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A fuzzy AHP analysis of potential criteria for initiatives in digital transformation for agribusiness

Uma análise *fuzzy* AHP de critérios potenciais para iniciativas de transformação digital para o agronegócio

Fellipe S. Martins, João Carlos F. B. Fornari Junior, Marcos Rogério Mazieri, and Marcos Antonio Gaspar

Nove de Julho University, São Paulo, SP, Brazil

Authors' notes

Fellipe S. Martins is now a full professor at the Information Technology and Knowledge Management Graduate School of Nove de Julho University (Universidade Nove de Julho – Uninove); João Carlos F. B. Fornari Junior received his master's in Information Technology and Knowledge Management from Uninove; Marcos Rogério Mazieri is now a full professor at the Project Management Graduate School of Uninove; Marcos Antonio Gaspar is now a full professor at the Information Technology and Knowledge Management Graduate School of Uninove.

Correspondence concerning this article should be addressed to Fellipe S. Martins, Rua Vergueiro, 235/249, Liberdade, São Paulo, SP, Brazil, ZIP code 01525-000. Email: fellipemartins@uni9.pro.br

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ABSTRACT

Purpose: Exploring criteria for digital transformation in agribusiness (DTA) and analyzing their potential importance (weight) and priorities (ranking) for future DTA projects.

Originality/value: Digital transformation (DT) has become increasingly central in agribusiness, fostering a rapid process of dependence on digital technologies for operational processes. However, the lack of consistent criteria for DTA may hinder progress towards project development and industrial applications, as well as obstruct further research due to potential conceptual, technical, and theoretical shortcomings.

Design/methodology/approach: A manual review of literature coupled with automatic text clustering tools was employed to elicit criteria and subcriteria. To analyze weights and rankings, two methods were used in tandem: fuzzy analytic hierarchy process (AHP) and fuzzy technique for order preference by similarities to ideal solution (Topsis) in order to aggregate responses from DTA specialists.

Findings: The criteria extracted from the literature were: knowledge management (analysis, monitoring, decision-making), automation (planting and harvesting, processing and manufacturing, maintenance, technology, machinery and tools), efficiency (costs, work and personnel, processes), and continuity (quality and food safety, environmental sustainability). The results point to a set of criteria anchored in the transition of operations to digital technologies yet bound by the physical limitations of a traditional non-digital business. This paper contributes to the development of the literature by providing a set of criteria for DTA projects and analyzing their possible importance according to a panel of specialists. Practical implications include a definition of areas and their potential relative importance for future implementations.

Keywords: digital transformation, agribusiness, multicriteria decision analysis, strategic management, project management

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RESUMO

Objetivo: Explorar critérios de transformação digital no agronegócio (*digital transformation in agribusiness* – DTA) e analisar sua importância potencial (peso) e prioridades (ranking) para futuros projetos de DTA.

Originalidade/valor: A transformação digital (TD) tem se tornado cada vez mais central no agronegócio, fomentando um rápido processo de dependência de tecnologias digitais para os processos operacionais. No entanto, a falta de critérios consistentes para a DTA pode dificultar o progresso no desenvolvimento de projetos e aplicações industriais, além de dificultar novas pesquisas devido a possíveis deficiências conceituais, técnicas e teóricas.

Design/metodologia/abordagem: Uma revisão manual da literatura, juntamente a ferramentas automáticas de agrupamento de texto, foi empregada para obter critérios e subcritérios. Para analisar pesos e *rankings*, foram utilizados dois métodos em conjunto: *fuzzy analytic hierarchy process* (AHP) e *fuzzy technique for order preference by similarities to ideal solution* (Topsis) para agregar respostas de especialistas em DTA.

Resultados: Os critérios extraídos da literatura foram: gestão do conhecimento (análise, monitoramento, tomada de decisão), automação (plantio e colheita, processamento e fabricação, manutenção, tecnologia, máquinas e ferramentas), eficiência (custos, trabalho e pessoal, processos) e continuidade (qualidade e segurança alimentar, sustentabilidade ambiental). Os resultados apontam para um conjunto de critérios ancorados na transição das operações para as tecnologias digitais, mas vinculados às limitações físicas de um negócio tradicional não digital. Este artigo contribui para o desenvolvimento da literatura fornecendo um conjunto de critérios para projetos de DTA e analisando sua possível importância de acordo com um painel de especialistas. As implicações práticas incluem a definição de áreas e sua potencial importância relativa para futuras implementações.

Palavras-chave: transformação digital, agronegócio, análise de decisão multicritério, gestão estratégica, gestão de projetos

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INTRODUCTION

The last decade has seen an increased interest in connected industries and markets, mediated by digital technologies, from which digital transformation (DT) emerges (Hausberg et al., 2019). Nevertheless, despite the maturation process of DT, it is not yet fully conceptually defined in theoretical and technical terms (Vial, 2019), although tentative propositions (Gong & Ribiere, 2021) and models (Gray & Rumpe, 2017; Zaki, 2019) started to emerge. More specifically, the case for its transposition to agribusiness, that is, digital transformation in agribusiness (DTA), still deserves discussion (Reis et al., 2018; Khanna, 2020), since it may partially overlap with neighboring concepts, such as intelligent agriculture (Chen & Yang, 2019), agriculture 4.0 (Weltzien, 2016; Rose & Chilvers, 2018), and digital agriculture (Ozdogan et al., 2017; Basso & Antle, 2020). Thus, this work aims to analyze DT in the context of agribusiness, elicit potential criteria for its execution from the extant literature using clustering algorithms and analyze them in an aggregate mechanism, by employing multicriteria decision analysis (MCDA) methods.

DT has been a continuous trending topic of interest in academia (Matt et al., 2015; Gong & Ribiere, 2021), and its maturation process now includes several areas of specialization (Hausberg et al., 2019). Within these areas, there is DTA (Zanuzzi et al., 2020; Cannas, 2021), being an object of research, particularly in countries and regions where agribusiness is a vital part of local economies, such as Brazil (Pacheco & Tonial, 2020; Lima et al., 2020; Kutnjak et al., 2020; Bergier et al., 2021).

The rationale behind DT is that firms from all industries research, invest and develop uses of digital technologies applied to their business models, which both affects and is affected by digital interactions among actors (Matt et al., 2015; Remane et al., 2017; Li, 2020). This provides a scenario in which organizations ought to renew their strategic plans (Gobble, 2018; Warner & Wäger, 2019), rethink portfolios (Isikli et al., 2018) and rebuild their businesses (sometimes from the ground up) (Margiono, 2020) to face such industrywide developments – especially when predigital or brick-and-mortar organizations are concerned (Chanias et al., 2019; Vojvodić, 2019).

However, the idea behind DT cannot be restricted to the mere process of analysis and application of technological tools to a business model (Verhoef et al., 2021), since technologies reflect and affect structures, strategies, and logics that support the transformation of organizations as a whole (Woodard et al., 2013), including (but not limited to) the digital domains (Tabrizi et al., 2019). Such logics affects businesses, particularly those that are still

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anchored in physical operations (Remane et al., 2017) and that face additional challenges in making the transition to the digital world (Barann et al., 2020) – examples of which include retail (Reinartz et al., 2019), manufacturing, and automotive industries (Kutnjak et al., 2020) and, as expected, agribusiness (Zanuzzi et al., 2020). That is, all DT stems from transformation, with varying degrees of feasibility bound to firm capabilities, industry characteristics, firm strategic positioning, and how their core activities may or may not adapt to digital scenarios (Culot et al., 2020).

In agribusiness, the evolution and applications of digital technologies were not any different. These added support and scalability for process improvement, production output increase, as well as gains and improvements in sustainable processes (Trivelli et al., 2019). Consequently, digital technologies have made their way to all production-wide aspects of modern, large-scale agribusiness, such as monitoring and sensorization (Triantafyllou et al., 2019; López-Morales et al., 2020), coordination, control, and production (Ciruela-Lorenzo et al., 2020), international supply chains (Sharma et al., 2020), as well as machinery (Lima et al., 2020) and personnel (Trukhachev et al., 2019).

Thus, digital technologies have become increasingly central in agribusiness models fostering a glaring dependence on such technologies for decision-making processes (Ugochukwu & Phillips, 2018). However, the lack of consistent criteria may hinder DTA projects from coming to fruition, as well as obstruct further research on the object due to potential conceptual, technical, and theoretical shortcomings. To address these limitations, this study employs a different approach to define a scope for DTA by employing two mechanical analyses along with a manual analysis of the extant literature, coupled with data collection and analysis using two MCDA methods.

LITERATURE REVIEW

The general overview of DT is that it is an area in expansion, and theoretical, conceptual, and technical inconsistencies have been noted (Gong & Ribiere, 2021). Whereas publications using the expression “digital transformation” are growing almost exponentially, most of them are difficult to compare and reproduce as DT is routinely employed as a vague synonym for other concepts or partial overlaps thereof (Verhoef et al., 2021). With the ongoing interest, investment, and development of digital technologies to mediate connected industries and markets (Nambisan et al., 2019), it is plausible that DT as a concept may become blurred – especially in non-

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academic literature – in close comparison to a selection of data- and tech-driven nomenclature, such as internet of things (IoT), industry 4.0, analytics, data science applied to business (among others), which makes DT to be often taken as a buzzword or silver bullet.

Thus, defining DT is complex for three main reasons: lack of proper theoretical definitions, lack of scope and boundaries inferred from literature reviews, and problems with empirical validation for proposed models. The first can be observed when definitions for DT – as the several ones studied by Vial (2019) demonstrate – are full of flaws, including recursive and tautological definitions, vague or imprecise perimeters, as well as elusive and specious meanings for words. As an example, the famous McKinsey report puts *digital* as "less about any one process and more about how companies run their business" (Schallmo & Williams, 2018, p. 3), ironically making it altogether absent in the definition. The second problem stems from the fact that comprehensive systematic reviews of literature, which improve theoretical boundaries to be defined, have only recently started to appear (Reis et al., 2018; Mahraz et al., 2019). The third immediate problem is that models that bridge theoretical and conceptual definitions to the technical or procedural aspects not only are recent (Gray & Rumpe, 2017; Zaki, 2019) but also lack empirical validation.

Consequently, DTA – as a subset of DT – inherits these issues. In addition, definition problems also arise when understanding agribusiness (Sánchez & Betancur, 2016; Mac Clay & Feeny, 2018), which explains why the studies on DTA have been few and far between (Zanuzzi et al., 2020; Cannas, 2021). As a result, eliciting criteria for DTA from possible definitions, reviews of literature, or models is a challenge, with its fragilities.

MATERIALS AND METHODS

To reduce such shortcomings, the following procedures were proposed (Figure 1). First, one must design a search expression that allows relevant constructs on DTA to be analyzed and review the potential criteria and subcriteria. To do so, we propose two different approaches: using automatic clustering mechanisms (mainly based on the *Analyse Lexicale par Contexte d'un Ensemble de Segment de Texte* [Alceste] algorithm) and a manual confirmatory literature review. With criteria and subcriteria defined, we follow along a data collection phase in which such data are fed to two different fuzzy MCDA methods (fuzzy AHP and fuzzy Topsis). Finally, we discuss the results.

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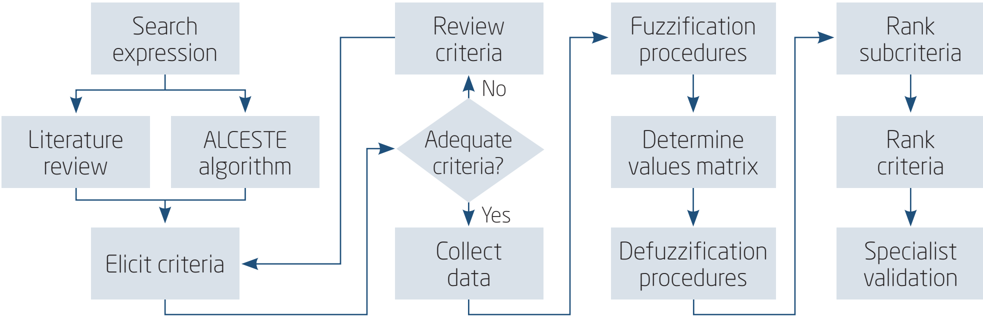
Figure 1

Proposed steps



Source: Elaborated by the authors.

Fuzzy AHP

In order to analyze which criteria potentially contribute to DT in agribusiness, one must select methods that may aggregate data from a variety of contexts. In this sense, and considering the potential conflicting criteria, the MCDA family of methods is the most adequate candidate as it allows decision makers to define priorities and weights in complex arrangements towards a single goal (Martins et al., 2017).

In that sense, fuzzy AHP accommodates both fuzzy logic, which provides flexibility in the input with the rigorous treatment of data from traditional AHP applications (Oliveira et al., 2017; Silva et al., 2020). It also allows respondents to focus on verbal descriptors or proportional pairs of concepts and leaving the transformation of linguistic items to numeric ones (triangular fuzzy numbers [TFN]) in the background (Nazari-Shirkouhi et al., 2017), which makes respondent fatigue (Olson et al., 2019) and social desirability (Cerri et al., 2019) less prone to happen. The proposed steps, thus, follow the procedures of Ayhan (2013) adapted by Felisoni and Martins (2019) and Silva Júnior et al. (2021).

Transforming a traditional AHP to a fuzzy AHP depends on a mapping of discrete values from an AHP to intervals or ranges that may take different forms. Fuzzy numbers may be defined by the establishment of a core, support points, and left/right-side bounds. A compromise that allows fast computing with accuracy is treating the responses as TFN, in which left cut ≤ central value ≤ right cut, composed of real numbers; the left side is a non-decreasing function; and the right side is a nonincreasing function (Felisoni & Martins, 2019) – see Table 1. Thus, each value in a traditional AHP Saaty scale is

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interpreted by a TFN composed of the same value taken as a central value, an n - 1 and n + 1 as left and right cuts. The intermediate numbers 2, 4, 6, and 8 are employed when decision makers display mixed perceptions, and their TFN are also n - 1 and n + 1, except for the edge numbers since, according to AHP, it is axiomatically impossible to have an importance smaller than equal, as well as a difference to be greater than absolute, thus, making the core value and the edge value the same in these cases.

Table 1

Saaty scale numbers, verbal descriptions, and TFN

Saaty scale*	Verbal descriptors	Triangular fuzzy numbers (TFN)
1	Equally important	(1, 1, 2)
3	Weakly more important	(2, 3, 4)
5	Moderately more important	(4, 5, 6)
7	Strongly more important	(6, 7, 8)
9	Absolutely more important	(8, 9, 9)

Source: Elaborated by the authors.

As an example of its application, a decision maker k can choose between two criteria X and Y. Using the verbal descriptors in the Saaty scale, they decide that the criterion X is moderately more important than Y, which is transposed numerically to (4, 5, 6). Looking in the opposite direction, Y is interpreted in the function of X as (⅙, ⅕, ¼) in the contribution matrix. Thus, each pairwise choice (criterion *versus* criterion) is stored as a tuple in $\tilde{d}_{ij}^{k}$ in Equation 1. Following Felisoni and Martins (2019), a weight balancing mechanism is used, in which the responses from strategic personnel are taken at full value and from other tiers in the organizations (tactical and operational personnel), weighted according to the following parameters.

Thus, the obtained pairwise TFN $\tilde{d}_{ij}^{k}$ indicate the k^{th} decision maker's choice of the i^{th} criterion over the j^{th} criterion and are incorporated in the contribution matrix ($\tilde{A}^{k}$). The tilde sign marks the tuple that contains the TFN thereof. As an example, $\tilde{d}_{25}^{3}$ represents the third decision maker's preference for the relationship between the second and fifth criteria, whose parameters (TFN) are l, m, and u – for example, (4, 5, 6):

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$$\tilde{A}^k = \begin{bmatrix} \tilde{d}_{11}^k \, \tilde{d}_{12}^k \, \ldots \, \tilde{d}_{1n}^k \\ \tilde{d}_{21}^k \ldots \ldots \tilde{d}_{2n}^k \\ \ldots \ldots \ldots \ldots \\ \tilde{d}_{n1}^k \, \tilde{d}_{n2}^k \, \ldots \tilde{d}_{nn}^k \end{bmatrix} \tag{1}$$

Since complex decisions commonly include more than one decision maker, all preferences for each pairwise TFN are combined into an averaged TFN $\left(\tilde{d}_{ij}\right)$, as in the subsequent equation:

$$\tilde{d}_{ij} = \frac{\sum_{k=1}^{k} \tilde{d}_{ij}^k}{k} \tag{2}$$

After the weight balancing mechanism and averaged choices, the final Ã matrix is as follows:

$$\tilde{A} = \begin{bmatrix} \tilde{d}_{11} \ldots \tilde{d}_{in} \\ \tilde{d}_{21} \ldots \tilde{d}_{2n} \\ \ldots \ldots \ldots \\ \tilde{d}_{n1} \ldots \tilde{d}_{nn} \end{bmatrix} \tag{3}$$

Next, in Equation 4, $\tilde{r}_i$ represents the geometric mean of the fuzzy comparison values for each criterion:

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{d}_{ij}\right)^{1/n}, \; i = 1, 2, \ldots, n \tag{4}$$

Following Ayhan (2013), the vector summation for each $\tilde{r}_i$ is elicited, and the (-1) power of the summation vector substitutes the original TFN in increasing order. This step is necessary as, in order to find the fuzzy weight of criterion i $\left(\tilde{w}_i\right)$, every $\tilde{r}_i$ must be multiplied by this reversed vector:

$$\tilde{w}_i = \tilde{r}_i \otimes \left(\tilde{r}_1 \oplus \tilde{r}_2 \oplus \ldots \oplus \tilde{r}_n\right)^{-1} = \left(lw_i, mw_i, uw_i\right) \tag{5}$$

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Then, the defuzzification of the TFN is necessary to obtain discrete weights for each criterion (M_i), using Chang and Chou's method for the center of area:

$$M_i = \frac{lw_i + mw_i + uw_i}{3} \tag{6}$$

And, finally, M_i is normalized using the following equation:

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i} \tag{7}$$

Fuzzy Topsis

As fuzzy AHP is known to have a few shortcomings, in which there could be potential inconsistencies between the crisp logic underneath AHP as a method and the addition of a fuzzy superstrate (Zhü, 2014), in order to mitigate such potential problems, a comparative approach is done using fuzzy AHP with a different fuzzy logic-based method – fuzzy Topsis. This has been consistently done, with comparable results – cf. Singh et al. (2018) and Yucesan and Gul (2020).

Fuzzy Topsis is an improved version of the original Topsis. In the original method, two main anchor points are defined from the ideal solution – the shortest geometric distance to the ideal solution is taken as the most positive anchor (or positive ideal solution – PIS), and the longest from the ideal solution is interpreted as the most negative (or negative ideal solution [NIS]).

In this section, we follow the procedures adapted by Lima Junior et al. (2014) and Nădăban et al. (2016). The linguistic variables were adapted from Wang and Elhag (2006). In fuzzy Topsis, decision makers (D_r) are presented with linguistic variables or descriptions in order to analyze the weights of criteria and how the alternatives would fit D_r ($r = 1, \dots, k$). Given r^{th} decision maker interpretation of the j^{th} criterion in C_j ($j = 1, \dots, m$), it is composed in $\tilde{W}_r^j$. The same happens in the alternatives, as $\tilde{x}_{ij}^r$ stands for the evaluation of the i^{th} alternative – for instance, A_i ($i = 1, \dots, n$) – for the j^{th} criterion for the r^{th} decision maker.

The aggregation of all weights for criteria and evaluation of alternatives are done according to the following equations:

$$\tilde{w}_j = \frac{1}{k}\left[\tilde{w}_j^1 + \tilde{w}_j^2 + \ldots + \tilde{w}_j^k\right] \tag{8}$$

$$\tilde{x}_{ij} = \frac{1}{k}\left[\tilde{x}_{ij}^1 + \tilde{x}_{ij}^r + \ldots + \tilde{x}_{ij}^k\right] \tag{9}$$

Then, one must compose the fuzzy decision matrix of the alternatives $(\tilde{D})$, as well as of the criteria $(\tilde{W})$ (Lima Junior et al., 2014):

$$\tilde{D} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & C_j & C_m \end{array} \\ \begin{array}{c} A_1 \\ A_i \\ A_n \end{array} & \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \tilde{x}_{1j} & \tilde{x}_{1m} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \tilde{x}_{nj} & \tilde{x}_{nm} \end{bmatrix} \end{array} \tag{10}$$

$$\tilde{W} = \left[\tilde{w}_1 + \tilde{w}_2 + \ldots + \tilde{w}_m\right] \tag{11}$$

Considering $\tilde{D}$ and $\tilde{W}$, the normalized fuzzy decision matrix is $\tilde{R} = \left[\tilde{r}_{ij}\right]$ (Nădăban et al., 2016), in which:

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+}\right) \text{ and } u_j^+ = max_i u_{ij} \text{ (benefit criteria)} \tag{12}$$

$$\tilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right) \text{ and } l_j^- = max_i l_{ij} \text{ (cost criteria)} \tag{13}$$

Then, one ought to elicit the PIS (A^+) and NIS (A^-), according to the following equations

$$A^+ = \left\{\tilde{v}_1^+, \tilde{v}_j^+ + \ldots + \tilde{v}_m^+\right\} \tag{14}$$

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$$A^{-} = \left\{\tilde{v}_1^{-},\ \tilde{v}_j^{-} + \ldots + \tilde{v}_m^{-}\right\} \tag{15}$$

in which $\tilde{v}_1^{+} = (1,1,1)$ and $\tilde{v}_1^{-} = (0,0,0)$.

One must also calculate the distances from both the PIS and NIS $\left(d_i^{+},\ d_i^{-}\right)$ for each alternative:

$$d_i^{+} = \sum\nolimits_{i=1}^{n} d_v\left(\tilde{v}_{ij},\ \tilde{v}_j^{+}\right) \tag{16}$$

$$d_i^{-} = \sum\nolimits_{j=1}^{n} d_v\left(\tilde{v}_{ij},\ \tilde{v}_j^{-}\right) \tag{17}$$

in which $d(\ldots)$ stands for the distance between fuzzy numbers (following the vertex method). For TFN, we follow the subsequent equation:

$$d\left(\tilde{x},\tilde{z}\right) = \sqrt{\frac{1}{3}\left[\left(l_x - l_z\right)^2 + \left(m_x - m_z\right)^2 + \left(u_x - u_z\right)^2\right]} \tag{18}$$

To rank alternatives, one needs to calculate the closeness coefficient (CC_i):

$$CC_i = \frac{d_i^{-}}{d_i^{+} + d_i^{-}} \tag{19}$$

Finally, one must rank the alternatives according to the CC_i in decreasing mode. However, this step is not done in this paper as we have no real alternatives (only the criteria to which alternatives may be compared in future studies).

Data collection procedures

To collect data for the purposes of this study, a questionnaire with the potential criteria and subcriteria was developed, refined by a small team of professors, and pretested. Pretest feedback helped in deploying mechanisms to facilitate comprehension. First, the meaning of each criterion and subcriterion was presented at the beginning of the questionnaire, and, again, in each section, respondents were reminded of the definitions. Second, to

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avoid social desirability (Cerri et al., 2019), primacy effects (Seninde & Chambers, 2020), and respondent fatigue (Olson et al., 2019), for each criterion, the subcriteria involved were randomly presented, which helps debiasing the preferences (Montibeller & von Winterfeld, 2015).

Data collection was carried out during the period from October 2020 until the end of the first quarter of 2021, during the coronavirus disease 2019 (Covid-19) pandemic. After the pretest and adjustments to the questionnaire, it was sent to a sample of professionals selected from companies that are directly involved in DTA projects ($n \approx 100$). Contact was made in person or by telephone, and, throughout the survey period, all respondents had direct access to the researchers to clarify doubts about the survey criteria. Respondents were sent reminders to fill out the questionnaire after two, four, and six weeks of the first contact.

RESULTS

To ensure all potential studies would be found, a "wider" search expression was used (*digit* transfor* agri**), which resulted in 454 published papers in the Web of Science database. For simplicity, and because this is not a systematic review of the literature, other databases were not used as they mostly overlap in content (Martín-Martín et al., 2018;). All resulting studies were individually read and classified using inclusion/exclusion criteria adapted from Liao et al. (2017) – Table 2. For conciseness, the full list of all excluded and included studies may be obtained from the authors.

Table 2

Exclusion and inclusion criteria used in the selection of the studies

	Criteria	Description	n
Exclusion	Search engine reason (SER)	Only the title, abstract, and keywords are in English but not the full text.	342
	No full text (NF)	The full text is not available.	
	Non-related (NR)	The paper is not an academic article (for example, editorial materials, conference reviews, contents, or forewords), or the combination of words in the paper is not related to both digital transformation (DT) and agribusiness.	

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Table 2 (conclusion)

Exclusion and inclusion criteria used in the selection of the studies

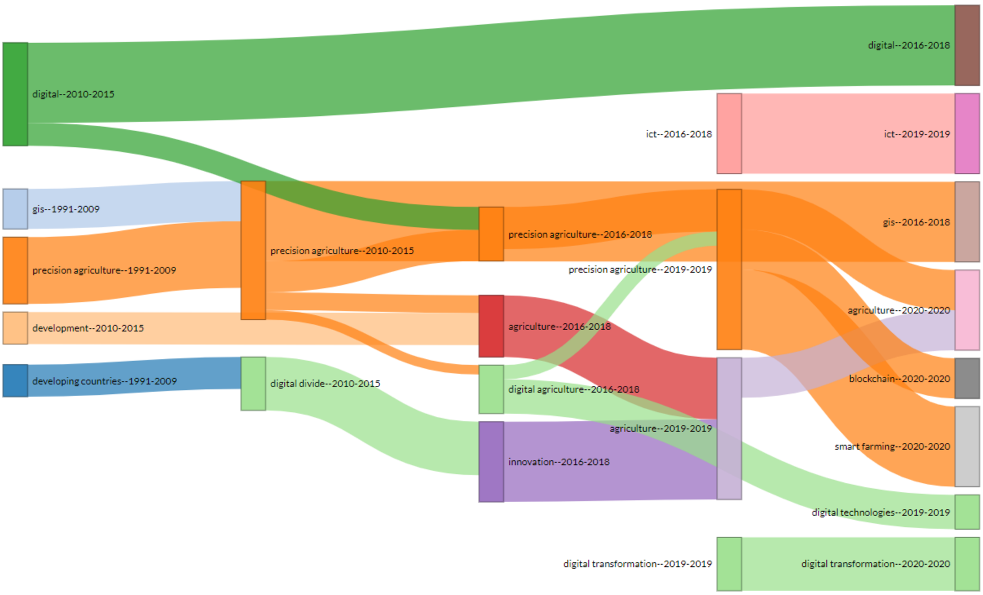
Criteria		Description	n
Exclusion	Loosely related (LR)	The paper does not focus on the review, survey, discussion, or problem-solving of both DT and agribusiness, yet these are part of the argumentation or cited in the paper.	25
Inclusion	Partially related (PR)	DT is used to support the description of some challenges, issues, or trends in agribusiness which a paper intends to deal with or is one of the techniques/tools employed in the analyses.	87
	Closely related (CR)	The research efforts of a paper are explicitly and specifically dedicated to both DT and agribusiness.	

Source: Adapted from Liao et al. (2017).

The included studies were then analyzed both manually and mechanically. The first mechanical analysis was performed using the R package Bibliometrix (Chinotaikul & Vinayavekhin, 2020) – Figure 2. The analysis of relevant content points to two core concepts: digital and precision agriculture.

Figure 2

Thematic evolution in DTA



Source: Elaborated by the authors using the R package Bibliometrix.

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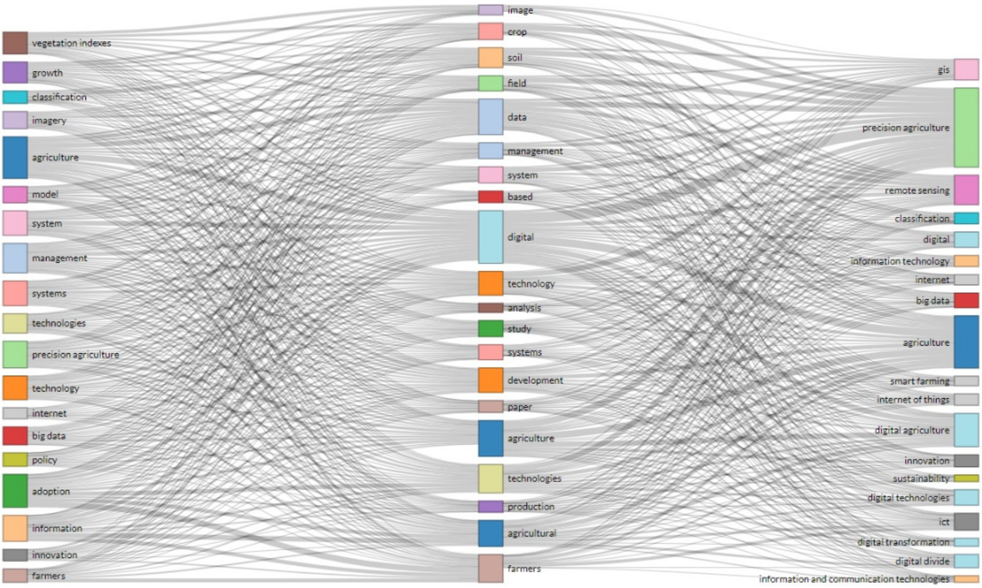
The first of these two concepts is a knowledge-based criterion emerges (Figure 3), which includes remote sensing for agriculture (Hinson et al., 2019; Weiss et al., 2020) and IoT technologies (Tzounis et al., 2017; Elijah et al., 2018; Khanna & Kaur, 2019), use of geographic information systems (GIS) (Sharma et al., 2018; Kotsur et al., 2019), and image classification (Zheng et al., 2019; Brogi et al., 2019), along with information and communication technologies, data management, and analysis (Panov et al., 2019).

Figure 3

Word cross-analysis



Source: Elaborated by the authors using the R package Bibliometrix.

In addition, the second cluster of terms suggests industrial-level production items, which point to automation as a whole, such as precision agriculture (Thompson et al., 2019; Sott et al., 2020), smart farming (Relf-Eckstein et al., 2019), and field management (Strizhkova et al., 2020). As a close consequence, some terms point to efficiency issues – production (Christiaensen et al., 2020), development (Lezoche et al., 2020), and labor and costs including farmers (Sapfirova et al., 2020; Shamin et al., 2019). Lastly, issues related to sustainability (both business- and environment-oriented) terms appear – sustainability in agribusiness (Hrustek, 2020), crop and disease detection (Francis & Deisy, 2019; Bharat, 2020), and soil and vegetation studies (Kuppusamy et al., 2021).

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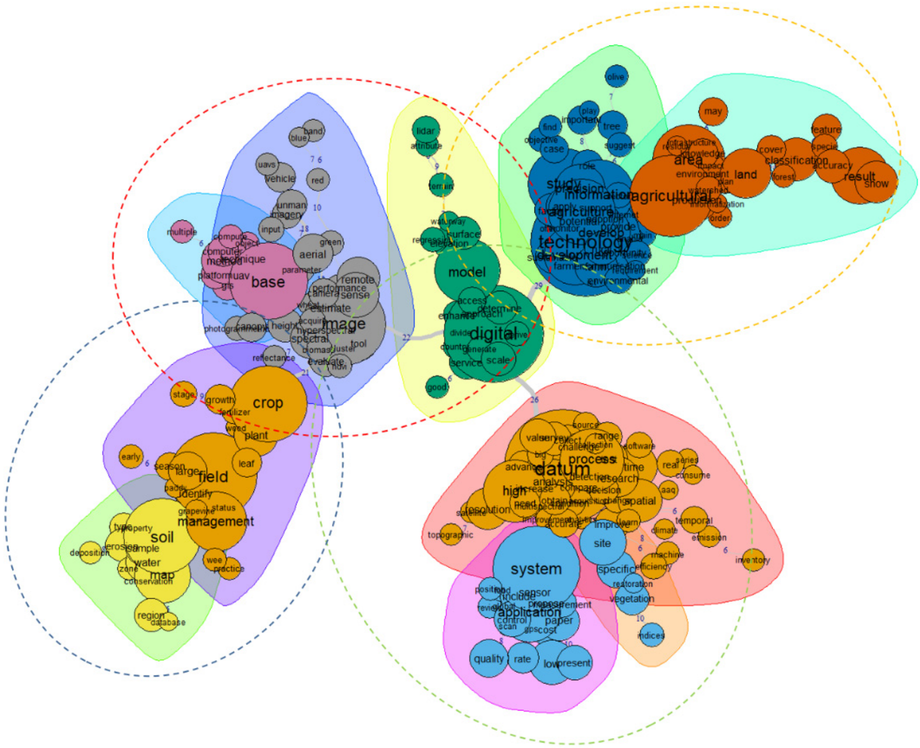
The second mechanical analysis was performed using the Alceste algorithm (through the Iramuteq software). This algorithm measures the co-occurrence of words in blocks of text splitting them into clusters (Figure 4). It works by reducing word forms to root forms (lemmatization, e.g.: transformation ~ transform) when lexical similarities allow. This algorithm is routinely used in text analysis to elicit possible constructs, as it removes the researcher's bias and leaves only the program to act according to the proximity and the use of words (Wagner et al., 2014; Martins et al., 2019).

The generated clusters support the ideas previously presented, that is, the existence of four potential main criteria (a central node and three offshoots). One focuses on knowledge management and its tasks – monitoring, analysis, and decision-making. The second cluster converges to automation and its components – planting and harvesting, processing and manufacturing, machinery technology and tools, along with machinery and industrial plant maintenance.

Figure 4

Specific terms clusters



Source: Elaborated by the authors using the software Iramuteq.

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As a bridge between them, the ever-going concerns with processes, costs, as well as work and personnel (especially considering the new technological dimensions), also emerge. Finally, the last cluster – firm continuity focuses on quality control and food safety from a business approach, along with environmental sustainability, tracking, and tracing. Thus, from the aforementioned analyses, the following criteria and subcriteria are proposed for initiatives in DTA (Table 3).

Table 3

Selected criteria for DTA

Criterion	Subcriterion	Description
Knowledge management	Analysis	Knowledge applied to the relationship of information as the basis of the DT process.
	Monitoring	Monitoring of results and direct activities, using digital mechanisms (remote sensing, satellite data, GPS guided machinery, etc.).
	Decision-making	Generation, creation, processing, and sharing of information and knowledge to aid decision-making.
Automation	Planting and harvesting	Implementation of digital processes to increase, control, and automatize planting and harvesting.
	Processing and manufacturing	Control of agricultural processing through digital controls and processes.
	Maintenance	Monitoring and upkeep of processes, machinery, industrial plants etc.
	Technology, machinery, and tools	Technological tools applied to the digitalization process.
Efficiency	Costs	Effective cost control and reduction through digital means.
	Work and personnel	Task, workload, and personnel planning, management, and execution.
	Processes	Business processes planning and execution through digital means.
Continuity	Quality and food safety	Quality control, traceability, testing etc.
	Environmental sustainability	Legal and institutional procedures concerning the environment and interactions with stakeholders.

Source: Elaborated by the authors.

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MCDA results and discussion

The data obtained are displayed as follows: first, the results for the fuzzy AHP procedures: sampling, TFN for all criteria and subcriteria, as well as the weights for each criterion, along with the obtained weights for each sub-criterion within a criterion. Then, the results for the fuzzy Topsis equivalent and a comparison of the results.

As for the minimum sampling for MCDA methods, previous literature does not define boundaries, although accepted studies range from three to 20 expert respondents, seldom exceeding these figures (Dey, 2010; Ali et al., 2015). Bearing this in mind, only professionals that ranked at least at a medium level in professional knowledge in both agriculture and digital technologies were filtered (n = 28). Respondents were also asked about their experience on business and knowledge management, age, and professional experience – agriculture: average = 3.48, standard deviation (SD) = 1.34; digital technologies: average = 3.71, SD = 1.01; business management: average = 3.64, SD = 0.98; knowledge management: average = 3.53, SD = 0.83; age: average = 39.17, SD = 8.38, and professional experience (in years): average = 15.28, SD = 7.33. Such responses point to the respondent pool being heterogeneous in academic and professional backgrounds with a balance in the skills and knowledge necessary to develop DTA projects – the medium to high average numbers happen because professionals at each end of the spectrum (agriculture and technology) balance each other. A qualitative question was provided to measure the effect of the current crisis on DTA projects, but no effects could be perceived since the demand for commodities is high, and the first impacts and restrictions on international logistics had already passed. Detailed and anonymous data of the respondents may be obtained from authors upon request.

The results for the four criteria are found in Table 4. Two main criteria are considered more important to DTA: efficiency (N_i = 0.345) and knowledge management (N_i = 0.334).

Table 4

Proposed DTA criteria (fuzzy AHP)

Criteria	*lw*	*mw*	*uw*	M_i	N_i
Knowledge management	0.286	0.338	0.398	0.340	0.338
Automation	0.192	0.221	0.254	0.222	0.220

(continue)

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Table 4 **(conclusion)**

Proposed DTA criteria (fuzzy AHP)

Criteria	*lw*	*mw*	*uw*	M_i	N_i
Efficiency	0.282	0.344	0.418	0.348	0.345
Continuity	0.091	0.097	0.105	0.098	0.097

Source: Elaborated by the authors.

This may be due to the fact that, whereas DTA promotes the digitalization of operations, agribusiness depends on physical production outputs – which are a tangible part of the operation – to survive. Thus, coordinating the daily activities and ensuring operations run smoothly are paramount. An alternative explanation is that the current literature on agribusiness points to managerial concerns being more focused on risk minimization in the long run than profit in the short run (Martins & Lucato, 2018). Commodity production also works on high-scale production, which may explain the conservativeness in the automation processes (Martins, Lucato et al., 2019). Either way, the coupling of efficiency and knowledge management is a natural development.

Automation comes in third place and, as before, this may be linked to the limited place of automated machinery and industrial plants as part of the whole operation in commodity industries (Bergerman et al., 2016). A second reason is that the main benefits of automation for DT may depend on technologies (such as fifth generation [5G] mobile network) still not fully available in areas where commodities production abound (Elijah et al., 2018). Last, there is continuity, which depends on local and international regulatory pressures, institutional pressures as well as market and consumer attention and requirements (Frolov & Lavrentyeva, 2019; Lin et al., 2020; Corallo et al., 2020).

The full data on all subcriteria can be found in Table 5.

Comparing the results with fuzzy Topsis takes into consideration the same division (criteria, subcriteria). First, we present the proposed DTA criteria (Table 6). As seen in Table 6, the results are marginally different (normalized fuzzy TFN l_{ij}, m_{ij}, u_{ij}). Criteria are presented in the same order as the fuzzy AHP table, despite differences:

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Table 5

Subcriteria rankings (fuzzy AHP)

	lw	*mw*	*uw*	M_i	N_i
Knowledge management					
Analysis	0.277	0.318	0.366	0.320	0.318
Monitoring	0.255	0.285	0.319	0.286	0.285
Decision-making	0.344	0.397	0.457	0.399	0.397
Automation					
Planting and harvesting	0.163	0.131	0.108	0.134	0.133
Processing and manufacturing	0.295	0.244	0.196	0.245	0.242
Maintenance	0.200	0.157	0.121	0.159	0.158
Technology and tools	0.544	0.468	0.407	0.473	0.468
Efficiency					
Costs	0.299	0.270	0.245	0.271	0.271
Work and personnel	0.412	0.394	0.374	0.393	0.392
Processes	0.368	0.337	0.309	0.338	0.337
Continuity					
Quality and food safety	0.527	0.500	0.474	0.500	0.500
Environmental sustainability	0.527	0.500	0.474	0.500	0.500

Source: Elaborated by the authors.

Table 6

Proposed DTA criteria (fuzzy Topsis)

Criteria	l_{ij}	m_{ij}	u_{ij}
Knowledge management	0.267	0.321	0.362
Automation	0.203	0.232	0.248
Efficiency	0.250	0.289	0.325
Continuity	0.114	0.122	0.128

Source: Elaborated by the authors.

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Mainly, what can be observed is that the ranking is the same, but the results differ slightly. Knowledge management and efficiency present a lower priority while automation and continuity present higher levels. These may be due to the time gap between the first round of MCDM collection (fuzzy AHP) and the second (fuzzy Topsis) but may also be due to intrinsic differences in computing rankings and weights according to the methods. Overall, the order of importance is kept, but these differences should be taken into consideration in further studies. The same happens in Table 7 – in general, the structure stays the same, yet differences in the spread of the TFN are more pronounced in fuzzy Topsis when compared to fuzzy AHP.

Table 7

Subcriteria rankings (fuzzy Topsis)

	l_{ij}	m_{ij}	u_{ij}
Knowledge management			
Analysis	0.265	0.319	0.384
Monitoring	0.187	0.224	0.289
Decision-making	0.365	0.378	0.403
Automation			
Planting and harvesting	0.161	0.191	0.221
Processing and manufacturing	0.214	0.223	0.247
Maintenance	0.187	0.196	0.204
Technology and tools	0.521	0.535	0.592
Efficiency			
Costs	0.178	0.185	0.197
Work and personnel	0.470	0.482	0.493
Processes	0.353	0.390	0.438
Continuity			
Quality and food safety	0.419	0.434	0.461
Environmental sustainability	0.615	0.630	0.684

Source: Elaborated by the authors.

The last step of the study is a specialist validation process. To do so, seven specialists analyzed the numerical data and qualitative responses (Table 8).

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The specialists were asked about the appropriateness of the elicited criteria and subcriteria, as well as potential aspects not covered in the extant literature. In addition, specialists were asked about technological trends for agribusiness that match these criteria and subcriteria besides their own take on theoretical and practical trends of DTA. The full answers to these questions may be obtained from the authors.

Table 8

Specialists' profile

	Location	Profile	Age
1	Brazil	Agriculture and environment secretary of a Southeastern Brazilian state	36
2	Portugal	University researcher in DTA	38
3	Brazil	Board member of an agribusiness multinational corporation	27
4	Brazil	University researcher in DTA	49
5	Austria	Chief executive officer (CEO) at a DTA company	45
6	Brazil	Executive at a Brazilian national organization for small and medium enterprises	53
7	Brazil	Director of research of a Brazilian agribusiness company	50

Source: Elaborated by the authors.

The qualitative responses point to an improvement in existing processes, solving real, existing problems, facilitating businesses, and integration with and within supply chains. This points to a potential boundary of DTA – agribusiness is still, at its core, a physical business, and further studies on the potential of brick-and-mortar businesses in the digital revolution are still needed. The specialists agree with the weights and organization of the criteria yet highlight the true potential of DTA beyond the criteria selected.

The knowledge management subcriteria present balanced results (N_i for the three subcriteria is quite close) – especially if considered that these tasks are possibly mostly done by the same teams, with a focus on decision-making. This task depends on the size of companies (medium to very large ones), as well as on internal decision process configurations – whereas most are investor-owned firms, a considerable minority are cooperatives, which alters legal and procedural aspects of decision-making (Martins & Lucato 2018). Decision-making may also be interpreted on two levels: strategic decision-making, which is more traditional, and farming task execution, in which efforts for automation start to appear (Bramley & Ouzman, 2019; Lowenberg-DeBoer et al., 2020).

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This leads to the imbalance in the subcriteria within the automation criteria. Especially in commodity-specialized areas, efforts in coordination and lean production have impacted organizational internal structure (Satolo et al., 2020). Thus, the search for such technologies allow flexibility in production planning and connection to international markets (Zhao et al., 2020; Lezoche et al., 2020; Contador et al., 2020), all the while aiming at operational efficiency, particularly cost reductions (Satolo et al., 2020; Kutnjak et al., 2020). This brings up the division in exploration and exploitation in agribusiness, which causes discrepancies between managerial aspirations and real-world performance levels, particularly during crises such as the current one (Felisoni & Martins, 2019). Lastly, continuity subcriteria, while they cannot be said to be residual, are not very significant on the whole (less than 10% of importance), which points to the longstanding criticisms of agribusiness (Ioris, 2018).

The four clusters are closely associated with base sciences related to the tasks executed in DTA projects – knowledge management stems from information technology and computer science; automation, from engineering; efficiency, from management; and continuity, from quality control and environmental studies (Pereira Ribeiro et al., 2020). A possible limitation, or, at least, an aspect worth considering, is that these branches may be due to a lack of coordination among these scientific communities. Further studies may shed light on this matter.

From the point of view of management as a science, this study shows that it is an important component of DT but not the only one and possibly not the one overseeing the rest of the criteria. While the weights obtained are only indicative of a specific case (Brazilian agribusiness), this promotes a reflection on the ongoing and future integration of management studies (including strategic management and organizational theories) towards organizational digitalization processes and permeability by other sciences and paradigms in future decision-making processes (Hess et al., 2016; Gupta & Bose, 2019). Multi- and interdisciplinary efforts, such as data science, may increasingly become a bridge between management and DT (Nambisan et al., 2019).

CONCLUSIONS, LIMITATIONS, AND FURTHER STUDIES

Our original goal was to elicit criteria and compile a list of such criteria and subcriteria from the extant literature. In addition, it was possible not only to map the knowledge on DTA existing in the literature but also measure

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the potential importance of each criterion/subcriterion when taken together, which was not researched elsewhere before. As such, this paper contributes to the development of the literature by providing an updated set of aspects to consider when developing DT projects in the agribusiness scenario.

DT is part of a new trend of multidisciplinary integration of digital technologies into business models, and agribusiness is following this trend. While it is not the purpose of this study, it points to a convergence in concepts that sometimes overlap (intelligent agriculture, digital agriculture, agriculture 4.0). So far, there is no comprehensive review of literature that analyzes both agriculture and DT, yet some specialized reviews were published: for specific technologies or methods such as blockchain, Sethibe (2019); artificial intelligence, Spanaki et al. (2021); or machine learning, Sharma et al. (2020); areas such as Brazil, Zanuzzi et al. (2020); or applications like purchasing and consumption, Samoggia et al. (2021). Nevertheless, no comprehensive analysis of criteria for DTA was presented before, and the lack of such information may hinder advances in the area from both academic and managerial standpoints.

Thus, this study's main contribution is extracting from the extant literature clusters of studies that are further analyzed as potential criteria for DTA projects. This is important because it provides a different approach to extracting constructs or criteria since developing measurements from flawed definitions (Vial, 2019; Gong & Ribiere, 2021) or from untested models may be theoretically fragile and professionally irresponsible. Whereas these four criteria still merit further research and validation, the current literature points to their stability and maturity, if the sheer number of studies in each is considered. In turn, this study has two limitations worth mentioning. First, the sampling was collected only in Brazil – whereas this area is a top world player in agribusiness, other places may provide different configurations and insights to DTA studies. Second, despite the number of respondents being more than the recommended in the literature, this does not provide a statistical validation of any models, and further studies may address this limitation by using the criteria provided in surveys, for instance.

Managerial implications

Up to date, there is no fully tested DT model, including for the agribusiness. Many studies cite specific technologies, tasks, processes, and concerns, linked to digital technologies that affect agribusiness, yet no study before has listed them in an aggregate manner. The selected criteria find ample

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support in the academic literature and were discussed with professionals and specialists directly involved in DT projects implemented specifically in agribusiness. This provides a high reliability that such criteria should be considered in future projects. In contrast, this study does not provide statistical modeling for these criteria, and the weights (proportions) should be taken with a grain of salt since differences may appear in real-world projects.

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