Zoo and built by Tracks Data Solutions (Salida, CO). Released in 2016, the ZooMonitor app is now in use at hundreds of zoos and aquariums around the world. The author is the product manager for this app. The survey of app users included a total of 25 questions. Questions relating to data use were included at the end of the annual satisfaction survey and participants were given the option to exit the survey or voluntarily continue to share their feedback on data use within their organisations. Participants in the data use survey were required to complete the questions.

A short survey on data use was administered to members of a working group comprised of experienced users of the ZooMonitor app that had voluntarily agreed to advise the Lincoln Park Zoo team on the needs of multi-institutional research as part of an Institute of Museum and Library Services-funded grant project (hereafter referred to as 'power users'). The survey was conducted to better understand the working group's data analytics needs to inform the design of new features in the ZooMonitor app. The survey featured 17 questions including on data use at their organisation and factors related to multi-institutional data sharing. Questions pertaining to data use were included at the start of the survey and were required to be completed.

The surveys conformed to Lincoln Park Zoo's policies on human subjects research and the guidelines of the British Psychological Society. All surveys were conducted voluntarily and participants were able to quit the survey at any time. When possible, surveys were conducted anonymously (e.g. general app users and AZA-accredited organisation surveys). The app power users survey was not conducted anonymously as this survey was part of broader, user research activities of a grant-funded research project. This research was evaluated by the chair of the Lincoln Park Zoo Institutional Review Board (IRB) and considered low risk to participants.

Survey questions

In each of the three surveys, participants were asked to rank how challenging different behaviour observation activities were (Table 1). For surveys of general and power users of the app, the list of behaviour observation activities included: 1) designing behaviour observation projects, 2) training observers on data collection protocols, 3) recording data and managing data collection, 4) analysing and sharing findings from data, 5) utilising findings from data to drive actions and 6) evaluating the success of data-driven actions. These survey participants were asked to rank each activity on a scale of one as most challenging to six as least challenging. For the survey of AZA-accredited organisations, activities two and six were not included in an effort to lower the overall effort required of respondents. In addition, these survey participants were asked to rank choices on a scale of one as least challenging to four as most challenging.

All three surveys asked participants to rank how challenging the following institutional factors were for behaviour observations: 1) staff knowledge and training to create projects, 2) staff knowledge and training to analyse data, 3) motivation and interest of front-line care staff (e.g. keepers and aquarists), 4) motivation and interest of leadership (e.g. curators and managers), 5) lack of success in gaining actionable insights from data, 6) trust in behaviour data and 7) equipment availability (e.g. tablets, computers, cameras). App users were asked to rank these factors on a scale of one as most challenging to seven as least challenging, whereas the AZA-accredited organisation survey asked participants to rank choices on a scale of one as least challenging to seven as most challenging. In the survey of general app users, there was an initial typographical error in the response labels for both the behaviour observation question and institutional factor question that replaced the word

Table 1. Overview of survey questions

Name	Question	Choices	Surveys included
Behaviour Observation Activities	Please rank how challenging the following behaviour observation activities have been at your organisation	Designing behaviour observation projects Training observers on data collection protocols[a] Recording data and managing data collection Analysing and sharing findings from data Utilizing findings from data to drive actions Evaluating the success of data-driven actions[a]	All
Institutional Factors	Please rank how challenging the following institutional factors have been at your organisation.	Staff knowledge and training to create projects Staff knowledge and training to analyse data Motivation and interest of front-line care staff (e.g., keepers and aquarists) Motivation and interest of leadership (e.g., curators and managers) Trust in behaviour data Lack of success in gaining actionable insights from data Equipment availability (e.g., tablets, computers, cameras, etc.)	All
Behaviour Observation Type	Given the following ways of conducting behaviour observations, please select the types of formal behaviour observations that your institution has conducted in the past year	General Behaviour Monitoring: behaviour observations that record a broad set of behaviours to provide general behavioural data/ information to stakeholders. Observations are generally ongoing with no defined start/end date. Targeted Behaviour Monitoring: behaviour observations that focus on better understanding a specific behaviour(s) of interest, such as pacing or courtship/ reproduction. Observations may be either ongoing or defined by a start/end date. Evaluative Observations: behaviour observations conducted to specifically monitor and/or evaluate key events, such as effectiveness of new enrichment or response to an enclosure move. Observations may be one-off or added to other forms of observation with start/end dates reflective of the event of interest. Internal Research Project: projects with specific start and end dates designed to address a specific research question that may involve manipulation of variables. Internal reflects your institution designed and completed the project. External Research Project: projects with specified start and end dates designed to address a specific research question that may involve manipulation of variables. External reflects the study was proposed by an outside institution/ researcher but was conducted at your institution by your staff.	AZA-Accredited Zoos & Aquariums
Project Success Percentage	To the best of your knowledge, what percentage of your observation projects have generated behaviour insights that have been used to guide animal care decisions?	NA	App Power Users

[a]These question choices were not included on the AZA-Accredited Zoos & Aquariums survey.

"challenging" with "important" (although the question wording did clearly state "challenging"). This error was quickly corrected but incorrect labels were present for 14 participants.

Data were also analysed for two additional questions from the AZA-accredited organisations survey. First, as a screening question participants were asked whether their organisation was currently conducting formal behaviour observations (defined as "observations with a fixed duration and using standardised scientific methods to sample behaviour") with the choices of "Yes", "No" and "Unsure". Next, participants were asked to share the type of observations being conducted from the following choices (Table 1): 1) general behaviour monitoring, 2) targeted behaviour monitoring, 3) evaluative observations, 4) internal research project and 5) external research project. Participants who selected "No" or "Unsure" on the preceding screening question on their organisation's current observation efforts were instructed to skip this question on observation type.

Data from one additional question in the app power user survey is included in this study. During this survey, participants were asked to estimate the percentage of observation projects that have generated insights that were used to guide animal care decisions.

Data analysis

Data were excluded from surveys where respondents failed to complete a question. For the AZA-accredited organisations survey, this resulted in 26 survey responses being excluded from the behaviour observation activities question, 36 being excluded from the institution factors question and two being excluded from the observation type question. For the app general users survey, 20 survey responses were excluded. All app power users completed the questions (i.e. no surveys excluded). In addition, for the AZA-accredited organisations survey, responses were excluded where the respondent indicated they were unsure of whether their organisation was currently conducting behaviour observations. This resulted in 16 additional survey responses being excluded from the behaviour observation activities question and institution factors question.

Table 2. The number of survey responses

Survey Name	Description	Total Participants	Study Participants[a]
AZA-Accredited Zoos & Aquariums	Strategic planning survey by the AZA Behaviour Scientific Advisory Group of institutional representatives of AZA-accredited organisations	230	188[b]/178[c]
App General Users	Annual satisfaction survey of users of the ZooMonitor app	49	29
App Power Users	Survey of members of a grant-related advisory group of advanced ZooMonitor users providing feedback on the app	20	20

[a]Survey responses were excluded based on several criteria (see Methods).
[b]The number of completed responses for the behaviour observation activities question.
[c]The number of completed responses for the institutional factors question.

To evaluate a difference in rank scores, a Friedman test was conducted for the behaviour observation activities question and institutional factors question. When a significant difference (i.e. $P<0.05$) was observed for a given survey, the Nemenyi test was conducted as a post-hoc analysis to identify pairwise differences between question choices.

As this study was exploratory in nature, several additional post-hoc tests were conducted. For the AZA-accredited organisations survey, the number of staff at an organisation was compared between organisations that did and did not conduct formal behaviour observations using a chi-square test. In addition, the Friedman tests of behaviour observation activities and institutional factors questions were analysed separately for organisations conducting formal behaviour observations to those not conducting observations. For all three surveys, the behaviour observation activities data were grouped into 'primary activities' (i.e. creating projects, training observers, recording data) and 'secondary activities' (i.e. analysing data, utilising findings, evaluating actions) and the distribution of the top two and bottom two ranks were compared using a chi-square test. This test was done to identify broad patterns in challenges throughout the behaviour observation process.

For presentation, ranks were transformed to place all three surveys on a scale such that a rank of one was least challenging and the maximum rank was most challenging. This involved reversing the ranking of the app user surveys to correspond to the rankings in the AZA-accredited organisations survey.

All statistical tests were performed using R statistical software (R Core Team 2023). The Friedman and chi-square tests were conducted using the Base package. The post-hoc Nemenyi test was performed using the frdAllPairsNemenyiTest function in the PMCMRplus package (Pohlert 2023). Data were visualised using the ggpubr package (Kassambara 2023).

Results

Survey demographics

The number of survey participants is shown in Table 2. Available demographic data varied by survey. For the AZA-accredited organisations survey, the majority of participants were at smaller organisations with less than 100 staff (n=191; 83% of participants). There were 13% of participants (n=29) at organisations with between 100 and 200 staff, 2% of participants (n=4) at organisations with between 200 and 300 staff and 3% (n=6) at organisations with over 300 staff members. The most common job roles for participants were animal supervisor or curator (n=106, 46%), animal caretaker (n=40, 17%), executive leadership (n=31, 13%), science/research/welfare staff (n=16, 7%) and veterinary staff (n=7, 3%).

For participants in the app general user survey that completed the optional data use questions, a similar number were at large organisations with over 300 staff (n=12, 41%) and medium organisations with 100 to 300 staff (n=11, 38%). Fewer responses came from employees at small organisations with under 100 staff (n=6, 21%). All participants worked at an accredited organisation (n=29, 100%) and these were primarily zoos (n=23, 79%) and located in North America (n=24, 83%). All had experience using the ZooMonitor behaviour recording app, with most currently using the app (n=23, 79%) and others having used it before but not currently using it (n=6, 21%). Roughly half of the participants had used the app for more than two years (n=15, 52%) and 31% (n=9) had been using the app for one to two years.

Demographic survey questions were not included in the app power user survey as these participants were involved in an ongoing grant-related project but prior knowledge of these participants would characterise most as being employed at large, AZA-accredited zoos.

Behaviour observation type

Responses to the AZA-accredited organisations survey indicated that roughly half of zoos and aquariums were conducting formal behaviour observations (n=117, 51%). Of the remaining organisations, 41% (n=94) indicated they were not conducting formal observations and 7% (n=17) were unsure. In comparing organisations that were conducting behaviour observations to those that were not, there was a significant difference based on organisation size (χ^2=19.60, df=6, P=0.003; Figure 1). Organisations that responded as not conducting formal behaviour observations were primarily represented by the smallest organisations with less than 50 staff. When organisations were grouped by staff number using bins of 100, no significant difference in the number of staff were observed between those organisations conducting behaviour observations and those not conducting observations.

For the institutions that indicated they were conducting formal behaviour observations in the AZA-accredited organisations survey, the most common types of observations were targeted behaviour monitoring (n=92, 79%), general behaviour monitoring (n=85, 73%) and evaluative observations (n=85, 73%), with fewer organisations conducting behaviour observations for internal research (n=58, 50%) or external research (n=45, 38%) purposes.

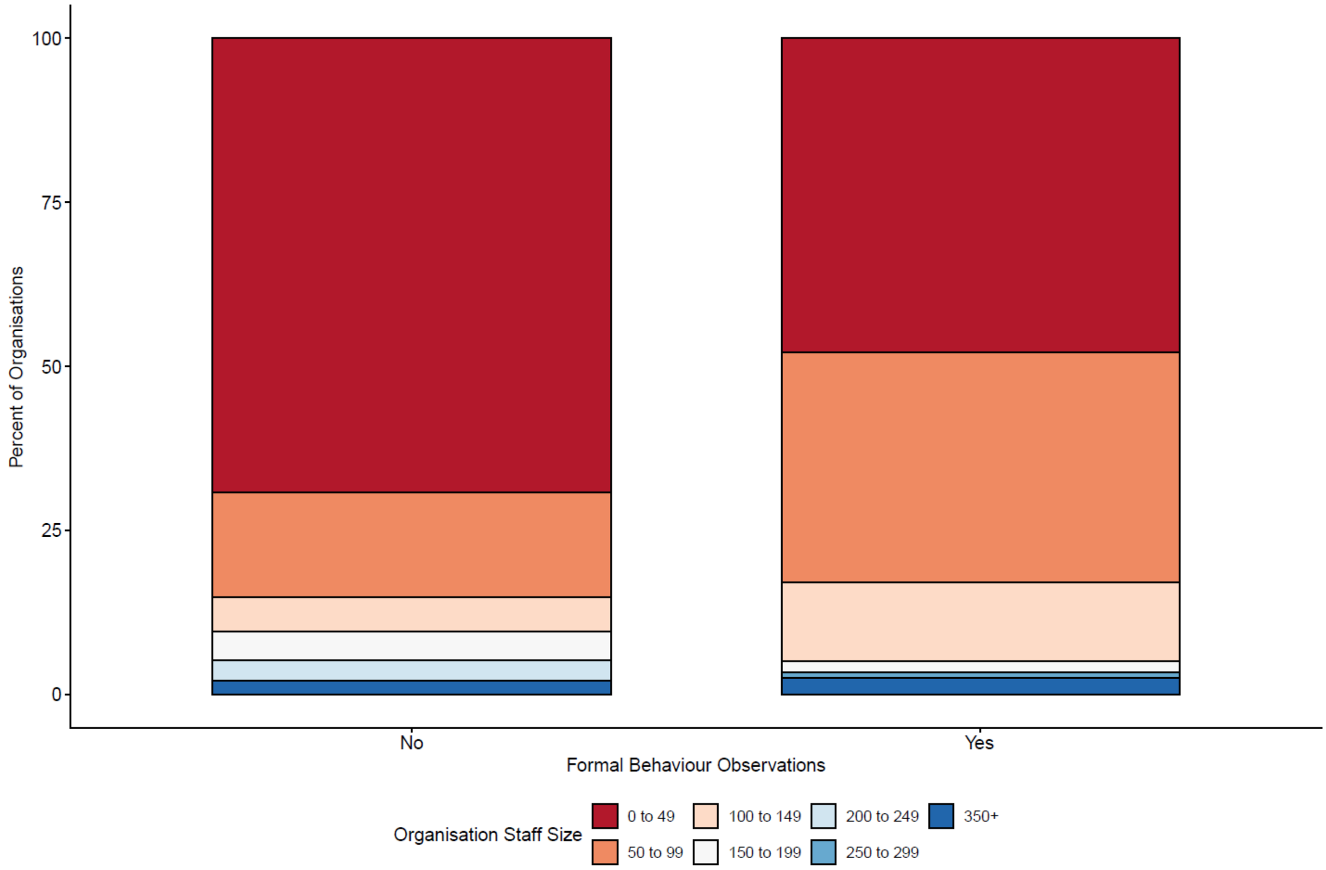

Figure 1. A comparison of the number of staff between organisations conducting formal behaviour observations to those not conducting observations, based on the responses to a community-wide survey.

Behaviour observation activities

In the AZA-accredited organisations survey, there was an overall significant difference in the ranking of how challenging different behaviour observation activities were (χ^2=29.718, df=3, P<0.001; Figure 2A). When the data from organisations that were conducting formal behaviour observations were analysed separately from those organisations that were reportedly not engaged in behaviour monitoring, there was a significant difference in ranking of activities for organisations that were conducting observations (χ^2=27.46, df=3, P<0.001) but not for organisations that were not conducting observations (P>0.05). A post-hoc analysis identified that designing projects was ranked as relatively less challenging than analysing data (P=0.047) and informing actions (P<0.001). Recording data was ranked as relatively less challenging than informing actions (P<0.001).

No significant difference was found between the ranking of behaviour observation activities in the general app users survey (Figure 2B). For app power users, there was a significant difference between the rank of behaviour monitoring activities (χ^2=29.06, df=5, P<0.001; Figure 2C). Post-hoc tests indicated that designing projects was ranked as relatively less challenging than analysing data (P=0.001), informing actions (P<0.001) and evaluating actions (P=0.013). In addition, recording data was ranked as relatively less challenging than analysing data (P=0.29) or informing actions (P=0.013).

When data were grouped to analyse the top two and bottom two ranks for the primary phases of behaviour monitoring (designing projects to recording data) versus the secondary phases (analysing data to evaluating actions), both the AZA-accredited organisations and app power user survey participants ranked the secondary phases as more challenging (AZA-accredited organisations: χ^2=24.308, df=1, P<0.001; app power users: χ^2=22.105, df=1, P<0.001) and there was a trend to significance for the app general users survey (P=0.095).

Institutional factors

In the general app user survey, there was a significant difference in the ranking by participants of how challenging different institutional factors were for behavioural monitoring (χ^2=13.345, df=6, P=0.038; Figure 3B). Post-hoc analysis identified that participants of this survey ranked staff knowledge and training to analyse data as significantly more challenging than equipment availability (P=0.015). Although there was also a significant difference between ranking of institutional factors on the AZA-accredited organisations survey (χ^2=14.632, df=6, P=0.023; Figure 3A), post-hoc testing failed to identify a significant difference in pairwise comparisons. When the data from institutions that were conducting formal observations were analysed separately from those that reported they were not conducting observations, there was a trend to significance for differences in rankings from

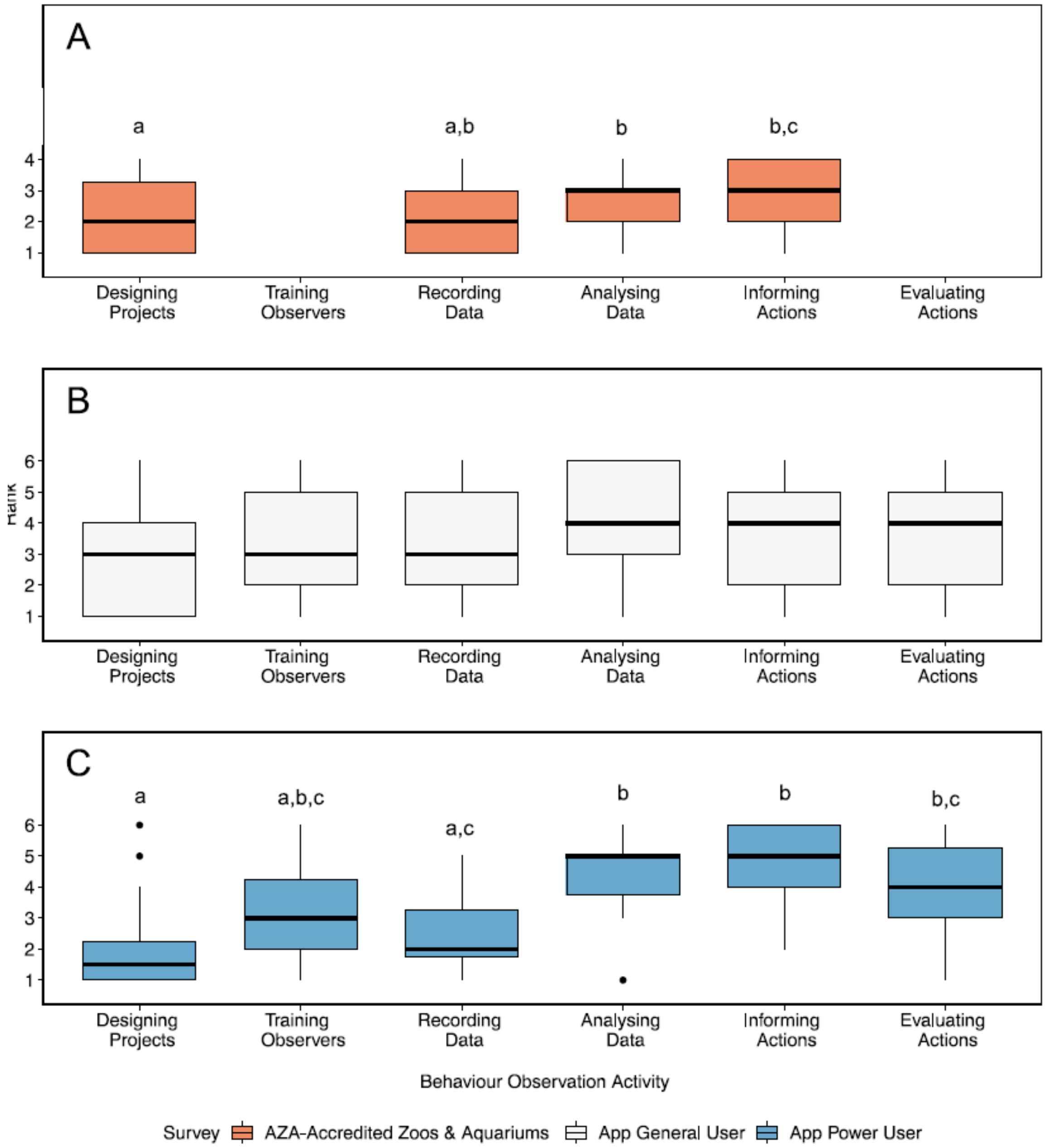

Figure 2. The relative ranking by survey participants (A: AZA-Accredited Zoos & Aquariums; B: App General User; C: App Power User) of how challenging different behaviour observation activities were. Higher ranks indicate more challenging activities. Letters denote significant pairwise differences.

institutions that were conducting observations (P=0.093). There was no significant difference in ranking of factors in the AZA-accredited organisations survey for organisations that were not conducting observations and by participants in the app power user survey (Figure 3C).

Project success

In the app power user survey, the estimated percentage of projects that generated insights that led to husbandry decisions ranged across participants from a minimum of 4% of projects leading to decisions to a maximum of 100% of projects leading to decisions with a mean of 58%.

Discussion

The goal of this study was to describe the state of behavioural monitoring programmes across AZA-accredited organisations and identify common challenges faced by zoo and aquarium professionals in developing successful behavioural monitoring programmes. As seen here, the first challenges to a behaviour monitoring programme may arise before its inception. Through a survey of AZA-accredited zoos and aquariums, nearly half of the organisations reported they were not conducting formal behaviour observations. Given the attention towards welfare in the zoological community and the value in recording behaviour as a low-cost,

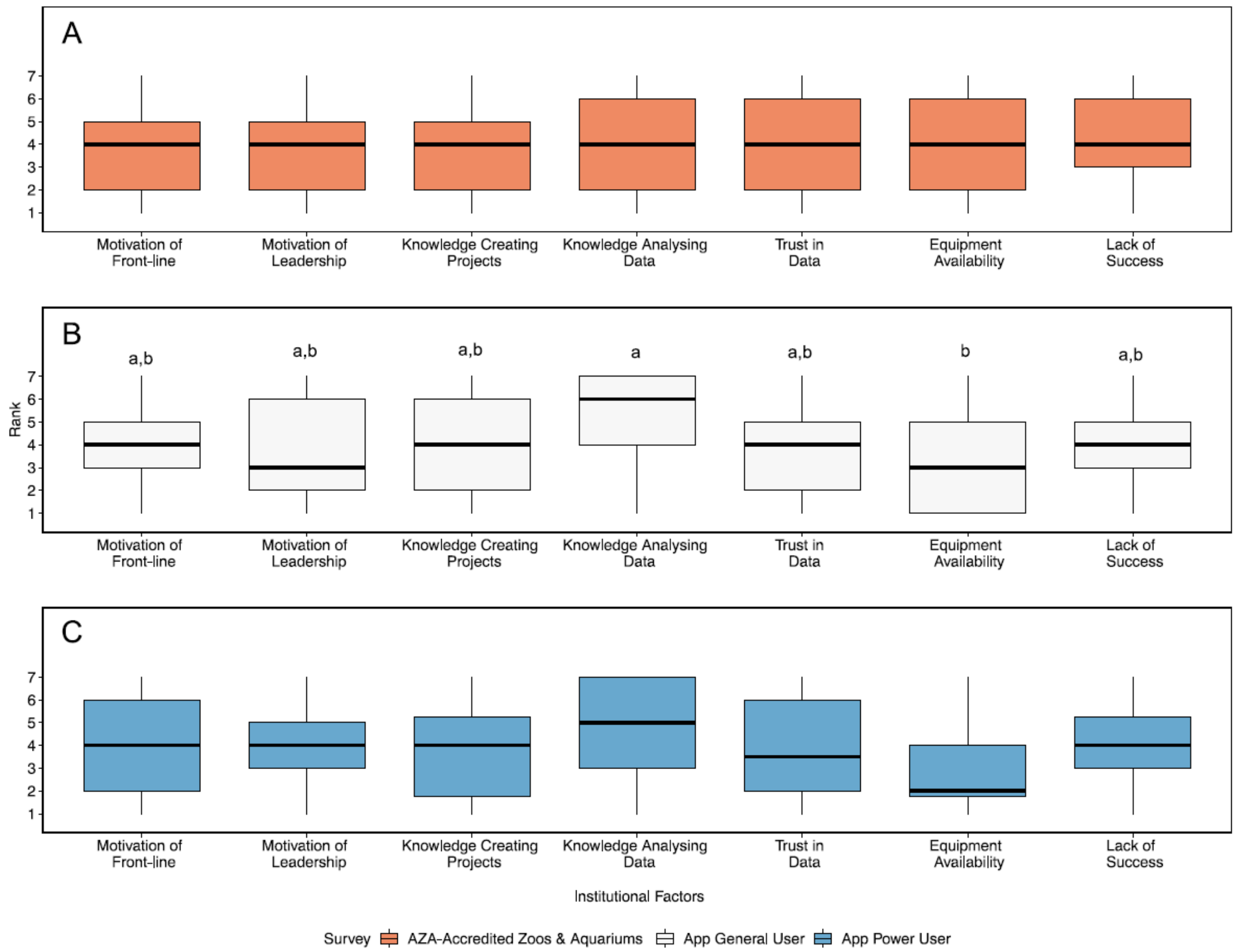

Figure 3. The relative ranking by survey participants (A: AZA-Accredited Zoos & Aquariums; B: App General User; C: App Power User) of how challenging different factors were on conducting behaviour observations. Higher ranks indicate more challenging factors. Letters denote significant pairwise differences.

accessible means to assess welfare, it is perhaps surprising that formal behaviour observations were not more widespread through the AZA community. Perhaps less surprising, there appeared to be a relationship to the size of the institution, with formal observations happening less frequently at organisations with less than 50 staff. When considering organisations with less than 100 staff, the proportion of organisations conducting behaviour observations was similar to those not conducting observations, suggesting this challenge may be most acute for the smallest organisations. However, it should be noted that the majority of organisations conducting behaviour observations were small zoos and aquariums (83% had less than 100 staff), suggesting that these challenges can be overcome and raising the potential for small zoos to collaborate more closely to share strategies for conducting behaviour observations with limited staff.

For those organisations conducting formal observations, it was encouraging to see that general behaviour monitoring that involved systematic, ongoing observations of animals was one of the most common ways behaviour observations were being conducted. This type of applied behaviour observations represents a valuable tool for zoos and aquariums seeking to use behaviour data to regularly inform decision-making (Galante and Margulis 2022; Watters et al. 2009).

When considering the challenges faced in behavioural monitoring, there appeared to be success in the initial steps of data collection. This may reflect the widespread availability of resources for learning behavioural sampling methodologies (e.g. Bateson and Martin 2021; Rose and Riley 2021) and tools for conducting behaviour observations (e.g. Wark et al. 2019). However, through survey responses from the AZA community and from users of a behaviour recording app, it was apparent that putting data into action was a challenge for many organisations. Through three independent surveys, the later phases of behaviour monitoring—analysing the data, utilising the data in decisions and evaluating those decisions—were rated as more difficult than earlier phases of designing projects, training observers and recording observations.

These challenges in behaviour monitoring may arise from specific institutional factors. This study evaluated the motivation and skills of staff, evidence of past successes in using data, logistical challenges in equipment availability and the general trust in behaviour data as potential barriers to a behaviour monitoring programme. In general, all factors were rated as similarly challenging by survey respondents with one minor exception—general app users identified staff knowledge and training to analyse data as the most challenging institutional factor. Although not significantly different from other factors, staff knowledge and training to analyse data was also ranked as the most challenging by app power users. Overall, no broad trends across the community were observed, suggesting that institutional challenges appeared to be primarily specific to the organisation.

It is notable that the challenges in using data persisted even for organisations with experienced behaviour monitoring programmes. For app power users, a mean of 58% of behaviour monitoring projects had led to decisions. Thus, 42% of the projects being conducted were not meeting the intended outcome.

Taken together, these results highlight the varied challenges faced by zoos and aquariums seeking to use the data from behaviour monitoring programmes to inform decisions. Logistical challenges such as organisational size are likely the first barrier to many. Beyond this, the difficulty of putting data into action may further hamper behaviour monitoring efforts. Although to the author's knowledge this is the first study to directly consider these challenges in zoos and aquariums, there has been extensive research on this topic conducted in other disciplines that may provide guidance. In education, public policies have placed pressure on schools to use data to guide their instruction and practices and a growing body of knowledge now exists on data-based decision-making in schools (Schildkamp 2019; Schildkamp et al. 2013). In business contexts, there has been research on the adoption and implementation of business intelligence systems, tools and processes intended to support decision-making (Ain et al. 2019; Wark 2022; Yeoh et al. 2008). In healthcare, the need for clinicians to incorporate evidence-based treatments into their practice has attracted considerable attention and spawned the field of implementation science (Bauer and Kirchner 2020; Nilsen 2015). There are several factors that may be relevant to the success of behaviour monitoring programmes.

Most directly, the results of the present study speak to a need for greater attention towards data literacy in zoos and aquariums. Data literacy is a more recent concept that refers to the knowledge and skills required to effectively use data (Ghodoosi et al. 2023; Mandinach and Gummer 2012). Research in schools on data use by teachers and administrators in higher education has shown data literacy to be linked to successful data-based initiatives (Lin et al. 2023; Schildkamp et al. 2017; Vanhoof et al. 2013). In their review, Ridsdale et al. (2015) defined 23 competencies of data literacy that they organised into five key knowledge areas, including a conceptual understanding of data, data collection, data management, data evaluation and data application. Thus, while data literacy includes those skills needed for data analysis (e.g. Wark et al. 2022; Plowman 2008), it also incorporates all components of the inquiry cycle, from how to frame questions to critically evaluating the outcomes of decisions (Gummer and Mandinach 2015). For behaviour research, Rose and Riley (2021) provide a helpful overview of many concepts that are fundamental to data literacy. Although the relative importance of specific data literacy competencies will vary with a person's role, a basic training for all staff in zoos and aquariums may be valuable and several organisations have started to explore this (S. Leard, L. Giffen and D. DuMerer, personal communication, 11 September 2023). It may also be necessary to structurally encourage data use and collaboration, as has been done in schools through the development of data teams (Schildkamp and Poortman 2015). Data teams involve a small group of teachers and several school leaders who work closely to use data to address questions. In some cases, these efforts may be facilitated by an outside data expert (van den Boom-Muilenburg 2023). Data teams provide an important professional development opportunity and can lead to improved data literacy and more positive attitudes towards data for some participants (Bolhuis 2019; Kippers et al. 2018; Poortman et al. 2022).

Although many different organisational factors have been identified as important for successful data-based efforts (Ain et al. 2019; Schildkamp et al. 2017), a key factor that has been frequently cited is that of top-down support of leadership (Nguyen et al. 2018; Rathore et al. 2022; Schildkamp et al. 2019; Yeoh and Koronios 2010). In their study on adoption of business intelligence systems by transportation and energy companies, Yeoh and Popovič (2016) argue that leadership support was the most critical factor for success of the companies they studied and should be addressed first when considering similar initiatives. The importance of leadership support has also been confirmed in zoos—Anderson et al. (2010) found the support of the zoo director was rated as the most important factor for a successful scientific programme. This importance is perhaps not surprising given the well-documented role these individuals play in change management (Reichenpfader et al. 2015). Research in schools on leadership practices identified five key actions for leaders in building effective data teams: 1) establishing a vision, 2) providing individualised support, 3) intellectual stimulation, 4) creating a climate for data use and 5) internal networking. Indeed, a recent study in zoos on the challenges faced in enrichment programmes highlighted the failure of managers to articulate clear goals as a key impediment to a programme's success (Tuite et al. 2022). Engaging leadership early in the implementation of a behaviour monitoring programme is likely crucial for buy-in and alignment.

Research has also highlighted the importance of data quality in driving successful data-based initiatives (Kerr et al. 2006; Schildkamp et al. 2017; Yeoh and Popovič 2016). For example, in comparing several urban school districts, Kerr et al. (2006) found the timeliness of data influenced its use for decision-making, with one school district that had to request data reports from an external party showing lower data use than teams that had direct access to the data. Timeliness is also likely to be a critical factor for data use in many zoos and aquariums, as behavioural changes may signal a change in welfare before other types of indicators. However this potential value only exists if the change is identified proactively and acted upon. A previous study introduced the potential of business intelligence tools for increasing the visibility of data that can help support proactive, timely decision-making (Wark et al. 2022).

Limitations and future considerations

Several potential limitations in the current study should be noted. The surveys in this study asked respondents to rank from a closed, fixed set of choices and the challenges presented in this study should be viewed as relative to each other (Fowler 2009). Furthermore, although behaviour observation activities are clearly defined and likely to be generally agreed upon, it is possible there were other important organisational challenges not considered in the current study. Future research is needed to explore factors at various levels, including the individual, team, system and organisation (Schildkamp 2019). Rank questions also limit the ability to interpret the degree of difference between choices. As all respondents were required to give each choice a rank, it is possible some survey participants ranked choices that they may not have perceived as challenging. Future surveys should consider including rating questions alongside ranking questions to identify the overall strength of preference in responses. Lastly, as with all surveys, there is the potential for selection bias. In this study, surveys were completed by a single member of each institution and their responses may not have represented the perspectives of others at their organisation. Future research should engage multiple staff within an organisation at different levels in the decision-making process to build a more robust understanding of the challenges in data use.

Conclusion

This study provides a pilot exploration of the challenges faced by zoos and aquariums in their behaviour monitoring programmes. It is apparent that many zoos and aquariums struggle with putting data into action. Considering the potential deluge of data that future technologies like automated behaviour monitoring (e.g. Zuerl et al. 2022) may bring, these challenges are likely to become exacerbated. Of course, many of the challenges in using data are not unique to zoological organisations and appear universal, providing an opportunity to learn from others. However it is imperative that zoos and aquariums focus on these challenges if they are to provide the best care possible for animals that meets their aspirations as science-based organisations and their ethical obligations to the animals. This study was a first exploration into these challenges and additional attention towards the use of data for decision-making in zoos and aquariums is needed. It is hoped that this study will encourage others to explore this line of research.

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