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Artificial intelligence meets dairy cow research: Large language model's application in extracting daily time-activity budget data for a meta-analytical study

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ABSTRACT

This study investigates the application of ChatGPT-4 in extracting and classifying behavioral data from scientific literature, focusing on the daily time-activity budget of dairy cows. Accurate analysis of time-activity budgets is crucial for understanding dairy cow welfare and productivity. Traditional methods are time-intensive and prone to bias. This study evaluates the accuracy and reliability of ChatGPT-4 in data extraction and data categorization, considering explicit, inferred, and ambiguous labels for the data, compared with human analysis. A collection of 55 papers on dairy cow behavior were used in the studies. Data extraction for eating, ruminating, and lying behaviors was performed manually and via ChatGPT-4. The artificial intelligence (AI) model's accuracy and labeling performance were assessed through descriptive and statistical analyses. Mixed model analysis was used to compare human and AI outcomes. Artificial intelligence and human time budget data showed significant differences for eating and ruminating but not for lying. ChatGPT-4 estimated daily eating time at 22.3% compared with 23.8% by humans. For ruminating, AI reported 33.4% against 31.7% by humans. Daily lying times were nearly identical, with AI at 44.4% and human analysis at 44.2%. The global accuracy in data extraction was ~75%, and labeling accuracy reached 67.3%, with significant variability across behavioral categories. In general, the AI model demonstrates moderate accuracy in extracting and categorizing behavioral data, particularly for inferred and ambiguous data. However, explicit data extraction posed challenges, highlighting AI's dependence on input quality and structure. The consistency between AI and human analyses for lying behavior underscores AI's potential for specific applications. ChatGPT-4 offers a promising complementary tool for behavioral research, enabling efficient and scalable data extraction. However, improvements in AI algorithms and standardized reporting in scientific literature are essential for broader applicability. The study advocates for hybrid approaches combining AI capabilities with human oversight to enhance the reliability and accuracy of dairy cow behavioral research.
Key words: dairy cow, behavior analysis, ChatGPT, artificial intelligence tool

INTRODUCTION

In recent years, artificial intelligence (**AI**) has played an increasingly crucial role in scientific research, revolutionizing the way data are collected, analyzed, and interpreted (Grimaldi and Ehrler, 2023). Artificial intelligence technologies have expanded the boundaries of what is possible, enabling researchers to efficiently process large datasets, identify complex patterns, and make data-driven decisions (Huang and Tan, 2023). Among the many advances in AI, generative models, particularly large language models (**LLM**), have proven transformative due to their ability to generate text, analyze complex information, and support knowledge synthesis (Chu, 2024).

Among these tools, ChatGPT (version 4.0; OpenAI), an advanced LLM, has gained attention. Based on the generative pre-trained transformer (GPT) architecture, ChatGPT excels in contextual understanding and coherent text generation (Tlili et al., 2023). First launched in 2022, ChatGPT has quickly found applications across various fields, including medicine (Dave et al., 2023; Fatima et al., 2024), education (Mai et al., 2024), and sci-

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The list of standard abbreviations for JDS is available at adsa.org/jds-abbreviations-25. Nonstandard abbreviations are available in the Notes.

entific research (Park, 2023). Its ability to process large volumes of textual data, combined with its human-like interaction capabilities, has made it a valuable tool for professionals engaged in scientific research (Huang and Tan, 2023). In this context, ChatGPT has demonstrated the ability to enhance efficiency and accuracy in time-intensive processes such as literature reviews, data extraction, and hypothesis generation. Several studies have highlighted its potential in streamlining scientific writing by organizing content, improving linguistic clarity, and synthesizing information from large text corpora (Huang and Tan, 2023; Park, 2023; Ray, 2023; Picazo-Sanchez and Ortiz-Martin, 2024). Furthermore, ChatGPT can assist in summarizing findings and even suggest new research directions. These capabilities make it particularly useful in fields requiring the integration of heterogeneous data, such as behavioral sciences and applied ethology (Luxem et al., 2022; Pereira et al., 2019).

In animal sciences, AI tools have been explored for their potential in diagnostic processes, educational resources, and management practices (Chu, 2024). One area of interest where AI shows particular promise is the study of cattle behavior, especially regarding the daily time-activity budget, which provides details on the percentage of time an animal spends in specific behavioral states throughout the day (Carenzi and Panzera, 2008). In recent years, this parameter has increasingly been used as a welfare indicator, investigating the extent to which the frequency and time spent performing specific behaviors by an individual deviate significantly from the behavioral repertoire (Huettner et al., 2021). It is influenced by environmental, nutritional, and management factors, and deviations from typical patterns may indicate stress, discomfort, or illness (Grant and Miner, 2015; Mammi et al., 2021; Magro et al., 2024; Lamanna et al., 2025b). Accurate analysis of the daily time-activity budget is essential for understanding the interaction between these factors and improving management practices to optimize welfare and productivity (Johansson et al., 2024). Additionally, animal personality could play a significant role in shaping time-activity patterns, influencing behaviors (Lamanna et al., 2024). Common methods for its evaluation, such as observational studies or manual analysis of data obtained from monitoring systems like accelerometers or video recordings, remain fundamental and provide valuable insights (Anderson and Perona, 2014; Abeni et al., 2023). However, these approaches are often limited by resource intensity, observer bias, and challenges in synthesizing findings across multiple studies. The emergence of AI tools like ChatGPT offers an opportunity to overcome these limitations by automating the extraction and synthesis of behavioral data from scientific literature. This approach has the potential to significantly reduce the time and resources required for data collection and analysis, enabling researchers to process large datasets more efficiently. Possible applications include identifying trends across multiple studies, standardizing data formats, and uncovering patterns that might otherwise remain hidden in fragmented sources. Among the key advantages are the ability to handle vast amounts of textual data, minimize human bias in data extraction, and improve reproducibility of results. However, this method is not without limitations: the accuracy of AI-driven extraction depends on the quality and consistency of the input data, and there may be challenges in interpreting nuanced or context-specific information found in scientific texts. Despite these potential obstacles, integrating AI tools into literature-based meta-analyses represents a promising step toward enhancing the scalability and precision of behavioral research in dairy cow studies.

In this context, our study aims to address these limitations by offering an innovative approach to efficiently extract and analyze data from existing literature, facilitating broader and more integrated meta-analytical evaluations. This study aims to explore the feasibility and effectiveness of using ChatGPT to extract data on the daily time-activity budget of dairy cows from scientific articles retrieved through a bibliographic search on Scopus (https://www.scopus.com/pages/home?display=basic#basic), Elsevier's citation database, with a specific focus on the behavioral parameters of eating, ruminating, and lying. By critically examining the existing literature and synthesizing findings through AI-assisted methods, this research seeks to develop a framework for leveraging AI in ethological studies. The objectives are 2-fold: to evaluate the performance of ChatGPT as a research tool for data extraction and synthesis, and to contribute to a deeper understanding of the existing bibliography on dairy cow behavior, providing a synthesis of the current state of knowledge. Positioned at the intersection of animal sciences and AI research, this study not only advances methodologies for studying animal behavior, but also highlights the broader implications of integrating AI technologies into scientific processes. With the continuous evolution of AI, its role in transforming research workflows and improving animal welfare is set to expand, making this study a timely and relevant contribution to the field.

MATERIALS AND METHODS

Literature Search and Human Data Extraction from Articles

The study was conducted based on information obtained from scientific articles regarding eating, ruminating and lying behaviors and time-activity budget management of dairy cows. Data collection was carried

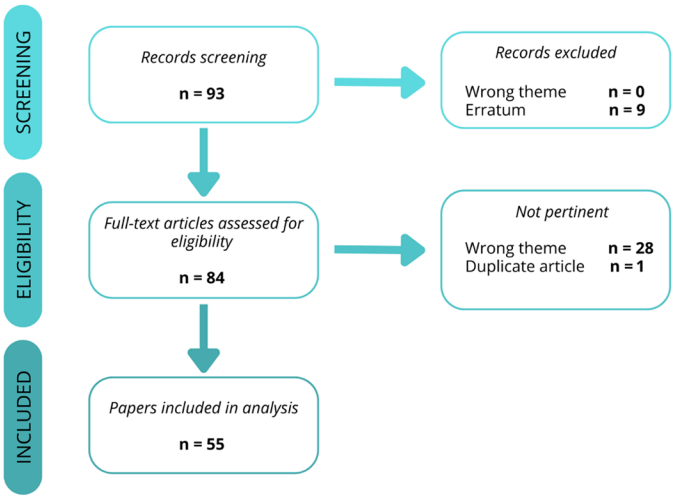

Figure 1. Flowchart of the literature review protocol (adapted from Moher et al., 2009).

out using Scopus, Elsevier's bibliographic and citation database. The research began in April 2024, following the flowchart outlined in the research protocol (Figure 1). During the title, abstract, and full-text screening phases, we verified that each selected study specifically referred to dairy cows (e.g., Holstein-Friesian, Jersey) and excluded any studies focusing on beef cattle, beef on dairy crossbreeds, or non-dairy animals to ensure consistency with the study objectives.

The literature search was conducted using the keywords "time budget" and "cows." The initial search identified a total of 93 articles, which were subjected to a preliminary review by reading their titles and abstracts. One article was excluded because it had not yet reached the final stage of publication, reducing the total to 92 articles. Subsequently, 8 articles were excluded due to the absence of a DOI, leaving 84 articles for further analysis. After an additional review, 28 articles were deemed irrelevant to the study's topics of interest, and 1 article was identified as a duplicate and consequently was excluded from the analysis to ensure the accuracy of the dataset, reducing the final number to 55 (Table 1). Although older studies might introduce some variability in the reported time-activity budgets due to outdated methodologies or management practices, they were included because they provide a critical test of the modelss robustness in handling complex data formats, such as graphical representations.

Each article was assigned a unique code (e.g., A1 for article 1) and organized in a dedicated folder to facilitate subsequent processing. These codes were used solely for internal organization and tracking purposes during data extraction and were not referenced in the statistical analysis or in the presentation of results. The articles were individually read and analyzed to extract data relevant to the behavioral parameters of interest in this study, with the analysis conducted by 2 different researchers to enhance the accuracy of the extracted data. Behavioral definitions were taken as reported in each individual article. However, not all studies relied on standardized ethograms, and the definitions of eating, ruminating, and lying behaviors varied in both specific-

Table 1. List of the 55 analyzed articles in the meta-analytical study

Article
Alzahal et al., 2006
Beggs et al., 2018
Blackie et al., 2011
Calegari et al., 2016
Cavallini et al., 2023
Cook and Nordlund, 2009
Cook et al., 2005
Cook et al., 2007
de la Guardia-Hidrogo and Paz, 2021
Dodzi and Muchenje, 2012
Doerfler et al., 2016
Eriksson et al., 2021
Gladden et al., 2021
González et al., 2003
Haselmann et al., 2022
Helmreich et al., 2014
Hetti Arachchige et al., 2013
Hut et al., 2021
Hut et al., 2022
Iqbal et al., 2023
Jiang et al., 2017
Johansson et al., 2024
Ketelaar-de Lauwere et al., 1996
Ketelaar-de Lauwere et al., 2000
Krawczel et al., 2012
Kronqvist et al., 2021
Løvendahl and Munksgaard, 2016
Marchesini et al., 2011
Mattachini et al., 2017
Mattachini et al., 2020
Matthews et al., 2012
Munksgaard et al., 2005
Neave et al., 2021
Nielsen et al., 2000
Norring et al., 2012
O'Driscoll et al., 2010
Olofsson, 1999
Olofsson and Wiktorsson, 2001
Oudshoorn et al., 2008
Shepley et al., 2020
Stefanowska et al., 2001
Stefanowska et al., 2002
Tofastrud et al., 2018
Toledo et al., 2022
Tucker et al., 2006
Tucker et al., 2007
Ungerfeld et al., 2014
Uzal and Ugurlu, 2010
Val-Laillet et al., 2008
Van Soest et al., 2024
Verdon et al., 2021
Walker et al., 2008
Wang et al., 2024
Winckler et al., 2015
Zebari et al., 2018

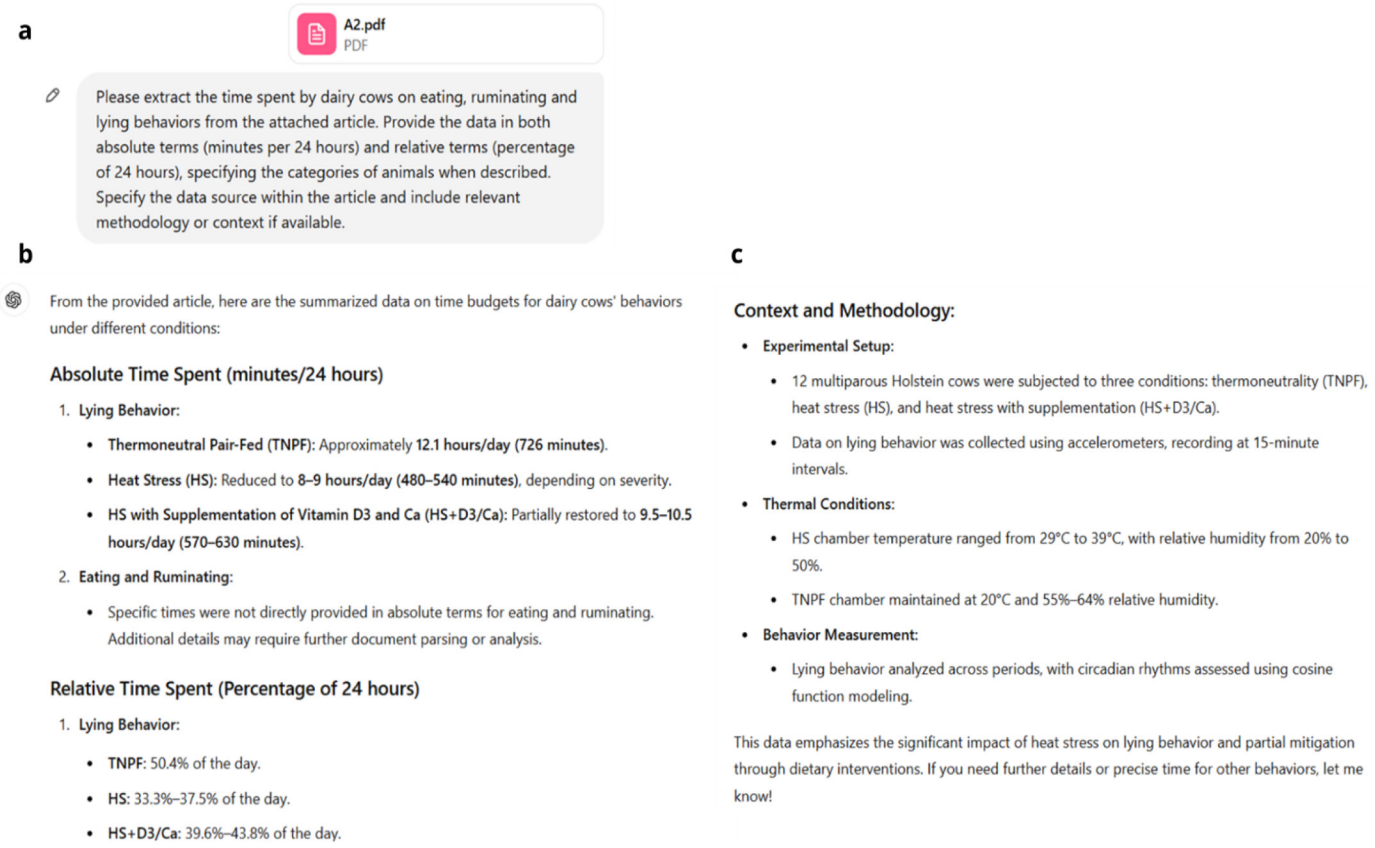

Figure 2. (a) Example of the command for behavioral data extraction using the AI program. The figure illustrates the command used to instruct ChatGPT to extract data on feeding, ruminating, and resting behaviors of dairy cows from scientific articles. The command requested data in both absolute terms (minutes per 24 h) and relative terms (percentage of 24 h), including animal categories and relevant methodological details when available. (b) Extracted data from the AI program, with the comparison of absolute and relative values. The figure presents an example of output generated by ChatGPT, detailing behavioral data of dairy cows, including the minutes and percentage of time spent on feeding, ruminating, and resting behaviors. The figure also highlights how the AI program distinguishes data when multiple categories (e.g., different animal groups) are present, showcasing the accuracy of the extraction process. (c) Methodological context extracted by the AI system. The figure demonstrates an example of contextual extraction performed by ChatGPT, including information about the methodology of the analyzed studies. Details such as sample size, animal categories, and experimental periods are reported to ensure an accurate interpretation of the behavioral data. This highlights the importance of integrating methodological details into data analysis.

ity and format. This variability was acknowledged during the extraction process and may have contributed to differences in interpretation. The parameters included the average percentage of time spent on eating, ruminating, and lying behaviors over a 24-h period. When studies reported overlapping measurements (e.g., rumination occurring during lying time), we carefully reviewed the methodology to determine whether the behaviors were quantified separately. Only explicitly distinct values for each behavior were included in the analysis. If there was ambiguity or overlap, such as lying time including rumination, we excluded those data points from the corresponding parameter-specific accuracy analysis to avoid double-counting. It is important to note that not all articles provided information on all 3 parameters, as these were not always the primary focus of the respective studies. Specifically, eating behavior was reported in 45 articles, ruminating in 22, and lying in 51. When data on a parameter were missing, they were excluded from the accuracy analysis. In the labeling process, if the AI identified the data as ambiguous, it was assumed to be correct. The behavioral parameters of interest were reported in a variety of formats across the reviewed articles. These formats included numerical data embedded within the text, tabular summaries, and graphical representations such as charts or plots. Depending on the study, the data were expressed in units such as minutes per day, percentages of a 24-h period, or occasionally both formats. The human-extracted data were organized into a Microsoft Excel spreadsheet titled "Data daily," where the article's unique code was reported alongside the data, including the author's name and year of publication. This spread-

a For each behavioral parameter (eating, ruminating, and lying), indicate whether the relative data was explicit, inferred, or ambiguous.

b **Detailed Clarifications:**

1. **Eating:**
   - **Absolute data** (hours/day) was explicitly provided in **Table 1**.
   - **Relative data** (percentage of 24 hours) was inferred by dividing hours spent eating by 24 hours and converting to a percentage.
2. **Ruminating:**
   - **Absolute data** (total minutes/day and breakdown for lying vs. standing) was explicitly provided in **Table 1**.
   - **Relative data** was inferred similarly through arithmetic conversion.
3. **Lying:**
   - Both **absolute data** (hours/day) and **relative data** (percentage of 24 hours) were explicitly stated in the table. No inference was required.

Behavioral Parameter	Relative Data (Percentage of 24 Hours)	Status	Explanation
Eating	13.3%–17.4%	Inferred	Explicit absolute data (hours/day) was given; percentage was calculated.
Ruminating	22.4%–27.9%	Inferred	Explicit absolute data (minutes/day) was given; percentage was calculated.
Lying	54.6%–65.4%	Explicit	Both absolute time (hours/day) and relative percentage were provided clearly.

Figure 3. (a) The AI program's categorization and accuracy assessment script. The figure illustrates the updated script used to evaluate ChatGPT's performance in extracting and categorizing data for each behavioral parameter (eating, ruminating, lying). The script identified whether the extracted percentage data were explicit (directly reported in the text), inferred (calculated from figures or tables), or ambiguous (unclear or contradictory), providing a comprehensive evaluation of the AI model's extraction and categorization capabilities. (b) The AI system's response to the categorization and accuracy script. The figure showcases an example of ChatGPT's response to the script for evaluating data extraction accuracy. The AI model categorized the data for each behavioral parameter (eating, ruminating, lying) into 3 types: explicit (data directly stated in the text), inferred (calculated or deduced from figures or tables), and ambiguous (lack of data or data with unclear or contradictory elements). These categorizations, alongside the extracted data, contribute to calculating total data accuracy and total label accuracy, enabling a detailed assessment of the AI's performance in recognizing and interpreting the nature of the reported data.

sheet served as a comprehensive repository, compiling information on the time allocation for each behavior and facilitating further analysis and interpretation.

Data Extraction from Articles with ChatGPT

The second phase involved extracting behavioral data using ChatGPT 4.0 (December 2024 version, OpenAI). The procedure is detailed in the following sections, with a description of each step in chronological order.

Phase 1: Article Preparation. The articles included from the bibliographic search were converted into PDF format, ensuring that the text was accessible and readable by the AI model.

Phase 2: Data Extraction Script. For each article, the following command was used (Figure 2a):

Table 2. Summary statistics for total data accuracy and total label accuracy of the AI model, based on 55 observations; the table presents the mean values, SD, SEM, and the 95% confidence intervals (upper and lower bounds)

Item[1]	Mean	SD	SEM	Upper 95% mean	Lower 95% mean
Total data accuracy, %	75.44	36.32	4.90	85.26	65.62
Total label accuracy, %	67.27	34.24	4.62	76.53	58.02

[1]Total data accuracy reflects the AI's ability to extract data, and total label accuracy assesses the AI's performance in assigning labels across categories (explicit, inferred, ambiguous).

> "Please extract the time spent by dairy cows on eating, ruminating and lying behaviors from the attached article. Provide the data in both absolute terms (minutes per 24 hours) and relative terms (percentage of 24 hours), specifying the categories of animals when described. Specify the data source within the article and include relevant methodology or context if available."

The AI system identified the values related to eating, ruminating, and lying behaviors both in absolute terms (minutes) and relative terms (percentage of the day; Figure 2b). Furthermore, when multiple animal categories (discriminant factor) were present with several data points for the same behavioral parameter, the AI application reported the different values distinctly for each category.

In addition to the data, the model extracted details about the methodological context (e.g., sample size, animal categories, experimental period), when available (Figure 2c).

Phase 3: Assessment of Data Categorization and Accuracy. For each article, the following script was subsequently executed (Figure 3a):

> "For each behavioral parameter (eating, ruminating, and lying), indicate whether the relative data was explicit, inferred, or ambiguous."

This modification aimed to evaluate the AI model ability to accurately identify whether the percentage data for each behavior was explicitly stated in the text, required calculations or inferences, or was ambiguous. Additionally, the overall data accuracy percentage was calculated by comparing the number of correct responses given by the AI application against the total number of identifiable data points in the article, as determined by human extraction by researchers.

The AI program classified its outputs into 3 categories for each behavioral parameter: explicit, when the data were directly stated in the text; inferred, when the data had to be deduced or calculated from figures or tables; and ambiguous, when the data were missing, unclear, or presented with contradictory elements (Figure 3b).

Phase 4: Integration of Results into the Excel Spreadsheet. All data automatically extracted by the AI model were recorded and integrated into the same Excel spreadsheet that contained the human-extracted data from the initial step of the study.

Subsequently, several fields were added in separate columns for each article in the dataset. These included the total data accuracy, calculated as the percentage of correct responses provided by the AI system compared with the total number of identifiable data points; and the behavioral parameter categorization, which recorded whether the data for eating, ruminating, and lying were classified by the AI as explicit, inferred, or ambiguous. The total label accuracy was also recorded by comparing the AI's classification with the actual presentation of the data in the original articles. In cases where the AI output was incorrect, a column titled "Problems (if Wrong)" was included. This allowed researchers to annotate the likely cause of the discrepancy, which could include ambiguous data (e.g., unclear or contradictory information), interpretation errors (e.g., miscalculations or incorrect inferences), text limitations (e.g., difficulties in parsing complex written content), or model limitations (e.g., inability to interpret images or tables accurately).

Statistical Analysis

Statistical analysis was performed using JMP Pro v18 software (SAS Institute, Cary, NC). The normal distribution of numerical data (time-activity budget) was assessed using the Shapiro–Wilk normality test. A P-value >0.05 was considered indicative of a normal distribution. Data are presented as a percentage (mean ± SD) for normally distributed variables. The correlation between data extracted by AI and manually extracted data (human) was analyzed using Pearson correlation test. Differences between data extracted by the 2 systems (fixed effect) were analyzed using a linear mixed model, where each included paper was considered as a random effect. Categorical data (labeling) were presented using proportions in the results section.

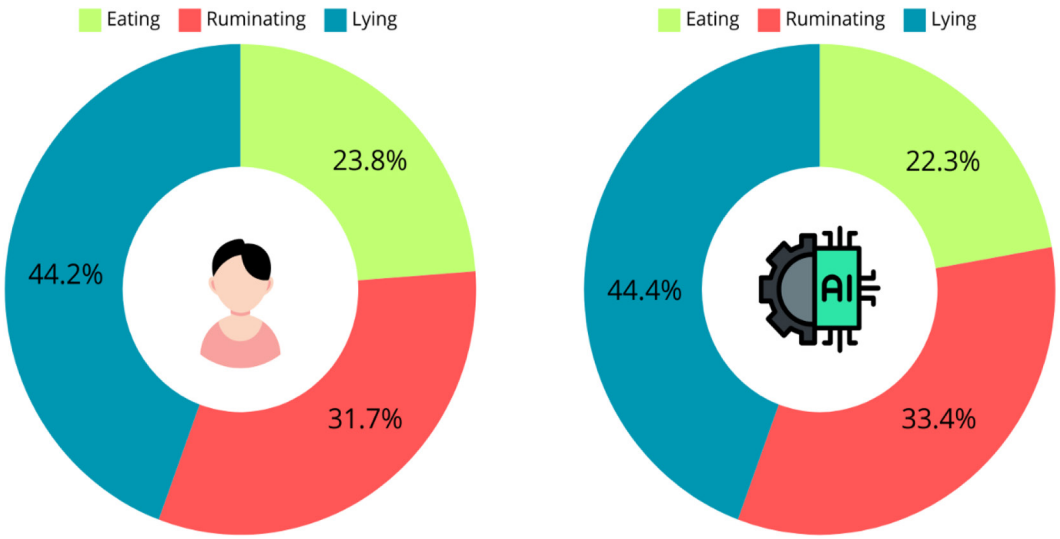

Figure 4. Comparison of time-activity budget between human and AI data extraction for eating, ruminating, and lying behaviors. The left chart represents the time distribution of eating, ruminating, and lying behaviors as extracted by human observation, and the right chart shows the same distribution extracted by the AI system. Note: 100% refers to the combined percentage of these 3 behaviors (eating, ruminating, and lying) and does not represent the entire time-activity budget of the dairy cow.

RESULTS

Time-Activity Budget Analysis: Comparison Between Human and AI Data Extraction

Specifically, the AI model accurately extracted 54.4% of the data related to eating behavior, 49.4% of the data associated with ruminating behavior, and 53.5% of the data concerning lying behavior. The eating behavior was reported in 45 articles, ruminating in 22, and lying in 51.

As reported in Figure 4, the 100% refers to the combined percentage of the 3 behaviors and does not represent the entire time-activity budget of the dairy cow. The mixed model analysis for eating time revealed a significant difference between the data extracted by humans and those extracted by AI (P = 0.0011). Specifically, the AI estimated the percentage of eating time at 22.5% (±1.6%), with a 95% CI ranging from 19.0% to 25.5%. On the other hand, human data extraction provided an estimated eating time of 23.8% (±1.6%), with a 95% CI between 20.5% and 27.0% (Figure 4).

For ruminating time, the analysis also revealed a significant difference between the AI and human-extracted data (P = 0.0228). The AI reported an estimated ruminating time of 33.4% (±1.2%), with a 95% CI spanning from 31.1% to 35.8%. Conversely, human data extraction provided a slightly lower estimate of 31.7% (±1.1%), with a 95% CI ranging from 29.4% to 34.0% (Figure 4).

For lying time, the analysis showed no significant difference between the data extracted by AI and humans (P = 0.8573). The AI estimated the percentage of lying time at 44.4% (±1.46%), with a 95% CI ranging from 41.4% to 47.3%. Similarly, the human estimate was 44.2% (±1.4%), with a 95% CI between 41.3% and 47.1% (Figure 4).

Accuracy and Consistency of AI in Data Extraction and Labeling

The analysis of total data accuracy, based on a total of 55 studies, revealed a mean of 75.4%. When data on a parameter were missing, they were excluded from the accuracy analysis. In the labeling process, if the AI identified the data as ambiguous, it was assumed to be correct. This metric reflects the comparison between the data extracted manually by humans and those extracted by the AI. On average, most estimates achieved a high level of precision relative to the reference data. However, the SD, equal to 36.3%, highlights considerable variability in the results: some observations were highly accurate, whereas others showed significant deviations. The SEM, calculated at 4.9%, confirms that this estimate is representative of the sample population. The 95% CI for the mean, ranging from 65.6% (lower bound) to 85.3% (upper bound), suggests with high certainty that the true mean of total data accuracy lies within this range. This interval reflects the balance between highly accurate observations and those with lower precision. Upon further examination, the observed inaccuracies can be attributed to several factors. In some cases, the data presented in the articles were ambiguous, containing unclear or contradictory information that made reliable extraction dif-

Table 3. Summary of the categorization results for eating, ruminating, and lying behaviors based on 55 observations; the table presents the number of correct (right; R) and incorrect (wrong; W) classifications made by the AI model across 3 categories: ambiguous, explicit, and inferred

	Eating			Ruminating			Lying		
Label	R	W	Total	R	W	Total	R	W	Total
Ambiguous	4	0	4	19	2	21	2	5	7
Explicit	17	13	30	4	5	9	18	14	32
Inferred	18	3	21	15	10	25	14	2	16
Total	39	16	55	38	17	55	34	21	55

ficult. Additionally, errors arose from miscalculations or incorrect inferences made by the AI during the interpretation process. Limitations in processing highly complex or nuanced textual descriptions also played a role, as did challenges in interpreting intricate images, figures, or tables embedded in the articles. These aspects highlight critical areas for improvement in the application of AI tools for literature-based data extraction, emphasizing the need for ongoing refinement to enhance their reliability and accuracy (Table 2).

Regarding labeling accuracy, the analysis of the 55 total observations showed a mean of 67.3%. This metric evaluates the AI accuracy in assigning labels to the data, specifically focusing on the categories "explicit," "inferred," and "ambiguous." The SD of 34.2% indicates substantial variation: some labeling instances were highly precise, whereas others showed higher margins of error. The SEM, at 4.6%, reflects a good reliability in the sample estimate. The 95% CI, ranging from 58.0% (lower bound) to 76.5% (upper bound), delineates the range within which the true mean of labeling accuracy for the overall population is likely to fall. This interval highlights that although there were instances of highly precise labeling, errors were also present in certain circumstances (Table 2).

The contingency table analysis for the categorization of eating behavior showed that out of a total of 55 articles, the data in 39 papers were correctly labeled, and 16 were labeled incorrectly. Among ambiguous data, the model correctly identified 4 cases (100% of ambiguous data), with no errors recorded in this category (0%). For explicit data, 17 cases were correctly categorized (56.7%), and13 were incorrect (43.3%). Finally, for inferred data, 18 were labeled correctly (85.7%) and 3 incorrectly (14.3%). Explicit data represent the majority category (54.6%), followed by inferred data (38.2%) and ambiguous data (7.3%; Table 3).

For ruminating behavior, the model correctly classified 38 articles (69.1%) and 17 incorrectly (30.9%). Among ambiguous data, 19 were correctly labeled (90.5%) and 2 were incorrect (9.5%). For explicit data, 4 were correct (44.4%) and 5 incorrect (55.6%), and for inferred data, 15 were correctly classified (60.0%) and 10 were incorrect (40.0%). Most of the data falls into the inferred category (45.5%), followed by ambiguous data (38.2%) and explicit data (16.4%; Table 3).

For lying behavior, the model correctly classified 34 articles (61.8%) and 21 incorrectly (38.2%). Among ambiguous data, 2 were labeled correctly (28.6%) and 5 were incorrect (71.4%). For explicit data, 18 were correct (56.3%) and 14 incorrect (43.8%), and for inferred data, 14 were correctly classified (87.5%) and 2 were incorrect (12.5%). Explicit data constitute the majority of the observations (58.2%), followed by inferred data (29.1%) and ambiguous data (12.7%; Table 3).

DISCUSSION

The study has 2 main objectives: to assess the effectiveness of ChatGPT as a research tool for data extraction and synthesis, and to enhance understanding of the existing literature on dairy cow behavior by offering a comprehensive summary of the current state of knowledge about the time-activity budget.

Time-Activity Budget Analysis: Comparison Between Human and AI Data Extraction

The analysis of eating behavior revealed slight but statistically significant differences between the time percentages extracted by human observation and AI analysis. Specifically, the AI estimated the percentage of time dedicated to eating at 22.3%, while human observation reported a slightly higher value of 23.8%. Despite this small numerical difference, both approaches confirm that eating constitutes a smaller proportion of the daily time-activity budget of dairy cows compared with other behaviors, such as lying and ruminating. The findings from this study align partially with previous research, which reported average eating times ranging from 19.4% to 32.4% of the daily time-activity budget, depending on factors such as management practices, feeding systems, and housing conditions. For example, studies have shown that cows in freestall systems tend to allocate ~3 to 5 h per day to feeding, with variations influenced by lactation stage, diet composition, and competition for feeding

space (Grant and Miner, 2015; Hut et al., 2021; Florit et al., 2023). A critical factor highlighted in earlier studies is the heterogeneity of conditions across different farm systems, which can significantly affect feeding behavior. Variables such as overcrowding, heat stress (Felini et al., 2024), hoof health issues (Buonaiuto et al., 2023), and limited feed bunk space disrupt normal feeding patterns. The accuracy of time-activity budget estimations varies substantially across studies, with some achieving high precision and others showing notable discrepancies. Differences in how data are presented, the level of detail reported, and the methodologies employed for data collection and analysis all contribute to these inconsistencies. In this study, the close alignment between AI and human estimates suggests that both methods effectively captured the overall time cows spent eating under the observed conditions, despite the variability introduced by these intrinsic study characteristics.

Stepping back to the time-activity budget, depending on the lactation phase, there is a tendency for increased feed intake during lactation, reflecting the growing energy requirements of cows throughout this period. During the dry period, the time spent eating is substantially longer, partly due to the composition of the ration, which tends to be coarser and bulkier, making it more challenging to ingest. Additionally, the absence of the time commitment required for milking allows cows to be more relaxed and dedicate more time to feeding, a factor that helps maintain their physiological balance during this productive rest phase. This phenomenon also highlights the challenge of avoiding excessive weight gain in cows during the final phase of lactation and the dry period, aiming to keep the body condition score as stable as possible. The literature indicates that DMI tends to increase progressively from the start of lactation until ~9 weeks postpartum (Kertz et al., 1991). During the transition period, cows face significant nutritional and physiological challenges. Grant and Albright (1995) divide the transition period into 2 main phases: the 5 to 7 d before calving, characterized by a 30% reduction in DMI, and the period from 0 to 21 d postpartum, during which feed intake should increase rapidly to support lactation. This dynamic is crucial for the welfare and productivity of cows, as a timely increase in feed intake is necessary to meet the metabolic demands of milk production, minimizing the risks of energy imbalances and metabolic disorders such as ketosis or fatty liver syndrome. In the study conducted by Hut et al. (2021), it was observed that the time spent feeding in primiparous cows increased by 88 min, starting 1 mo before calving and continuing to the ninth month of lactation, then remaining stable until the end of the lactation phase. In contrast, cows in their second or subsequent lactations showed a reduction of ~30 min in feeding time, from 1 mo before calving to 1 mo after. This suggests that experience gained during previous lactations may influence feeding behavior. After calving, until the sixth month of lactation, feeding time increased by 11 min in cows in their second lactation and by 24 min in cows in their third or subsequent lactations. These results suggest that more mature cows may adapt more quickly to changes in dietary requirements, showing a greater ability to regulate in response to the increasing metabolic demands of lactation (Hut et al., 2021).

Other studies have reported a significantly higher percentage of time spent feeding in cows housed in freestall systems, with an average of 32.4% ± 0.3%, and a further increase in grazing situations, where this value can reach ~60% throughout the day (Ishiwata et al., 2008). These data highlight the importance of housing type in shaping cows' feeding behavior.

Moreover, climatic conditions and seasons can further influence these behaviors. Previous studies have shown that feeding time tends to increase in autumn (30.8%) and decrease in spring (22.1%; Ray and Roubicek, 1971; Uzal and Ugurlu, 2010), suggesting that external factors such as climatic and seasonal variations can significantly affect cows' feeding habits, confirming how housing type and environmental conditions play a crucial role in herd management.

Other critical factors to consider are group size and available space at the feeding area. In the study conducted by Uzal and Ugurlu (2010), it was observed that reducing the number of individuals in a herd led to an increase in feeding time when each cow had between 0.8 and 1.0 m of space at the feeding area. These data suggest that larger feeding spaces promote less competition among cows; conversely, limited access to feed can increase the occurrence of aggressive interactions and displacements typical of situations where feeding space is insufficient (Huzzey et al., 2006). The study by DeVries et al. (2004) further confirmed these results, demonstrating that doubling the feeding space per cow, specifically from 0.5 to 1.0 m, led to a 57% reduction in aggressive behaviors among animals. This highlights how cow welfare and productivity can be substantially improved in environments where resources are optimally distributed and easily accessible.

The analysis of ruminating behavior revealed a significant difference between the time percentages extracted by human observation and AI analysis. Specifically, the AI estimated the percentage of time dedicated to ruminating at 33.4%, whereas human observation reported a slightly lower value of 31.7%. Despite this numerical difference, both methods agree in highlighting that ruminating occupies a substantial portion of the daily time-activity budget of dairy cows, second only to lying

behavior when considering the 3 analyzed behaviors. The results align with findings in the literature, where cows typically spend an average of 32.3% of their daily time budget ruminating, corresponding to ~7.75 h per day (Grant and Miner, 2015). This consistency suggests that ruminating behavior is primarily driven by physiological factors, with external environmental conditions and management practices exerting a more limited influence compared with other behaviors, such as eating.

However, variations in measurement methodologies, including direct observation versus automated monitoring systems, have been noted in previous studies and remain a contributing factor to observed discrepancies across datasets. This study's comparison between AI and human observation demonstrates that both methodologies can effectively capture ruminating behavior, albeit with slight variations in reported percentages. Other research agrees that lactating cows spend an average of 7 to 10 h per day ruminating, regardless of the housing system used (Schirmann et al., 2012; Tucker et al., 2021).

Previous studies have also highlighted a positive correlation between rumination time and cow productivity, suggesting that prolonged rumination may indicate greater production efficiency (Soriani et al., 2012; Antanaitis et al., 2018). Higher milk production requires increased feed intake, which can result in longer rumination time compared with low-yield cows (Stone et al., 2017). Several studies have shown that rumination time is positively correlated with milk yield, particularly in cows during early lactation (Kaufman et al., 2018a). Furthermore, a positive relationship between rumination time and milk yield has been observed across all lactation phases, with a positive association between rumination time and fiber dietary content and milk fat content in cows in their third or subsequent lactations (Kaufman et al., 2018b). According to the study by Antanaitis et al. (2018), inseminated cows exhibit longer rumination time compared with nonpregnant cows, which instead show reduced rumination time.

Rodenburg (2011) observed that rumination time decreases by ~10 min per day in the last 5 d before calving, with an even more pronounced reduction on the day of calving, ranging from 220 to 350 min per day. Soriani et al. (2012) reported a variable reduction in rumination time during the final week of pregnancy, with a significant decrease observed the day before calving in nearly all cows. In the study by Hut et al. (2021), rumination time increased by 17 min in cows in their second lactation and by 28 min in cows in their third or subsequent lactations from 1 mo before to 1 mo after calving. Despite the observed declines immediately before calving, rumination during the prepartum period was overall the highest compared with other production phases. This suggests that any declines in rumination time due to calving are quickly compensated by a rapid resumption of rumination behavior, reflecting cows' ability to quickly adapt to postpartum metabolic demands.

Some studies that specifically examined the relationship between rumination time and lying time found no significant correlation (Schirmann et al., 2012), whereas others observed a negative correlation (Stone et al., 2017). However, rumination time appears to be more influenced by the physical and chemical composition of the diet, particularly by NDF intake (Beauchemin, 2018). This suggests that dietary factors, such as the quality and quantity of fiber consumed, play a more decisive role in modulating rumination time than lying time or other behavioral variables (Cavallini et al., 2021, 2022; Palmonari et al., 2021).

Schirmann et al. (2011) observed a reduction in rumination time following the regrouping of cows, with the lowest values recorded on the day of regrouping for cows that remained in their original pen and the following day for those moved to a new pen. This phenomenon was particularly evident in heifers introduced for the first time into the lactating cow group (Ferlizza et al., 2020); compared with multiparous cows, heifers show a slower increase in rumination time after calving. This suggests a slower adaptation of heifers to milking procedures, highlighting the need for specific management approaches to facilitate a smoother transition (Soriani et al., 2012).

A reduction in rumination time can be an indicator of stressful conditions (Anderson and Muir, 2005; Bristow and Holmes, 2007), illness (Collier et al., 1982), or pain (Anderson and Muir, 2005). The relationships between rumination time, metabolic conditions, and cow health reinforce the usefulness of automatic rumination measurement as a herd management tool. Such monitoring allows farmers to promptly identify animals more likely to develop health issues, thereby facilitating early intervention and improving the overall management of herd welfare and productivity.

The analysis of lying behavior revealed no significant difference between the time percentages extracted by human observation and AI analysis ($P = 0.8573$). Specifically, the AI estimated the percentage of time spent lying at 44.4%, and human observation reported a very similar value of 44.2%. This high level of agreement between the 2 methodologies suggests a strong consistency in detecting and quantifying lying behavior, emphasizing the robustness of both approaches in capturing this essential aspect of dairy cow activity.

Animal comfort is commonly assessed through lying time, as sufficiently long rest periods are associated with improved productivity and reduced physical stress (Overton et al., 2002). Ensuring that cows have access to optimal resting conditions promotes higher milk yields, contributes to better health, and reduces the risk of stress-

or posture-related diseases (Buonaiuto et al., 2023). O'Driscoll et al. (2008) observed resting times ranging from 11 to 12 h per day. Previous studies reported an average of 12 to 13 h of daily rest for cows (Jensen et al., 2005; Munksgaard et al., 2005), whereas Grant and Miner (2015) highlight that dairy cows achieve optimal productive performance with ~12 to 14 h of rest per day.

Additionally, resting time increases as lactation progresses. Chaplin and Munksgaard (2001) found that cows in early lactation (<100 d) spent significantly less time lying down compared with those in late lactation (>200 d). Hut et al. (2021) also recorded a decrease in resting time of 113 min for cows in their second lactation and 130 min for those in their third or subsequent lactations. These findings suggest that the lactation phase significantly affects cows' resting behavior, with cows in late lactation dedicating more time to rest compared with those in earlier phases. This reduction in lying time in cows during early lactation may be explained by the fact that in order to meet the nutritional demands associated with higher milk production, cows must spend more time feeding and, consequently, less time resting.

The relationship between milk yield and resting time has been the subject of several studies. In the study by Bewley et al. (2010), a trend of reduced resting time with increased production levels was observed, in line with most studies examining this relationship. Løvendahl and Munksgaard (2005) found a negative correlation between resting time and milk yield ($r = -0.26$), suggesting that higher-yielding cows tend to spend less time lying down. Similarly, Fregonesi and Leaver (2001) observed that high-yielding cows spend less time resting compared with lower-yielding cows. These results indicate that the increased energy demands associated with high milk production may lead cows to spend more time feeding and engaging in other activities, thereby reducing resting time.

Additionally, resting time is influenced by the animals' reproductive status (Silper et al., 2017). On the day of estrus, cows exhibit a significant increase in motor activity, spending more time walking, which results in reduced resting time (Silper et al., 2015). Calving is also associated with a reduction in lying time (Miedema et al., 2011), whereas previous studies suggest that once this phase is over, resting time increases as lactation progresses, both in tiestall barns (Chaplin and Munksgaard, 2001) and in freestall systems (Munksgaard et al., 2005; Bewley et al., 2010). However, it has not yet been thoroughly examined whether these changes in resting time are attributable to postpartum recovery, physiological changes during the transition period, variations in milk production, or pregnancy status. There is also no evidence suggesting that such short-term variations in resting time during calving have a direct impact on animal welfare.

The study by Uzal and Ugurlu (2010) highlighted how the season significantly influences the time cows spend lying down. Specifically, the results showed that resting time is statistically higher in spring (50.9%) compared with winter (40.5%); during winter, cows tend to reduce resting time and spend more time standing and eating. According to the authors, this change in the time-activity budget can be attributed to unfavorable environmental conditions (Uzal and Ugurlu, 2010). In summer, a reduction in resting time is observed, especially in farms with insufficient ventilation, where cows tend to crowd under cooling systems to alleviate heat stress. Additionally, during the summer period, cows' resting behavior is also influenced by the presence of flies; animals tend to group in corners of the barn or under fans to protect themselves from insects, thereby reducing lying time. This phenomenon is particularly evident in farms equipped with outdoor paddocks, where environmental conditions and the presence of insects substantially influence cows' behavioral repertoire.

Accuracy and Consistency of AI in Data Extraction and Labeling

The present study assessed the accuracy of and consistency of the AI in extracting and labeling behavioral data from published dairy cow studies. Overall, the AI demonstrated moderate accuracy (75.44%) in data extraction and slightly lower accuracy (67.27%) in labeling, with significant variability across specific behavioral categories. These results reinforce the notion that AI can serve as an effective supplementary tool in behavioral studies, but its performance remains context-dependent.

A notable finding was the variability observed across behavioral categories and labeling types, with inferred and ambiguous data showing higher accuracy compared with explicit data. In contrast, explicit behavioral markers often require nuanced contextual understanding, which remains a limitation for AI systems trained on large but heterogeneous datasets. The discrepancy in AI's performance across different behaviors (eating, ruminating, and lying) further emphasizes the complexity of behavioral annotation tasks. For instance, a review by Debauche et al. (2021) discusses machine learning approaches for detecting farm animals' behaviors, including lameness, grazing, and rumination. Additionally, Antanaitis et al. (2023) examines the use of innovative technologies, such as the RumiWatch system, to monitor ruminating, eating, and locomotion behaviors around calving in dairy cows. The research suggests that combining data on rumination time, eating time, drinking, activity, and down time could help construct a sensitive calving alarm. These studies indicate that AI and advanced monitoring technologies are being ac-

tively researched to improve the accuracy of detecting and analyzing eating and ruminating behaviors in farm animals.

Interestingly, ambiguous data showed mixed results across behavioral categories, with eating and ruminating achieving higher accuracy compared with lying behavior. This outcome suggests that not all ambiguous data present the same level of complexity to AI systems, potentially due to the differing visual and temporal characteristics associated with each behavior. Upon further examination, these discrepancies can be traced back to specific factors influencing AI performance. Behavioral data were often reported in diverse formats, including text, tables, and graphical representations, which posed substantial challenges for ChatGPT in maintaining consistency and accuracy during data extraction. This heterogeneity required the AI model to adapt to multiple contexts, often leading to errors or omissions in the final outputs. Furthermore, ChatGPT demonstrated particular difficulty in extracting explicitly stated data. Although the model excelled in interpreting inferred or ambiguous information, it struggled to accurately identify and contextualize explicit data points, especially when subtle nuances or methodological specifics were involved. Another critical limitation was the dependency on human oversight for validating AI outputs. Although ChatGPT automated a significant portion of the data extraction process, the results frequently required review and correction by human researchers, which reduced the potential for fully autonomous AI applications in this context. The model also faced challenges in interpreting complex images, poorly formatted tables, or figures embedded in PDF files. These visual elements often contained valuable information that the AI system either misinterpreted or entirely overlooked. Additionally, the diverse methodologies, environmental conditions, and management practices reported in the studies contributed to variability in both human and AI-extracted data, further complicating direct comparisons.

The observed variability, reflected in the large SD and wide CI, raises important questions about the standardization of datasets used to train AI models. Similar concerns have been raised in other studies (Chen et al.,2023), where inconsistent data annotation and varying definitions of behavioral categories were identified as key contributors to AI performance variability.

From a practical perspective, the discrepancies observed between the time-activity budget values extracted from human observation and those obtained via AI were generally minimal. However, these differences reflect the distinct strengths and limitations of the 2 approaches. Although human observation, is capable of capturing subtle contextual nuances, it can be influenced by perceptual biases, fatigue, and time constraints. In contrast, AI offers consistent, objective, and scalable analysis but remains highly sensitive to the quality, clarity, and structure of the input data. Its reliability depends heavily on well-structured textual information and standardized data formats; in cases of ambiguous descriptions, inconsistent formatting, or complex visual elements such as figures and tables, its accuracy decreases significantly. Despite these limitations, both methodologies converge in identifying general trends in dairy cow behavior, suggesting that AI represents a valuable complementary tool for time-activity budget analysis, particularly when applied to datasets characterized by clear and standardized reporting. The capacity of AI for continuous and large-scale data processing opens up new possibilities for more precise and efficient monitoring of animal welfare and productivity. However, the implementation of AI-based analysis in behavioral studies also raises ethical considerations, including data privacy, potential misinterpretation of behavior without human oversight, and the need for transparent algorithmic decision-making.

Although AI demonstrates strong performance with inferred and, in some cases, ambiguous data, its reliability diminishes significantly when it comes to explicit classifications requiring nuanced contextual understanding. This aligns with findings from Langer et al. (2025), who emphasized the importance of integrating AI tools with human oversight to ensure accuracy and consistency in behavioral studies.

Future research should focus on refining AI algorithms to better address inconsistencies, with particular attention to improving performance in explicit data labeling. Furthermore, the development and use of larger, more standardized datasets, combined with hybrid approaches that integrate AI and human validation, could help bridge current performance gaps and enhance reliability across diverse behavioral categories.

Limitations of the Study

This study has several limitations that need to be considered to properly interpret the results. First, the relatively small number of articles included in the analysis may have limited the representativeness of the findings and, consequently, their broader applicability. Expanding the dataset to include a larger number of studies would likely provide a more comprehensive assessment of AI's performance in extracting behavioral data from the literature.

Another important limitation is the inconsistency in the behavioral parameters reported across the selected studies. In particular, rumination behavior was often entirely absent from the datasets rather than being poorly described or inaccurately presented. This lack of consistency in the availability of key parameters made it

difficult to fully evaluate AI's effectiveness across all behavioral categories.

Additionally, the variability in how data were collected and presented across the studies introduced further challenges. Artificial intelligence tools rely heavily on the clarity, structure, and format of the data they process, and discrepancies in these aspects can significantly affect their accuracy and reliability.

These limitations emphasize the importance of standardizing both data collection and reporting protocols in future research on dairy cow behavior. Doing so would enhance the consistency and quality of the data available, ultimately allowing AI tools to deliver more reliable and meaningful insights. Another important limitation lies in the potential overgeneralization of behavioral patterns across diverse study conditions. Although this study aimed to provide a general overview of eating, ruminating, and lying behaviors, we acknowledge that behavioral data are influenced by multiple variables such as housing type, breed, lactation phase, and management practices. The aggregation of data from studies with heterogeneous designs may obscure meaningful distinctions that could emerge from stratified analyses. Unfortunately, most of the included articles did not consistently report these critical contextual variables, which prevented subgroup comparisons based on environment or animal specific characteristics. We recognize that such generalizations could limit the biological validity of our findings, and we encourage future studies to incorporate stratified analyses based on standardized metadata to ensure more accurate and context-sensitive conclusions.

Finally, although human-extracted data served as the reference for evaluating AI performance in this study, it is important to acknowledge that human interpretation is not infallible. Individual differences in language comprehension, subject expertise, and interpretation of ambiguous content can introduce bias or error, especially when processing complex scientific texts. Although human review is widely accepted in literature-based meta-analyses, it does not represent an absolute ground truth. Future studies could benefit from the development of a synthetic validation dataset, in which behavioral values are intentionally embedded in standardized formats (e.g., tables, figures, and narrative descriptions). Such a dataset would provide a more objective and controlled benchmark for comparing the extraction performance of both human and AI methods.

Future Perspectives and Practical Applications

The findings of this study open several promising avenues for future research and technological development. One of the primary areas of focus should be the refinement of AI algorithms to improve their ability to interpret explicitly stated data and context-specific details more accurately. Enhancing AI's comprehension of nuanced textual and graphical information could substantially reduce the dependency on human oversight, making the data extraction process more autonomous and efficient. Furthermore, efforts should be directed toward the standardization of datasets used for AI training in behavioral research. Harmonizing the format, structure, and reporting guidelines of scientific articles would enable AI systems to achieve more consistent performance across diverse datasets.

Hybrid approaches, combining AI-based automation with human expertise, represent another promising direction for future research. By leveraging the strengths of both AI and human researchers, these integrated methods could optimize both accuracy and efficiency in data extraction and synthesis. Additionally, the integration of AI tools with advanced monitoring technologies, such as accelerometers, video surveillance systems, and real-time sensors, could enable continuous and dynamic data collection. Such integration would not only improve the accuracy of behavioral assessments, but also allow for real-time monitoring and management of dairy cow welfare.

Cross-disciplinary collaboration between AI developers, veterinary scientists, and ethologists will also play a crucial role in advancing the application of AI in animal behavior research. These collaborations can foster innovation and ensure that AI tools are tailored to meet the unique challenges of behavioral studies. Social media platforms, increasingly important in veterinary education, can serve as valuable conduits for disseminating AI-driven insights, helping veterinarians and farmers adopt more sustainable practices (Lamanna et al., 2025a). Furthermore, future efforts should prioritize the development of AI systems capable of real-time data extraction and analysis, enabling immediate and actionable insights to improve farm management, optimize animal welfare, and promote farm sustainability (Gasparini et al., 2024; Koakoski et al., 2024; Cavallini et al., 2025). Through these advancements, AI technologies have the potential to enhance behavioral research and contribute significantly to improving both scientific understanding and practical applications in dairy farming systems.

CONCLUSIONS

This study explored the potential of ChatGPT-4 in extracting and analyzing behavioral data (eating, ruminating, lying) from scientific literature on dairy cows. The AI achieved a mean data extraction accuracy of 75.4% and a labeling accuracy of 67.3%, with better

performance on inferred and ambiguous data, but limitations in interpreting explicitly reported information. Significant differences were found between human and AI extracted data for eating and ruminating behaviors but not for lying behaviors, indicating varying levels of reliability across behavioral parameters. These findings highlight AI potential as a valuable supplementary tool for behavioral research, particularly in time-intensive tasks such as meta-analyses and literature reviews. However, the study underscores the necessity of human oversight and methodological improvements to address AI's current limitations. Future improvements such as domain-specific training, refined prompt strategies, and developing hybrid human AI workflows may enhance reliability and broaden AI's applicability in animal welfare and behavior studies.

NOTES

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Nonstandard abbreviations used: AI = artificial intelligence; LLM = large language model.

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