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1. 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, Liere-Netheler, Packmohr, Pakura, & Vogelsang, 2019). Nevertheless, despite the maturation process of Digital Transformation, it is not yet fully conceptually defined in theoretical and technical terms (Vial, 2019), although tentative propositions (Gong & Ribiere, 2020) and models (Gray & Rumpe, 2017; Zaki, 2019) start to develop. More specifically, the case for its transposition towards Digital Transformation in Agribusiness (DTA) still deserves discussion (Reis, 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, Gacar, & Aktas, 2017; Basso & Antle, 2020). Thus, this work aims to analyze Digital Transformation in the context of agribusiness, elicit potential criteria for its execution from the extant literature using the ALCESTE algorithm and analyze them in an aggregate mechanism, by employing Fuzzy Analytical Hierarchical Process.

Digital transformation has been a continuous, trending topic of interest in academia (Matt, Hess, & Benlian, 2015; Gong & Ribiere, 2020) and its maturation process now includes several areas of specialization (Hausberg et al., 2019). Within these areas is Digital transformation in agribusiness (DTA) (Zanuzzi, Selig, Pacheco, & Tonial, 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, Figueiredo, Barbieri, & Seki, 2020; Kutnjak, Pihir, & Tomicic-Pupek, 2020; Bergier, Papa, Silva, & Santos, 2021).

The rationale behind Digital Transformation is that firms across all industries research, invest and develop uses of digital technologies applied to their business models, which both affect and are affected by digital interactions among actors (Matt et al., 2015; Remane, Hanelt, Nickerson, & Kolbe, 2018; Li, 2020). This provides a scenario where organizations ought to renew their strategic plans (Gobble, 2018; Warner & Wäger, 2019), rethink portfolios (Isikli, Yanik, Cevikcan, & Ustundag, 2018), and rebuild their businesses (sometimes from the ground up) (Margiono, 2020) to face such industry developments – especially when pre-digital or 'mortar-and-brick' organizations are concerned (Chanias, Myers, & Hess, 2019; Vojvodić, 2019).

However, the idea behind digital transformation cannot be restricted to the mere process of analysis and application of technological tools to a business model (Verhoef, Broekhuizen, Dong, Fabian, & Haenlein, 2021), since technologies reflect and affect structures, strategies and logics that support the transformation of organizations as a whole (Woodard, Ramasubbu, & Tschang, 2013), including (but not limited to) the digital domains (Tabrizi, Lam, Girard, & Irvin, 2019). Such logics affect businesses, particularly those that are still anchored in physical operations (Remane et al., 2018) that have additional challenges in making the transition to the digital world (Betzing et al., 2019) - examples of which include retail (Reinartz et al., 2019), manufacturing and automotive industries (Kutnjak et al., 2019) and, as expected, agribusiness (Zanuzzi et al., 2020). That is, all digital transformation 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, Orzes, Sartor, & Nassimbeni, 2020).

In agribusiness, the evolution and applications of digital technologies was 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-wise aspects of modern, large-scale agribusiness such as monitoring and sensorization (Triantafyllou, Sarigiannadis, & Bibi, 2019; López-Morales, Martínez, & Skarmeta, 2020), coordination, control and production (Ciruela-Lorenzo, Aguilla-Obra, Rosa, Padilla-Meléndez, & Plaza-Angulo, 2020), international supply chains (Sharma, Kamble, Gunasekaran, Kumar, & Kumar, 2020) as well as machinery (Lima et al., 2020) and personnel (Trukhachev, Bocrishev, Khokhlova, Ivashova, & Fedisko, 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 coming to fruition, as well as obstructing 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 analysis along with a manual analysis of the extant literature, coupled with data collection and analysis using Fuzzy Analytical Hierarchical Process. This paper contributes to the development of the literature by providing a set of criteria for DTA projects.

2. Digital Transformation in Agribusiness – potential criteria

The general overview of Digital Transformation is that it is an area expanding in leaps and bounds, yet is plagued by theoretical, conceptual and technical inconsistencies (Gong & Ribiere, 2020). Whereas research and publications using the expression “Digital Transformation” are growing almost exponentially, much of it is 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, Wright, & Feldman, 2019), it is plausible that DT as a concept may become blurred – especially in non-academic literature – in close comparison to a selection of data- and tech-driven nomenclature such as Internet of Things, 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, 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, 2018:03), 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, Benabbou, & Berrado, 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, Digital Transformation in Agribusiness – as a subset of DT – inherits these issues. In addition, definition problems also arise when understanding and defining 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 their own fragilities. To reduce such shortcomings, the following procedures were proposed – see Figure 1.

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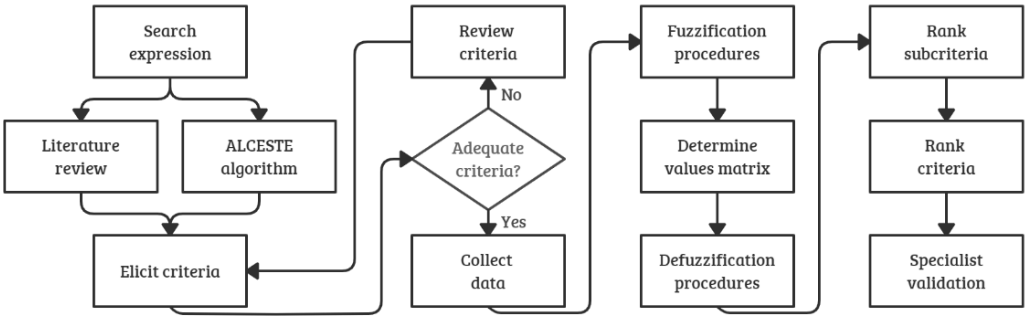
Figure 1 Proposed steps.



Source: Developed by authors.

First, one must design a search expression that allows relevant constructs on DTA to be analyzed. To ensure all potential studies would be found, a "wider" search expression was designed (*digit* transfor* agri**) which resulted in 454 published papers, from 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, Orduna-Malea, Thelwall, & López-Cózar, 2018; Martín-Martín, Thelwall, Orduna-Malea, & López-Cózar, 2021). All resulting studies were individually read and classified using inclusion / exclusion criteria adapted from Liao, Deschamps, Loures, & Ramos (2017) – see Table 1. For conciseness, the full list of all excluded and included studies may be obtained from the authors.

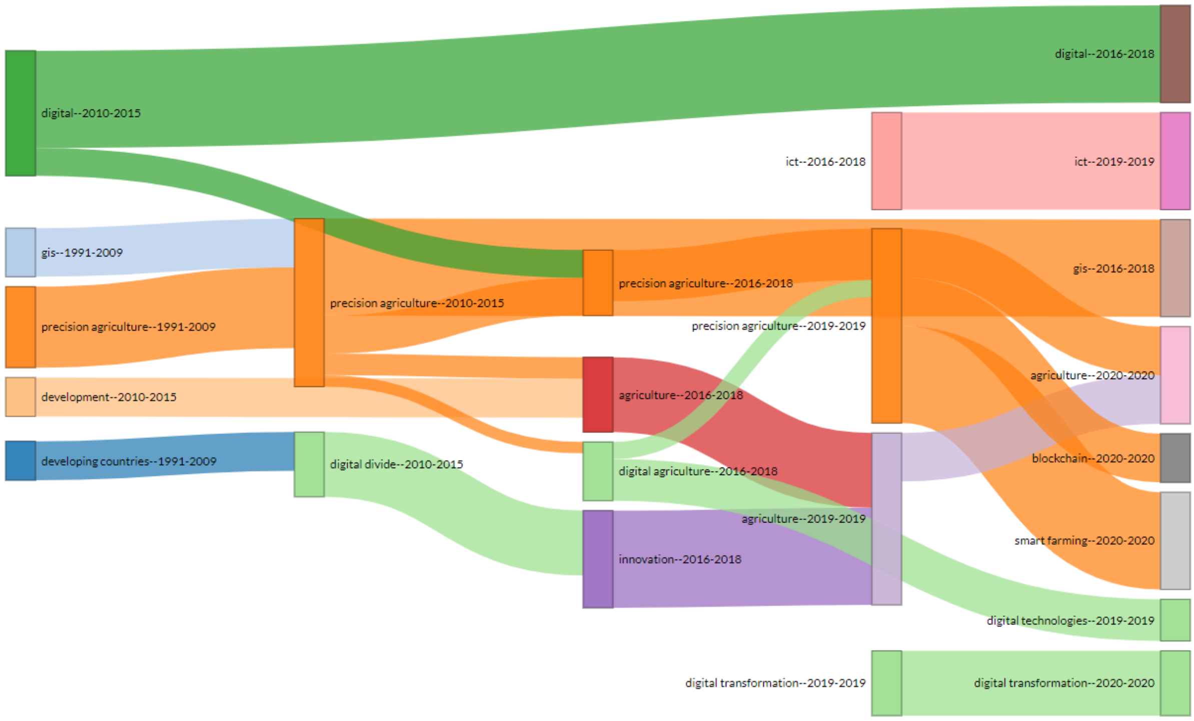
Table 1 Exclusion and inclusion criteria used for selecting the studies – Adapted from Liao et al (2017).

	Criteria	Description	*n*
Exclusion	Search engine reason (SER)	A paper has only its title, abstract, and keywords in English but not its full-text.	
	Without full text (WF)	A paper without full text to be assessed.	**342**
	Non-related (NR)	A 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 and agribusiness.	
	Loosely related (LR)	A paper does not focus on the review, survey, discussion, or problem solving of both digital transformation and agribusiness yet these are part of the argumentation or cited in the paper.	**25**
Inclusion	Partially related (PR)	Digital transformation is used to support the description of some challenges, issues, or trends in agribusiness that 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 digital transformation and agribusiness.	

The included studies were then analyzed both manually as well as mechanically. The first mechanical analysis was performed using the R package Bibliometrix (Chinotaikul &

Vinayavekhin, 2020) – see Figure 2. The analysis of relevant content points to two core concepts – ‘digital’ and ‘precision agriculture’.

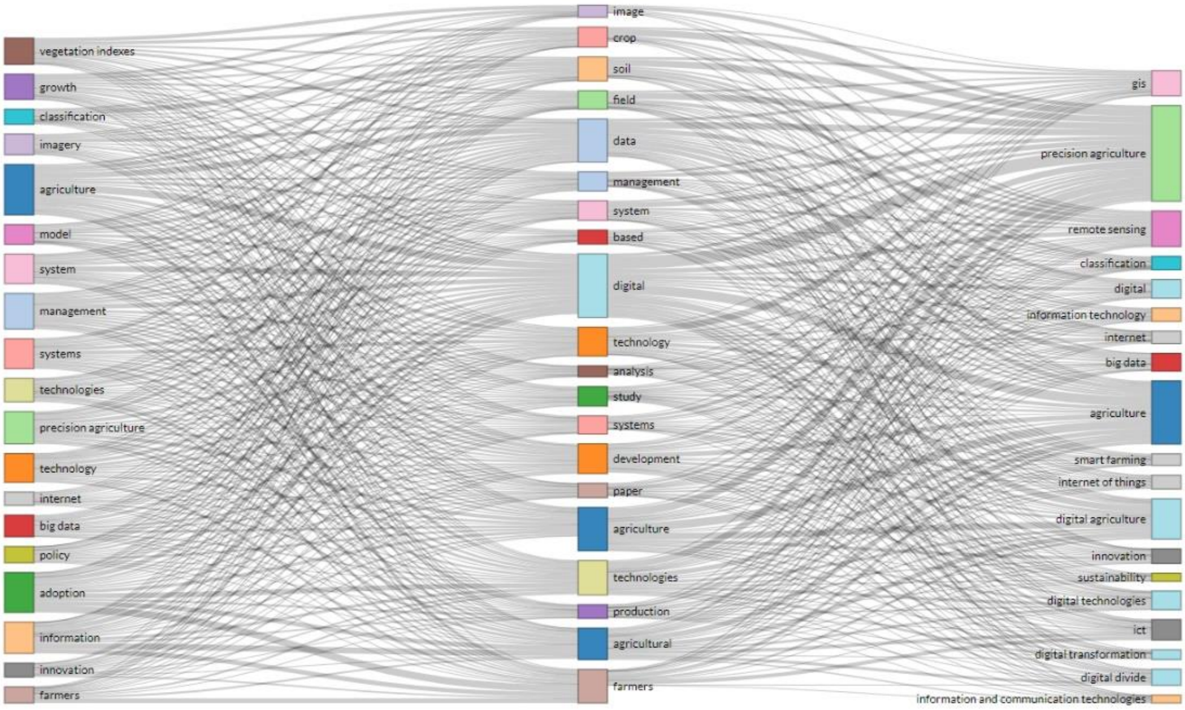
Figure 2 Thematic evolution in DTA



Source: Developed by authors using the R package Bibliometrix.

The first of these two concepts is a knowledge-based criterion emerges – see Figure 3, which includes remote sensing for agriculture (Hinson, Lensink, & Mueller, 2019; Weiss, Jacob, & Duveiller, 2020) and internet of things (IoT) technologies (Tzounis, Katsoulas, Bartzanas, & Kittas, 2017; Elijah, Rahman, Orikumhi, Leow, & Hindia, 2018; Khanna & Kaur, 2019), use of geographic information systems (GIS) (Sharma, Kamble, & Gunasekaran, 2018; Kotsur, Veselova, Dubrovskiy, Moskvin, & Yusova, 2019) and image classification (Zheng. Kong, Jin, Wang, Su, & Zuo, 2019; Brogi, Huisman, Pätzold, von Hebel, Weihermüller, Kaufamnn, van der Kruk, & Vereecken, 2019), along with information and communication technologies, data management and analysis (Panov, Panova, Malofeev, & Nemkina, 2019).

Figure 3 Word cross-analysis



Source: Developed by authors using the R package Bibliometrix.

In addition, the second cluster of terms suggest industrial-level production items, which point to automation as whole, such as precision agriculture (Thompson, Bir, Widmar, & Mintert, 2019; Sott, Furstenau, Kipper, Giraldo, Lopez-Robles, Cobo, Zahid, Abbasi, & Imran, 2020), smart farming (Relf-Eckstein, Ballantyne, & Phillips, 2019), field management (Strizhkova, Tokarieva, Liubchych, Pavlyshyn, 2020). As a close consequence, some terms point to efficiency issues – production (Christiaensen, Rutledge, & Taylor, 2020), development (Lezoche, Hernandez, Díaz, Panetto, & Kacprzyk, 2020) and labour and costs including farmers (Sapfirova, Volkova, & Petrushkina, 2019; Shamin, Frolova, Makarychev, Yashkova, Kornilova, & Akimov, 2019). Lastly, issues elated 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, Shanmugananthan, & Tomar, 2021).

The second mechanical analysis was performed using the ALCESTE algorithm (through the Iramuteq software). This algorithm measures cooccurrence of words in blocks of text splitting them in clusters – see Figure 4. It works by reducing word forms to root forms (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, Hansen, & Kronberger, 2014; Martins, Santos, & Silveira, 2019).

The generated clusters support the ideas previously presented, that is, possibly the existence of four main criteria (a central node and three offshoots). One focuses on knowledge management and its tasks – monitoring, analysis and decision making. A 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.

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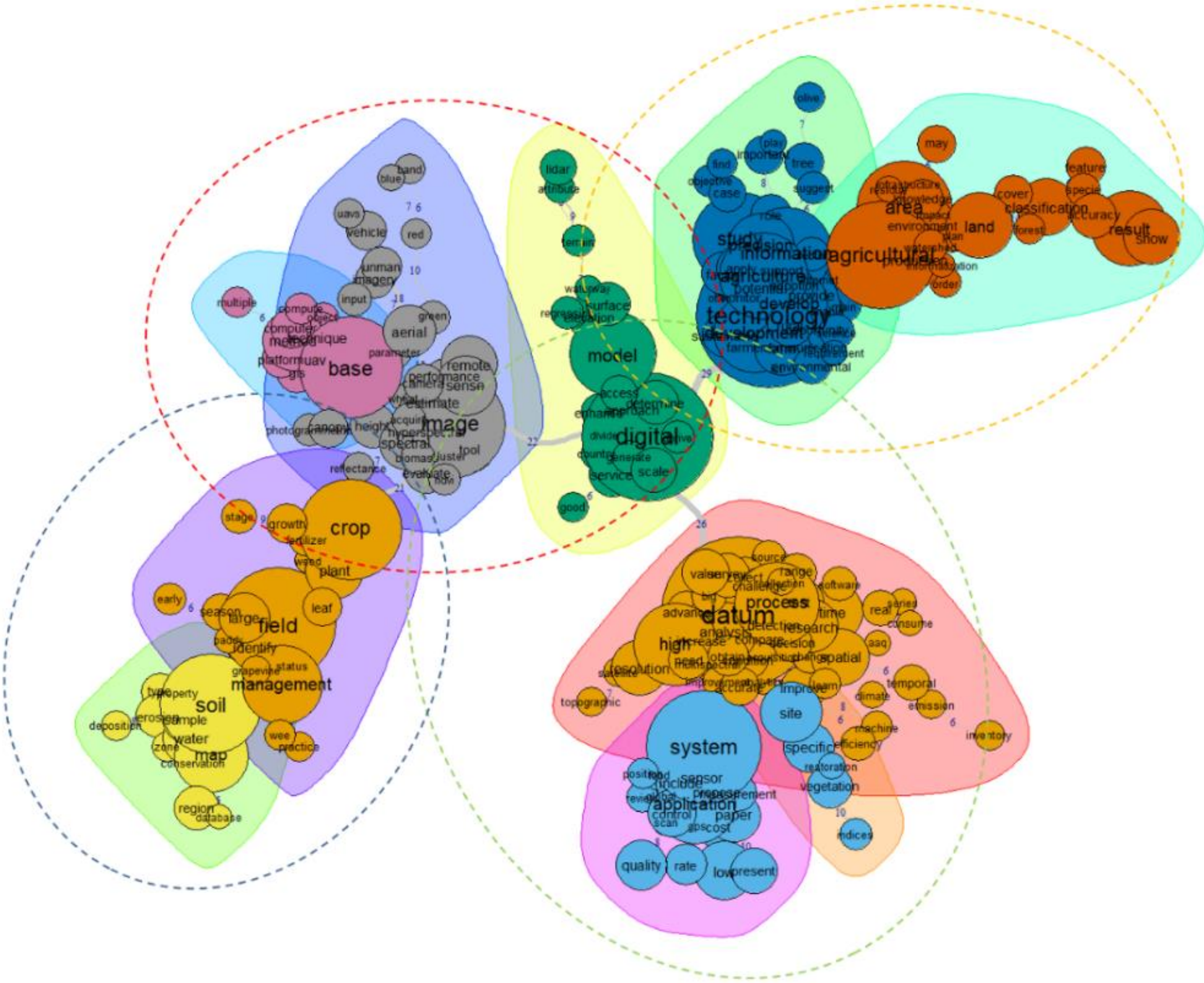
Figure 4 Specific terms clusters.



Source: Developed by authors using the software Iramuteq.

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, a less cited but still important part – firm continuity concerns with 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 sub-criteria are proposed for initiatives in DTA – see Table 2.

Thus, it is possible to aggregate all these criteria in an analysis, gathering data from professionals in the area. To do so, Fuzzy Analytical Hierarchical Process is employed.

Table 2 Selected criteria for DTA.

Criteria	Sub-criteria	Descriptor
Knowledge management	Analysis	Knowledge applied to the relationship of information as the basis of the digital transformation 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 & harvesting	Implementation of digital processes to increase, control, and automatize planting and harvesting.
	Processing & manufacturing	Control of agricultural processing through digital controls and processes
	Maintenance	Monitoring and upkeep of processes, machinery, industrial plants, etc.
	Technology, machinery & tools	Technological tools applied in the digitalization process.
Efficiency	Costs	Effective cost control and reduction through digital means
	Work & 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

3. Fuzzy Analytical Hierarchical Process

In order to analyze which criteria potentially contribute to digital transformation in agribusiness, one must select methods that may aggregate data from a variety of contexts. In this sense, and considering the concepts from Table 2, the Multicriteria Decision Analysis (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, Santos, & Vils, 2017).

In that sense, Fuzzy Analytical Hierarchical Process (Fuzzy AHP) accommodates both fuzzy logic which provides flexibility in the input with the rigorous treatment of data from traditional AHP applications (Oliveira Neto, Oliveira, & Librantz, 2017; Silva, Shibao, Librantz, Santos & Neto, 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) to the background (Nazari-Shirkouhi, Miri-Nargesi, & Ansarinejad, 2017), which makes respondent fatigue (Olson, Smyth, & Ganshert, 2019) and social desirability (Cerri, Thøgersen, & Testa, 2019) less prone to happen. The proposed steps, thus, follow the procedures in Ayhan (2013) adapted in Felisoni and Martins (2019) and Silva Jr, Martins & Librantz (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 defining a core, support points and left/right side bounds. A compromise that allows fast computing with accuracy is treating the responses as fuzzy triangular numbers (TFN), where left cut ≤ central value ≤ right cut, composed of real numbers and in which the left side is a nondecreasing function and the right side is a nonincreasing function (Felisoni & Martins, 2019) – see Table 3. Thus, each value in a traditional AHP Saaty scale is interpreted by a triangular fuzzy number 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 triangular fuzzy numbers are also *n-1* and *n+1*, except for the edge numbers since according to AHP it is axiomatically impossible to there be 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 (see the TFNs for 1 and 9).

Table 3 Saaty scale numbers, verbal descriptions and triangular fuzzy numbers.

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)

As an example of its application, let a decision-maker *k* choose between two criteria *X* and *Y*. Using the verbal descriptors in Saaty scale, he decides that the criterion *X* is moderately more important than *Y*, which is transposed numerically to (4, 5, 6). Looking at the opposite direction, *Y* is interpreted in 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 the 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) is weighted according to the following parameters.

For each response from non-strategic tiers, $\tilde{d}_{ij}^{k}$ values receive a *p* weight, where for each tactical personnel's $\tilde{d}_{ij}^{k}$, 0.33 is added if below the strategic average or 0.33 is deducted if beyond the strategic average. The same happens to operational personnel responses, with 0.66 penalty/reward weight.

Thus, the obtained pairwise TFNs $\tilde{d}_{ij}^{k}$ indicates 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):

$$\tilde{A}^{k} = \begin{bmatrix} \tilde{d}_{11}^{k} & \tilde{d}_{12}^{k} & \dots & \tilde{d}_{1n}^{k} \\ \tilde{d}_{21}^{k} & \dots & \dots & \tilde{d}_{2n}^{k} \\ \dots & \dots & \dots & \dots \\ \tilde{d}_{n1}^{k} & \tilde{d}_{n2}^{k} & \dots & \tilde{d}_{nn}^{k} \end{bmatrix} \quad (1)$$

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

$$\tilde{d}_{ij} = \frac{\sum_{k=1}^{k} \tilde{d}_{ij}^{k}}{k} \quad (2)$$

After the weight balancing mechanism and averaged choices, the final $\tilde{A}$ matrix is as follows:

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

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

$$\tilde{r_i} = \left(\prod_{j=1}^{n} \tilde{d}_{ij}\right)^{1/n}, \quad i = 1, 2, \dots, n \tag{4}$$

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

$$\begin{aligned} \widetilde{w_i} &= \tilde{r_i} \otimes (\tilde{r_1} \oplus \tilde{r_2} \oplus \dots \oplus \tilde{r_n})^{-1} \\ &= (lw_i, mw_i, uw_i) \end{aligned} \tag{5}$$

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

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

All these procedures are executed for all criteria and then the sub-criteria. Whereas the obtained final weights might be used to find the best combinations, such alternatives are inexistent in the literature and may be part of further studies.

4. Data collection procedures

To collect data for the purposes of this study, a questionnaire with the potential criteria and sub-criteria was developed, refined by a small team of professors and pre-tested. Pre-test feedback helped in deploying mechanisms developed to facilitate comprehension. First, the meaning of each criterion and sub-criterion was presented at the beginning of the questionnaire and again in each section respondents were reminded of the definitions. Second, to avoid social desirability (Cerri et al., 2019), primacy effects (Seninde & Chambers, 2020) and respondent fatigue (Olson et al., 2019), for each criterion, the sub-criteria involved were randomly presented which helps debiasing the preferences (Montibeller & von Winterfeld, 2015).

Data collection was carried out during the period from October 2020 till the end of the first quarter of 2021, during the Covid-19 pandemic. After the pre-test and adjustments made to the questionnaire, it was sent to a sample of professionals selected from companies that are directly involved in DTA projects (*n* = 100). Contact was made in person or 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 the questionnaire after 2, 4, and 6 weeks of contact.

5. Results and discussion

The data obtained is displayed as follows – sampling, triangular fuzzy numbers for all criteria and sub-criteria as well as the weights for each criterion, along with the obtained weights for each sub-criterion within a criterion.

As for the minimum sampling for MCDA methods, previous literature does not define boundaries, although accepted studies range from 3 to 20 expert respondents, seldom exceeding these figures (Dey 2010; Yadav & Sharma 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, s.d. = 1.34; digital technologies: average = 3.71, s.d. = 1.01; business management: average = 3.64, s.d. = 0.98; knowledge management: average = 3.53, s.d. = 0.83; age: average = 39.17, s.d. = 8.38, and professional experience in years: average = 15.28, s.d. = 7.33. Such responses point to the respondent pool to be 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 in each end of the spectrum (agriculture – 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 demand for commodities is high and the first impacts and restrictions on international logistics had already passed. Detailed, anonymized data on the respondents may be obtained from authors upon request.

The results for the four criteria are found in Table 4. Ni stands for the proportion in importance (total sum = 1). Two main criteria are considered more important to DTA – Efficiency (34.5%) and Knowledge Management (33.8%).

Table 4 Proposed DTA criteria.

Criteria	*lw*	*mw*	*uw*	M_i	N_i	%
Knowledge management	0.286	0.338	0.398	0.340	0.338	33.8
Automation	0.192	0.221	0.254	0.222	0.220	22.0
Efficiency	0.282	0.344	0.418	0.348	0.345	34.5
Continuity	0.091	0.097	0.105	0.098	0.097	9.7

This may be due to the fact that whereas DTA promotes digitalization of operations, agribusiness depends on physical production outputs – which is 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 current literature on agribusiness points to managerial concerns to be more focused on risk minimization on 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, & da Silva, 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, Billingsley, Reid, & van Henten, 2016). A second reason is that the main benefits of automation for DT may depend on technologies (such as 5G) still not fully available in areas where commodities production abound (Elijah et al., 2018). Last comes continuity – which depends on local and international regulatory pressures, institutional pressures as well as market and consumer attention and requirements (Frolov & Lavrentyeva, 2019; Lin, Luo, & Luo, 2020; Corallo, Latino, Menegoli, & Striani, 2020).

The full data on all sub-criteria can be found on Table 6:

Table Final weights for each criterion / subcriterion.

	lw	*mw*	*uw*	M_i	N_i	%
Knowledge management						
Analysis	0.277	0.318	0.366	0.320	0.318	31.8
Monitoring	0.255	0.285	0.319	0.286	0.285	28.5
Decision making	0.344	0.397	0.457	0.399	0.397	39.7
Automation						
Planting and harvesting	0.163	0.131	0.108	0.134	0.133	13.3
Processing and manufacturing	0.295	0.244	0.196	0.245	0.242	24.2
Maintenance	0.200	0.157	0.121	0.159	0.158	15.8
Technology and tools	0.544	0.468	0.407	0.473	0.468	46.8
Efficiency						
Costs	0.299	0.270	0.245	0.271	0.271	27.1
Work and personnel	0.412	0.394	0.374	0.393	0.392	39.2
Processes	0.368	0.337	0.309	0.338	0.337	33.7
Continuity						
Quality and food safety	0.527	0.500	0.474	0.500	0.500	50.0
Environmental sustainability	0.527	0.500	0.474	0.500	0.500	50.0

The last step of the study is a specialist validation process. To do so, five specialists analyzed the numerical data and qualitative responses. The qualitative responses point to improvement in existing processes, solving of 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 mortar-and-brick businesses in the digital revolution are still needed. The specialists agree with the weights and organization of the criteria, yet criticize the true potential of DTA beyond the criteria selected.

The Knowledge Management sub-criteria present balanced results (N_i for the three sub-criteria 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 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 et al., 2018). Decision-making may also be interpreted in two levels – strategic decision making, which still is mostly traditional, and farming task execution, in which efforts for automation start to appear (Bramley & Ouzman, 2019; Lowenberg-DeBoer, Huang, Grigoriadis, & Blackmore, 2020).

This leads to the imbalance in the sub-criteria within the Automation criteria. Especially in commodity-specialized areas (such as Brazil), efforts in coordination and lean production have impacted organizational internal structure (Satolo, Hiraga, Zoccal, Goes, Lourenzani, & Perozini, 2020). Thus, the search for technologies that allow flexibility in production planning and connection to international markets (Zhao et al., 2020; Lezoche, 2020; Contador, Satyro, Contador, & Spinola, 2020), all the while aiming at operational efficiency, particularly cost reductions (Satolo et al., 2020; Kutnjak et al., 2020). This brings up the divide in exploration and exploitation in agribusiness which affect discrepancies between managerial aspirations and real-world performance levels, particularly during crises such as the current one (Martins et al., 2020). Lastly, continuity sub-criteria, while cannot be said to be residual, are not very significant in the whole (less than 10% of importance), which point to the longstanding criticisms of Brazilian agribusiness (Torres, Moran, & Silva, 2017; 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) (Sousa & Rocha, 2019). A possible limitation or at least an aspect worth consideration is that these branches may be due to 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 criteria. While the weights obtained are only indicative of a specific case (Brazilian agribusiness), this promotes a reflection of 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).

6. Conclusions, limitations and practical implications

Digital transformation is part of a new trend of multidisciplinary integration of digital technologies to 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 sometime overlap (Intelligent Agriculture, Digital Agriculture, Agriculture 4.0). So far, there is no comprehensive review of literature that analyses both agriculture and digital transformation, yet some specialized reviews were published – for specific technologies or methods such as blockchain (Sethibe, 2019), artificial intelligence (Spanaki, Sivarajah, Despoudi, & Irani, 2021) or machine learning (Sharma et al., 2020); areas such as Brazil (Zanuzzi et al., 2020); or applications like purchasing and consumption (Samoggia, Monticone, & Bertazzoli, 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 area 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, 2020) or from untested models may be theoretically fragile and professionally irresponsible. Whereas these four criteria still merit further research and validation, the current literature point to their stability and maturity, if the sheer number of studies in each is considered. On the other hand, this study has two limitation 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 be 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 provided criteria in surveys, for instance.

To date, there is no fully tested digital transformation model, which includes 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 support in the academic literature and were discussed with professionals and specialists directly involved in digital transformation projects implemented specifically in agribusiness. This provides a large measure of trust that such criteria should be considered in future projects. By contrast, this study does not provide statistical modelling 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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