# Equity Crowdfunders' Human Capital and Signal Set Formation:
# Evidence from Eye Tracking


## Abstract

Signaling theory typically assumes that attention is always given to observable signals. We study signal receivers' formation of signal sets—the signals to which receivers attend and that they can use for subsequent interpretations. Drawing on a cognitive perspective, we argue that signal receivers' human capital influences the volume and type of signals they attend to and the time they take to form signal sets. Using eye tracking, we show that equity crowdfunders do not attend to many signals that are easily observable on a campaign page, and that differences in crowdfunders' human capital uniquely affect their signal set formation.


## Introduction

According to signaling theory (e.g., Spence, 1973), firms of unobservable high quality can ease resource attraction by conveying signals to prospective resource providers (Bergh et al., 2014; Colombo, 2021; Connelly et al., 2011). In early studies, these signals, when isolated or congruent, were assumed to yield nearly uniform attention (Drover et al., 2018). More recently, scholars have begun investigating the ways in which the effectiveness of signals for resource attraction can differ when signals are combined with other (potentially conflicting) signals (Anglin et al., 2018; Courtney et al., 2017; Paruchuri et al., 2021; Plummer et al., 2016; Scheaf et al., 2018). When firms send numerous signals simultaneously, individuals will attend to and evaluate a set of signals, rather than isolated signals (e.g., Steigenberger & Wilhelm, 2018). Scholars have further documented that signal effectiveness can differ depending on the receiver's ability to recognize signals and the value placed on them (Connelly et al., 2011; Scheaf et al., 2018). In particular, depending on their regulatory focus (Ciuchta et al., 2016), their coaching experience (Ciuchta et al., 2018), or whether they are employees or financiers (Vanacker & Forbes, 2016), signal receivers react differently to certain signals.

By focusing on the relationship between signals and firms' ability to attract resources, prior studies have not provided *direct* evidence of signal attention or signal interpretation, which are two distinct cognitive processes that cause signal (in)effectiveness (e.g., Drover et al., 2018; Vanacker et al., 2020). To increase our understanding of signal effectiveness, we need to focus more explicitly on these cognitive processes that underlie signaling theory (Drover et al., 2018). Signal attention is particularly relevant because if individuals' attention is not caught in the first place, signal interpretation cannot take place. Given that attention determines which signals will be evaluated, the issue of how signal receivers direct their attention to signals is salient (van Knippenberg et al., 2015). Signaling theory, however, "clearly sees actors as rational agents" (Bergh et al., 2014, p. 1354) and thus takes attention to observable signals as a given. As a consequence, signaling theory "does not adequately explain how individuals allocate attention to […] signals" or "the volume and types of signals individuals attend to" (Drover et al., 2018, p. 210).

However, in multi-signal contexts, signal attention is not guaranteed given people's bounded rationality (Simon, 1971). As Simon (1971, p. 40) observed, "a wealth of information creates a poverty of attention." Our aim in this study is to increase our understanding of signal receivers' variations in signal set formation, where a "signal set" refers to a portfolio of signals to which an individual attends and that can be used for subsequent signal interpretation (Drover et al., 2018). Specifically, we focus on the size of the signal set (i.e., the number of different signals investors attend to), the time investors take to form signal sets, and the relative composition of their signal set (i.e., the relative importance of the type of information in focus, such as team, financial, or product information). To do so, we adopt a cognitive perspective of signaling (Drover et al., 2018), which suggests that to make sense of uncertain, complex, and information-rich environments, individuals use heuristics when attending to the information available to them (Mitchell et al., 2007; Tversky & Kahneman, 1974). The cognitive view further suggests that education can, to some degree, affect the use of heuristics (Tversky & Kahneman, 1974) and that "experts" develop scripts that allow them to process information more effectively and efficiently (Baron & Ensley, 2006; Lord & Maher, 1990; Smith et al., 2009). Accordingly, we focus on an individual's human capital (i.e., education and experience (see Becker, 1994; Colombo & Grilli, 2005; Dimov & Shepherd, 2005)) as an antecedent of signal set formation.

We focus on the context of equity crowdfunding for several reasons. First, it represents a market with abundant information asymmetry and uncertainty, making a signaling theory lens particularly pertinent (Ahlers et al., 2015; Baid & Allison, 2019). Second, in equity crowdfunding, all communication with crowd investors occurs in a public arena online, presenting scholars and investors with equal access to the available information. Third, the small size of investments reduces the incentives to conduct costly and detailed due diligence (Vismara, 2018). The limited due diligence and heterogeneity among crowd investors (Hervé et al., 2019) makes understanding variation in signal set formation across these receivers even more crucial.

In our study, we use state-of-the-art webcam-based remote eye tracking technology, which allows researchers to investigate people's eye movements during behavioral processes, thereby allowing them to examine where and how people direct their attention, as well as what factors constitute drivers of attention (Duchowski, 2017; Meissner & Oll, 2019). Consistent with our hypotheses, we find that crowd investors with more general human capital (i.e., higher overall education levels and/or general entrepreneurial experience) construct larger signal sets, take more time to form signal sets, and have a different signal set composition relative to those with less general human capital. Conversely, investors with specific human capital (i.e., equity crowdfunding experience and/or industry-specific experience) construct smaller signal sets, take less time to form signal sets, and have a different signal set composition relative to those without context-specific human capital.

Our study contributes to the signaling literature in the following manners. Research has established that the effectiveness of signals can differ across audiences (e.g., Ciuchta et al., 2016, 2018; Scheaf et al., 2018; Vanacker & Forbes, 2016). Different cognitive processes may explain this finding; for example, a signal may facilitate resource attraction for one receiver but not for another because receivers differ in their observation and/or valuation of a signal, as well as in what other signals they observe that may mitigate the original signal. Our study takes an important step towards opening the black box of signaling effectiveness by focusing explicitly on how variations in receivers' human capital influences their signal attention, which is a precondition for signals to be interpreted and hence to be effective. As such, we qualify cognitively-inspired theories of signaling, which have suggested that "it is probable that highly observable signals will always be attended to” (Drover et al., 2018, p. 217). Our research also has implications for the equity crowdfunding literature, which we explore later in the manuscript.

From a methodological perspective, eye tracking has been extensively applied in other disciplines such as health and medicine, finance, psychology, and marketing (e.g., Adhikari & Stark, 2017; Bott et al., 2020; Duclos, 2015; Semmelmann & Weigelt, 2018), yet is still rarely used in entrepreneurship generally and entrepreneurial finance particularly (Meissner & Oll, 2019). A notable exception is Du, Li, and Wang (2019), who use eye tracking to show that as more reward options are provided in a reward crowdfunding campaign, backers’ fixation density decreases, indicating that they focus less as more options are presented to them. We extend this novel stream of research by leveraging webcam-based remote eye tracking to further unravel how people attend to signals in a real-world setting and why some signals capture attention, while others do not.

## Theory

### Background Literature

Signaling theory has increased our understanding of when prospective investors choose to fund new ventures in an environment fraught with uncertainty and informational asymmetry (Baid & Allison, 2019; Bergh et al., 2014; Colombo, 2021; Connelly et al., 2011). Firms can ease resource attraction through signaling with their boards (Certo, 2003), team member characteristics (e.g., Plummer et al., 2016), early accomplishments (Hallen, 2008), and endorsement relationships (Anglin et al., 2020; Plummer et al., 2016; Stuart et al., 1999). Firms can also benefit from conveying low-cost signals, including visual cues, optimistic speech, press releases, and forecasts (Ahlers et al., 2015; Anglin et al., 2018; Mahmood et al., 2019; Steigenberger & Wilhelm, 2018;

Vanacker et al., 2020). Signaling comprises both signal attention and signal interpretation (e.g., Drover et al., 2018; Vanacker & Forbes, 2016). To date, signaling studies have often focused on the direct link between signals and firms' ability to attract resources without investigating the underlying cognitive processes of attention and interpretation. Signal attention, a crucial element of signal effectiveness, has been taken for granted (Drover et al., 2018). The main purpose of this paper is to increase our understanding of signal attention by examining variations in receivers' signal set formation. This signal set subsequently serves as input for the next cognitive stage – signal interpretation.

To explain variations in signal set formation, we draw on a cognitive perspective in which cognition captures "all processes by which sensory input is transformed, reduced, elaborated, stored, recovered and used" (Neisser, 1967, p. 4). The cognitive perspective maintains that people seek information to reduce uncertainty and information asymmetries but, at the same time, are subject to a variety of limitations (Bitektine, 2011; Mitchell et al., 2007; Tversky & Kahneman, 1974). Specifically, people are boundedly rational in their ability to scan, collect, and process large amounts of information (Cyert & March, 1963; Simon, 1976). Attention restricts the processing of the enormous array of information that is continuously available from sensory and memory sources, and one of its critical roles is to preferentially select only particular information for detailed processing (LaBerge, 1995; Van Knippenberg et al., 2015). Individuals are likely to selectively attend to and process evaluative information: rather than equally weighting all information that comes along, individuals engage in satisficing behavior, drawing on low-effort strategies to collect information, and rarely focus on all available information (Simon, 1976).

Within entrepreneurship, a substantial research stream on cognition has developed (e.g., Mitchell et al., 2007; Smith et al., 2009). Some of this research shows how investors try to limit information overload when making investment decisions. This is not surprising, as satisficing behavior is particularly likely in multi-signal contexts in which the cost of information collection is high—as is the case in many entrepreneurial finance contexts, including crowdfunding (Drover et al., 2018).[1]

Considering investors' selective attention and satisficing behavior, interesting questions arise: how many and which signals do investors pay attention to when investing? Cognitive psychology theories of skill acquisition (Anderson, 1982) suggest that important differences in individuals' attentional processes depend on their experience and knowledge of the subject matter (Hitt et al., 2001). Both are an outcome of human capital investments (Ployhart & Moliterno, 2011). We therefore investigate crowdfunders' general and specific human capital—as proxies for knowledge and experience—as antecedents of signal attention and signal set formation (Becker, 1994).

Broadly, human capital includes the acquired knowledge, skills, and capabilities that enable people to act (Coleman, 1988). General human capital is not directly related to a certain job or task. In our context, this task represents the investment evaluation of an equity crowdfunding campaign. It, for instance, comprises an individual's overall education (e.g., Bruns et al., 2008; Forbes, 2005a; Rauch & Rijsdijk, 2013). For investment evaluations, general entrepreneurial

[1] Equity crowdfunding campaigns contain many signals related to the idea, product, team, financials, campaign dynamics, campaign characteristics, and strategy, among other elements (Ahlers et al., 2015). Moreover, a detailed assessment is costly given equity crowdfunders' small investments (Cumming et al., 2021a). Accordingly, incentives for equity crowdfunders to engage in a detailed investigation of a campaign may be limited. Overall, universal attention to all observable signals should not be taken for granted in this research context (Scheaf et al., 2018), even when signals are easily observable on a campaign page.

experience also contributes to general human capital (e.g., Dimov & Shepherd, 2005). Specific human capital is directly related to the task at hand (Shepherd & Wiklund, 2006). An important form of specific human capital is domain-relevant experience. Drawing on prior research within entrepreneurial finance (e.g., Bruns et al., 2008; Colombo & Grilli, 2005; Dimov & Shepherd, 2005), domain-relevant experience includes prior experience with investing in equity crowdfunding campaigns and/or prior experience within the industry of the fundraising venture.

**Hypotheses**

***General human capital and signal set formation***

For several reasons detailed below, we expect investors with more general human capital to differ in their signal attention processes from investors with less general human capital. Specifically, we expect those with more general human capital to form larger signal sets, take more time to form signal sets, and form signal sets with a different relative composition.

First, investors with high general human capital possess more facts, concepts, and ideas that can be transformed into verbalized rules, techniques, and methods that they can check against and implement to solve a task, as compared to their low general human capital peers (Becker, 1994). Therefore, they are thought to have the cognitive resources needed to collect and process a broader set of information. Conversely, those with fewer cognitive resources may examine fewer information cues due to their narrower understanding (Shah & Oppenheimer, 2008), and they may not be aware of the importance of, for example, the team, the idea, financials, and relationships among other elements. At the same time, investors with more general human capital are likely to show the ability for "integrative complexity" (Goll & Rasheed, 2005; Wiersema & Bantel, 1992)—defined as "the capacity and willingness to tolerate different points of view" and to "generate linkages between points of view, […] to confront trade-offs, and to appreciate interactive patterns of causation" (Tetlock et al., 1993, p. 500). This would suggest that the signal set composition is likely broader and different for equity crowdfunders with more general human capital, relative to those with less general human capital.

Second, equity crowdfunders with high general human capital are likely to act more rationally and be more conscious during their signal set formation. Indeed, general human capital includes knowledge that is context- and content-independent (Becker, 1994). Therefore, the application of general human capital to a specific task, such as investing in equity crowdfunding, depends on a set of unintegrated knowledge structures that must be held in working memory and attended to in a step-by-step manner (Anderson, 1982), resulting in slower, more explicit, and more consciously-aware attentional processes (Nahapiet & Ghoshal, 1998). In this vein, having more general human capital may lead to a greater need for decision comprehensiveness and thus may require more information and more thorough attentional processes (e.g., Jansen et al., 2013). Goll and Rasheed (2005, p. 1005), for example, highlight that the "collection of information and its careful analysis are fundamental to higher education in most disciplines." Moreover, equity crowdfunders with more general human capital may be more aware of some of their cognitive limitations. For example, scholars have argued that more highly-educated people are more aware of commonplace biases and are also less likely to commit them (Forbes, 2005b; Lichtenstein & Fischoff, 1977), thereby adopting a more rational, comprehensive information-processing style (Lord & Maher, 1990). Overall, investors with more general human capital are expected to search for more information and take a longer time to make a decision.

Taken together, we hypothesize that:

***Hypothesis 1a:*** *Equity crowdfunders with more general human capital will form larger signal sets than those with less general human capital.*

***Hypothesis 1b:*** *Equity crowdfunders with more general human capital will take more time to form signal sets than those with less general human capital.*

***Hypothesis 1c:*** *Equity crowdfunders with more general human capital will have a different signal set composition than those with less general human capital.*

***Specific human capital and signal set formation***

We further expect that signal attention will differ based on investors' specific human capital. Specifically, we expect that investors with specific human capital (i.e., with experience relevant to the crowdfunding campaign) will form smaller signal sets, take less time to form signal sets, and form signal sets with a different relative composition than those without such capital.

First, investors with specific human capital already have a stock of relevant knowledge in place, which explains why they (*think* they) need less information to guide their decision-making (Forbes, 2005a). They develop more focused, automatic "schema" or "scripts" that influence their signal set formation (Zacharakis & Meyer, 2000), or, as Hodge and Pronk (2006, p. 268) state, they are "better able to predefine their information needs" and "execute focused searches to acquire relevant information." Accordingly, equity crowdfunders with prior domain-specific experience are likely to construct smaller signal sets more quickly. Reliance on cognitive shortcuts developed through the accumulation of domain-relevant knowledge and experience has also been observed among professional investors. Indeed, investors frequently look for elements typically considered "success factors," such as the team, when screening firms (e.g., Ciuchta et al., 2018). Similarly, investors might quickly dismiss an investment opportunity based on a limited set of signals and have been reported to often stop screening business plans after a quick “one-minute test” (Maxwell et al., 2011). Similarly, equity crowdfunders’ previous context-specific experience may also affect their signal sets’ relative composition; preexisting knowledge structures that are a function of their prior domain-specific experience may push them to focus more or less on specific information signals (Lord & Maher, 1990) compared to people without prior domain-specific experience. Building on this notion, scholars have shown that people with domain-specific experience in analyzing public firms and their financial statements access different pieces of information in financial reports (Hodge & Pronk, 2006).

Second, it is not only unconscious, already-formed cognitive schemas that are likely to influence investors’ signal set formation. People with domain-relevant experience also usually form consciously available beliefs (that can be, but are not necessarily accurate) regarding the most important factors for firms’ success (Shepherd et al., 2017); they *believe* they know what will occur in the future or can work through inevitable challenges (Jansen et al., 2013).[2] Accordingly, they may have a greater feeling of control and/or higher levels of risk acceptance (Jansen et al., 2013). People that perceive less risk or have a greater feeling of control because they believe they know the success factors (or can influence them) search for less information and take less time to make decisions (Forbes, 2005a). Consequently, equity crowdfunders with domain-specific experience may also consciously search for a more limited set of information cues that (dis)confirm whether projects fit with their beliefs of what drives success. They might thereby ignore other potentially relevant informational cues.

[2] Tversky, & Kahneman. (1974), *1124*; emphasis added) highlight that “these heuristics are quite useful [to cope with information-rich environments], but *sometimes* they lead to … errors”.

Third, Forbes (2005a) suggests that people with domain-relevant experience will be familiar with the available sources of information. For example, people with prior equity crowdfunding experience will be more aware of the structure of a typical equity crowdfunding campaign and the information available in such campaigns. Consequently, such people will be quicker in scanning equity crowdfunding campaigns and can do so in a more focused manner.

Overall, we expect that equity crowdfunders with context-specific experience will construct smaller signal sets that have a different relative composition and will construct signal sets more quickly than investors without domain-relevant experience. Thus:

***Hypothesis 2a:*** *Equity crowdfunders with specific human capital will form smaller signal sets than those without specific human capital.*

***Hypothesis 2b:*** *Equity crowdfunders with specific human capital will take less time to form signal sets than those without specific human capital.*

***Hypothesis 2c:*** *Equity crowdfunders with specific human capital will have a different signal set composition than those without specific human capital.*

## Method

### Eye Tracking

This study uses eye tracking, a behavioral research method measuring eye gaze—the positions and movements of the eye—that objectively measures people's attention, their spontaneous responses to visual stimuli, and what they see and miss when looking at visual content (Duchowski, 2017; Holmqvist et al., 2011). Eye tracking systems follow the gaze of individuals looking at stimuli on a screen to identify which areas are seen and for how long. This allows researchers to register the movements of a participant’s eyes during behavioral processes, thus offering “insights into the cognitive processes underlying a wide variety of human behaviors” (Ashby et al., 2016, p. 96).

To explore variations in signal set formation among people with different levels of human capital, we first conducted a pilot study (for details, see Online Appendix A1). Its purpose was to validate our theoretical assumptions, evaluate the feasibility of the eye tracking approach, and anticipate any modifications needed in our large-scale study of signal set formation. The pilot study showed that people with different human capital vary in the extent to which they ignore signals and focus on different signal sets. Hence, we decided to conduct a large-scale eye tracking study to formally test our hypotheses.

For the main study, we used a remote software and webcam-based eye tracking solution offered by EyeSee (https://eyesee-research.com/) that relies on images taken by participants’ web-cameras and on software to track people’s eye-gaze remotely. Unlike traditional hardware-based solutions that use hardware modules to take videos of users’ eyes, emit infrared rays, and receive reflected optical features (as used in the Pilot Study), remote webcam-based eye tracking solutions capture ocular movements in a stream of image frames produced from the webcam and use these images of the participant’s face and eyes as input (Hansen & Ji, 2010). An algorithm is then employed to calculate the exact position of the eyes, correlate eye direction to the image on the screen, and output the predicted eye gaze coordinates (Hansen & Ji, 2010). In particular, they extract gaze information through a geometric model of the eye and the eye area, to which the image of the participant’s eye is compared. Remote software and webcam-based eye tracking tools infer gaze direction from observed eye shapes, such as pupil centers and iris edges. Following these principles, the EyeSee software detects the face and the head pose of the participant, identifies the eye areas and eyes, and then allocates the pupil and the iris. Thereafter, the gaze estimation is conducted with iris tracking, correcting for head pose.

EyeSee guarantees a sampling rate of 12 Hz to 28 Hz, with an average of 15Hz, depending on the quality of the webcam (EyeSee, 2013).[3] A sampling rate of 15 Hz translates into recording 15 gaze points per seconds, or one gaze point every 0.066 milliseconds. Regarding the absolute precision and accuracy of the gaze estimation, assuming an average respondent's distance from the screen of 60cm/23.6in, EyeSee offers an average visual angle degree (also called root mean square (RMS) of intersample distances in the data) of 1.8°.[4] On an average 38.1cm/15in laptop screen (approx. 31cm/12.2in x 17.5cm/ 6.9in), this translates into a mean error of 3.75 % of the screen width along the x-axis (1.2cm/ 0.5in) and 8.72 % of the screen height along the y-axis (1.5cm/ 0.6in). That is, EyeSee ensures high accuracy for studies in which AOIs are bigger than 1.2cm x 1.5cm (on an average 38.1cm/15in laptop screen), which is the case in our study in which AOIs, on average, were 12.4cm width x 3.5cm height (st.dev. 8cm width x 2.7cm height).

Recently, remote webcam-based eye tracking is increasingly successfully used to answer behavioral research questions in domains such as decision sciences, cognitive and neurosciences (Federico & Brandimonte, 2019), and health and medicine (Adhikari & Stark, 2017; Bott et al., 2020). While traditional hardware-based eye tracking solutions are more performant and precise

[3] It is noteworthy that these accuracy tests were performed in 2013. Since then, both EyeSee specialists (O. Tilleuil, personal communication, December 11, 2020) and researchers in the field of remote webcam-based eye tracking (Semmelmann & Weigelt, 2018) have confirmed that the accuracy and precision of the gaze estimation in general and the sampling frequency in particular has significantly improved, due to the continuous increase in image quality and resolution of webcams. Indeed, most webcam resolutions are currently 1280x720 pixels, with 30 frames per second being the minimum sampling frequency for most cameras.

[4] While state-of-the-art hardware-based eye tracking solutions such as Eyelink 1000+ or Tobii EyeX can reach an accuracy of 0.15° - 0.3° average visual angle degree, other comparable webcam- and software-based eye tracking solutions offer an average visual angle of 4.16°. Such an average visual angle of 4.16° has been nonetheless considered to allow for accurate data acquisition (Semmelmann & Weigelt, 2018).

than remote webcam-based systems, webcam gaze extractions have been proven to be highly correlated ($\rho = 0.6$) with the values calculated with state-of-the-art hardware-based eye tracking (Kooiker et al., 2016). The signals collected by remote webcam-based eye tracking have been proven to be suitable for different eye tracking tasks such as fixation, pursuit, and free viewing tasks and for tasks where the focus is on determining where a participant's attention is drawn, such as where gaze location is sufficient, for example, to report the time spent in a certain AOI (Anderson et al., 2011; Semmelmann & Weigelt, 2018). However, this is only the case (1) as long as stimulus AOIs are specific, of reasonable size, and not too close together, and (2) the image rendering technology avoids using the extreme periphery of the screen (Semmelmann & Weigelt, 2018). These conditions are satisfied in our study, as we are interested solely in the amount of time participants dedicate to observing each of the campaigns' AOIs (i.e., gaze location is sufficient). Moreover, the AOIs are of significant size (average size 12.4cm width x 3.5cm height), fixed, placed at sufficient distance from neighboring AOIs with no overlaps, and concentrated in the central parts of the screen (see Figure 1).

The most significant advantage of remote webcam-based eye tracking as compared to traditional in-the-lab hardware-based eye tracking solutions is the lack of geographical restrictions to collect eye feature data on large sample sizes. This provides an opportunity to obtain larger, more diverse participant samples required for the generalization of results without the need for any special equipment or hardware. Sample size and diversity are particularly relevant, since the complexity of eye movement data for each individual participant involves substantial variability across subjects in a given study, which in turn implies the need for large study samples. Webcam-based eye tracking technology hence has the potential to eliminate the logistical (and financial) barriers to conducting large-scale eye tracking studies faced by in-the-lab infrared-based eye tracking solutions.

A second important advantage afforded by the use of desktop web cameras in eye tracking is the unobtrusive capture of eye movement data, which translates into greater ecological validity. Since they do not resort to stationary head pose constraints such as mouth pieces or chin-rests, webcam-based eye-gaze tracking methods do not constrain participants, allowing them the freedom of movement that is characteristic of real-life scenarios. Such unrestrained locomotor dynamics do not influence the participants' natural task behavior, allowing for natural and dynamic interactions with the task at hand. Thus, webcam-based eye tracking tools offer an attractive solution for participant-oriented studies and bring eye tracking studies within reach of many studies for which an infrared system is not employable, while still maintaining high standards of rigorous and precise measurement.

Taken together, the above advantages of using remote webcam-based eye tracking solutions have the capacity to significantly change the landscape of eye tracking studies in management and entrepreneurship research.

**Participants, stimuli campaigns, and procedure**

We recruited participants from Prolific, an international online panel of adult respondents that connects researchers with participants for surveys and experimental projects. Prolific has been found to provide access to respondents that are more diverse and to produce data of higher quality than comparable behavioral research crowdsourcing platforms (Peer et al., 2017). We used multiple screening criteria on the platform by only recruiting participants who were fluent in English, had a 95% approval rate on Prolific, had a desktop device equipped with a webcam, and had investment experience (i.e., experience with exchange-traded commodities or funds, government bonds, stocks, unit trusts, angel (syndicate) investing, private equity funds, venture capital funds, options, or crowdfunding—as in Van Balen et al., 2019).

Of the 713 initial participants[5] who passed the screening and started the eye tracking session, we excluded 175 due to initial calibration errors or technical issues regarding head pose or environmental conditions. Since remote webcam-based eye tracking solutions such as EyeSee measure eye gaze relative to the camera being used, they require formal calibration. The calibration procedure is an important step in which the geometric characteristics of the user's eyes and the position properties of the working environment are estimated so the eye tracking can produce fully-customized and accurate gaze points. In a first step, the system needs to detect and localize the eyes. First, the position of the participant's face and head pose are captured. On that basis, the system identifies the eye areas and eyes, and allocates the pupil and the iris. One calibration point is used to detect a face, with the camera rotated correctly and the face in the center of the occupied zone. Another goal of this initial set-up check is to eliminate possible reflections and to establish a suitable environment (e.g., face illumination, backlight, video quality and ambient lighting). Concretely, participants are able to view their own face and locate it properly in an oval area indicated by the eye tracking algorithm.

Once their face is in the correct area, they have the correct posture, and environmental factors are deemed appropriate, the system determines parameter values that position the gaze on the monitor screen, permitting information from the image domain to be converted to the gaze

[5] We used a G*Power analysis (Faul et al., 2007) to determine our recruitment goal for the number of participants from Prolific and further considered that some participants would drop from the final sample due to calibration or technical issues (based on EyeSee's experience).

domain (Cristina & Camilleri, 2018). In the case of EyeSee, based on the nine calibration points displayed on the screen, mapping translates the iris and gaze angles of the participant to the screen coordinates (see Online Appendix A2, Figure 1). In particular, the participant first monitors the gradually appearing and disappearing individual red points and then the software processing of the calibration data takes place. After the calibration is done, it is tested and validated when the respondent identifies five other points on the screen (see Online Appendix A2, Figure 2). Based on the distance between the estimated gaze direction of the participant looking at the specific dot and the known position of the dot on the screen, the system decides whether the calibration was successful. If the distance calculated is too high, another calibration process is initiated up to a maximum of two times. If the calibration cannot be successfully validated in the second round either, the session is not considered valid.[6] The number of participants we had to remove due to calibration errors was not exceptional. In fact, it is common for eye tracking solutions to have a high percentage of the sample that is inappropriate for data analysis due to technical barriers (Semmelmann & Weigelt, 2018).

We further eliminated 23 respondents who did not answer the attention check correctly. We ended up with a sample of 515 participants, the majority of whom evaluated two campaigns, resulting in 915 usable data points. Of these respondents, 69% were male, and they were on

[6] Besides the initial calibration, the eye tracking process is constantly monitored during and after the session. First, *during* the session, the head pose as well as environmental conditions such as lighting are constantly monitored. In case of the detection of head movements or changes in the illumination conditions, the participant receives an error message and a request to correct them. In case of too much head movement or drastic changes in the light conditions that are not corrected after the error message display, a recalibration is performed. If the software detects suspicious patterns in gaze movement, an error message will be displayed, the algorithm is interrupted, and a recalibration will be performed. As an additional safeguard, a dummy stimulus in the form of a red dot can be included on the screen during the session, to probe whether it is observed by participants. Second, *after* the session, the algorithm automatically estimates the probability that the session was successful based on the registered environmental factors. Third, for respondents for which the algorithm's estimation does not offer a definite answer, a manual check is performed by eye-tracking specialists.

average 34 years old (SD = 12). Thus, our sample's demographics closely mirror those of equity crowdfunding investors, both in terms of gender (Bapna & Ganco, 2020) and age (Hervé et al., 2019).

As stimuli, we developed two fictional equity crowdfunding campaigns. To ensure the campaigns possessed psychological realism (Colquitt, 2008), we based the visuals and the presentation of each venture on a combination of real-life cases, changing all identifying details. The first campaigned involved a curated food delivery service with personalized menu proposals based on a matching algorithm. The second campaign portrayed a membership-based subscription for restaurant discounts that allows diners to pay less during more quiet periods and at the same time helps restaurants address underutilized capacity issues. We chose these two options because although the products were sufficiently novel to the market, advanced knowledge was not required to assess their investment potential.

The campaigns contained information typically included in an equity crowdfunding campaign.[7] Specifically, they included nine areas of interest (AOIs): the features of the product/ service, details about the founding team, characteristics of the target market, information about previous investors, the company's forecasted financial data, details about the strategy, equity campaign dynamics, equity campaign characteristics, and critique by potential backers (i.e., comments). In order to ensure that the campaigns appeared as close to reality as possible, we used both text and images to describe these features. All information provided in the campaigns could be grouped under one of the nine above-mentioned, predefined general AOIs. The information signals under each AOI (or sub-AOIs) was grouped together independently of the website tab it

7 See, for example, the UK platform Seedrs: https://www.seedrs.com/investment-opportunities.

was located on. For example, sub-AOIs referring to “the product” that can be found on the home page, the market page, and other pages (see Figure 1).

[Insert Figure 1 here]

Before the start of the session, participants were given an explanation of the investment task at hand and were clearly informed that their eye movement information would be collected. Thereafter, respondents were required to download an application that granted control of their screen. The application blocks the screen of the respondent and the whole session is done in the maximum window size, with no possibility of scrolling through the window or changing window size. Thereby, the screen location of a given page element and AOI is fixed and known. Downloading the application and stimuli locally on the respondents’ devices avoided issues of Internet latency or bandwidth. Thereafter, each participant went through the aforementioned calibration procedure.

After successful calibration, participants were directed to the online crowdfunding project webpage and the eye tracking session started. The developed platform simulated a real equity crowdfunding platform in which participants could see the campaign in a webpage format and navigate between the various page tabs (see Figure 1). An eye tracking algorithm was integrated with this simulated equity crowdfunding platform, collecting participants’ eye movement data (see Figure 2 for an example of an exploratory heat map). The participants watched the two campaigns consecutively in random order. After the first campaign, participants were asked about their intentions to back the project and their previous experience in the industry of the venture presented. We also included a question aimed at detecting inattention and satisficing response behavior. Next, the process was repeated for the second campaign. As a last step, participants were required to enter their demographic information and background experience regarding their general and specific human capital.

[Insert Figure 2 here]

## Measures

### *Dependent variables*

In eye tracking studies, the attention respondents pay to AOIs constitutes a fundamental unit of analysis (Holmqvist et al., 2011). AOIs are regions of a displayed stimulus that include all information belonging to an object, while eye gazes to other objects are excluded (Holmqvist et al., 2011). Eye tracking technology uses the position of an eye gaze (the center of the gaze at a particular point in time) to infer what individuals are paying attention to at any specific moment. We constructed several measures related to signal set formation, namely *signal set size, time taken to form a signal set,* and *relative composition of the signal set*. To measure signal set size, we counted how many of the nine different campaign AOIs participants gave visual attention during the investment task. We measured the time taken to form a signal set as the total time spent by a participant on looking at all AOIs of each campaign. We then used the natural log of this measure. As a measure of relative composition, for each of the AOIs, we computed a relative measure of dwell time on the respective AOI as related to the total time participants spent looking at all AOIs of the campaign (i.e., what proportion of the total time was spent on each of the AOIs over the trial). Dwell time is a typical eye-tracking measure (Duchowski, 2017; Holmqvist et al., 2011).

### *Independent variables*

To account for general human capital, we followed previous research and gathered participants' *post-secondary education* level by asking them whether they had acquired a tertiary education degree (Bachelor, Master, or higher) or not (coded as a dummy) (Colombo & Grilli, 2005). We also measured *entrepreneurial experience* (Dimov & Shepherd, 2005) by asking participants to indicate whether they had personally (co-)founded any new ventures before (zero for no, one for yes).

Specific human capital was measured by respondents' *previous equity crowdfunding experience* through asking them whether they had ever invested in any equity crowdfunding campaigns (zero for none, one for existing experience). We also measured *previous industry-specific experience* by asking participants to indicate whether they had any previous work experience in the industry of the venture the equity crowdfunding campaign of which they had just evaluated (zero for none, one for existing experience).

***Controls***

Because prior research has suggested that sustained attention abilities and informational needs may change with age (Korniotis & Kumar, 2011), we controlled for respondents' *age* (in years at the time of data collection). Furthermore, since gender has an effect on information processing regarding investments, we added *gender* as a control (zero for male and one for female). To ensure that the results were not influenced by differences between the two campaigns presented, we controlled for the *campaign* (coded one and two). Moreover, to account for order effects and the fact that attentional processes are likely affected by mental fatigue, we controlled for whether the campaign was the *first* one being *evaluated* (one indicating it was, zero indicating it was the second). Lastly, since the perceived desirability of an investment might influence information processing, we accounted for participants' *willingness to invest* in the equity crowdfunding campaign. This was captured by asking participants about the probability that they would invest in the deal (on a scale from one [low] to seven [high]) (e.g., Murnieks et al., 2016).

## Results

Means, correlations, and standard deviations for the variables are presented in Table 1. Importantly, correlations between our measures of general and specific human capital are insignificant or low.

[Insert Table 1 here]

Table 2 provides the results for signal set size and time taken to form a signal set, whereas Table 3 presents the results for signal set composition.

[Insert Table 2 here]

To test hypotheses H1a and H2a regarding the effect of general and specific human capital, respectively on the signal set size, we ran a Poisson regression, which takes into account that our dependent variable is a count measure. As can be seen in Table 2 (Model 1), the coefficient for post-secondary education is positive and significant ($\beta$=0.086, p =.025), and the coefficient for entrepreneurial experience is positive and marginally significant ($\beta$=0.080, p = .095), indicating that equity crowdfunders with more general human capital form larger signal sets than those with less general human capital. Thus, our results support Hypothesis 1a. Furthermore, the coefficient for equity crowdfunding experience is negative and statistically significant ($\beta$=-0.173, p=.002), and the coefficient for industry-specific experience is negative and marginally significant ($\beta$= -0.088, p=.098), lending support for Hypothesis 2a: equity crowdfunders with specific human capital form smaller signal sets than those without specific human capital.

We then tested hypotheses H1b and H2b regarding the effect of general and specific human capital, respectively, on the time taken to form a signal set. For this purpose, we ran a Tobit regression, which takes into account that our dependent variable can only take positive values. As presented in Table 2, Model 2, the coefficients for post-secondary education and entrepreneurial experience are both positive and significant (post-secondary education: $\beta$=0.158, p=.040; entrepreneurial experience: $\beta$=0.209, p=.030), indicating that equity crowdfunders with more general human capital will take more time to form a signal set than those with less general human capital. Thus, Hypothesis 1b is supported. Regarding Hypothesis 2b, the coefficient for equity crowdfunding experience is negative and statistically significant ($\beta$=-0.439, p=.000), and the coefficient for industry-specific experience is negative and marginally significant ($\beta$=-0.191, p=.061). These findings support Hypothesis 2b, indicating that equity crowdfunders with specific human capital will take less time to form a signal set than those with no specific human capital.

Next, we ran nine Tobit regressions to better understand the effects of human capital on the relative composition of investors' signal sets. Tobit regressions are appropriate because our dependent variable is bounded between zero (no visual attention to a particular AOI) and one (100% of time attended to a particular AOI). For each of the nine AOIs presented in the campaign, we examined whether differences in human capital influence the percentage of total campaign evaluation time participants spent on that particular AOI. The results are displayed in Table 3.

[Insert Table 3 here]

Regarding the influence of general human capital, the results show that participants with post-secondary education spent a larger amount of time during campaign evaluation paying attention to aspects regarding the team ($\beta$=0.060, p=.033), market ($\beta$=0.049, p=.064), investors (β=0.021, p=.098), and strategy (β=0.020, p=.095) than those with no post-secondary education. Similarly, participants with previous entrepreneurial experience spent more time investigating information regarding the team (β=0.109, p=.001), investors (β=0.026, p=.082), and strategy (β=0.027, p=.064) but less time on product information (β=-0.046, p=.012), than those with no previous entrepreneurial experience. Thus, Hypothesis 1c was supported.

Regarding the effect of specific human capital, the results show that participants with equity crowdfunding experience spent a smaller share of time on aspects referring to the team (β=-0.103, p=.015) investors (β=-0.041, p=.029), financials (β=-0.152, p=.005), and strategy (β=-0.051, p=.004) and a bigger share of their time on product information (β=0.038, p=.071) than those with no equity crowdfunding experience. Similarly, participants with previous industry-specific experience spent less of their total time on market (β=-0.078, p=.032) and financials (β=-0.089, p=.057) than those with no previous industry-specific experience. These results support Hypothesis 2c.

## Discussion

This study contributes to the limited theoretical and empirical understanding of how different investors attend to different observable signals. Drawing on a cognitive perspective, we theorized on how investors' general and specific human capital influences their signal set formation. We focused on the equity crowdfunding context in which investors operate in an information-rich environment (e.g., Mahmood et al., 2019) and signaling has been a prominent theoretical lens to explain campaign success (e.g., Ahlers et al., 2015; Vismara, 2016). Using an eye tracking study, we find evidence consistent with our hypotheses.

### Theoretical Contributions

Our study highlights that even observable signals are not always attended to, a hitherto traditional assumption made in signaling theory (Bergh et al., 2014; Drover et al., 2018). Certainly, previous research has highlighted that signal receivers differ in manners that determine how they react to signals and thus that signal effectiveness differs across audiences (Scheaf et al., 2018). Vanacker and Forbes (2016), for example, revealed that employees and financiers respond differently to firms' reputation-related signals. However, these differences can be explained by two underlying cognitive processes that have often remained unobservable, namely differences in individuals' attention to and/or interpretation of these signals (e.g., Drover et al., 2018; Plummer et al., 2016; Vanacker et al., 2020). Our study is one of the first to provide *explicit* evidence regarding the information signals people attend to, and more importantly adds new knowledge regarding how signal set formation differs across receivers. Consistent with Drover and colleagues' (2018) call, it is essential to open the "black box" of signaling by studying one of its central cognitive components, signal attention, to further increase our understanding of signaling effectiveness.

We extend cognitively-inspired theories of signaling by detailing new, relevant ways in which a specific group of signal receivers – prospective crowd investors – differ (i.e., in their human capital) and by showing the number of signals and which signals they pay attention to. By shedding light on how general and specific human capital influences investors' attention to signals and their signal set formation, we advance the field's understanding of receiver signal set formation in a multi-signal context. Our evidence highlights that investors with different levels of human capital differ significantly in the breadth (i.e., the number of signals) and depth (i.e., amount of time they attend to specific signals) of their signal sets when looking at the same funding campaign. By doing so, we contribute to the limited research on how crowdfunders work (e.g., McKenny et al., 2017; Stevenson et al., 2019; Vismara, 2018; Zafar et al.,2021). We provide novel evidence regarding how prospective equity crowdfunders actually *view* crowdfunding campaigns. For example, our evidence shows that equity crowdfunders on average only view four signals (out of the nine distinct signals in the campaign). They place particular focus on product-related signals, campaign dynamics (including the amount already raised and the number of investors that have committed) and campaign characteristics (including equity offered and target funding). The significant attention to product-related signals is relevant, as this has received limited attention in the equity crowdfunding literature. Similarly, while previous studies focused extensively on entrepreneurs' human capital as a signal, the relative amount of time the average crowdfunder spends focusing on team-related characteristics is surprisingly low (although investors with general human capital attend more to team data). Our findings suggest that the results of studies that focus on human capital may be driven by a specific subset of crowdfunders.

**Methodological Contributions: the Biological-based Approach in Entrepreneurship Research and Eye Tracking**

Our study contributes to expanding the nascent line of research on biological and psychophysiological perspectives in entrepreneurship (e.g., Nicolaou et al., 2021). Psychophysiological measurement is relatively new to entrepreneurship research. See, for example, Shane, Drover, Clingingsmith, and Cerf (2020) for a recent example of a functional magnetic resonance imaging (fMRI) study and several studies deriving psychophysiological measures from entrepreneurs' facial expressions (e.g., Jiang et al., 2019; Stroe et al., 2020; Warnick et al., 2021). Given that the eye is the only "visible part of the brain" (Janisse, 1977), eye tracking can serve as another type of such psychophysiological measurement that has gathered wide interest as a promising non-survey-based source of behavioral data, and a marker of arousal, cognitive effort, and attention (Meissner & Oll, 2019). Moreover, by drawing on a cognitive view of signaling theory and with the help of eye tracking, this study answers the call of Nicolaou et al. (2021, p. 10), "to marry the traditional economic, sociological, and psychological factors with their biological perspective in entrepreneurship models."

Our study expands entrepreneurship scholars' standard methodological tool kit by proposing eye tracking as a novel way to examine constructs that are otherwise difficult to reliably report or observe, such as investors' attention processes. Few studies in organizational and entrepreneurship research have adopted this method thus far, despite its clear promise (Du et al., 2019; Meissner & Oll, 2019). Our study reveals its use for building a more in-depth cognitive view of signaling, and eye tracking can also provide a powerful method to examine other psychological constructs such as emotional arousal and cognitive load. As such, its potential applications may extend beyond signaling to inform entrepreneurship scholars interested in learning or training, or information search and decision making in contexts other than equity crowdfunding.

Moreover, our study is the first to apply remote webcam-based eye tracking technology in organizational research. Previous eye tracking studies in business research (including Du et al., 2019) have predominantly been conducted in the lab using desktop-based or mobile systems (Meissner & Oll, 2019). Only two studies were conducted in non-lab settings, both relying on glasses to track eye movements (Meissner & Oll, 2019). Leveraging recent technological advances, we were able to run an eye tracking study online, thereby enabling us to test our hypotheses on a substantially larger and more relevant sample of individuals (i.e., those with investment experience). This not only increases the external validity of our results, it broadens the method's potential for application (i.e., moving beyond a specialized eye tracking lab).

## Limitations and Additional Avenues for Future Research

This study has some limitations that could open avenues for future research. First, our eye tracking method allowed us to focus on signal attention, but it raises some concerns about the ecological validity of our research. While our design ensures sufficient procedural representativeness (Grégoire et al., 2019), we acknowledge that it does not completely rule out other biases (e.g., actor-observer bias) that may affect the observed outcomes. Future studies that use different research designs can further validate our results.

Further, one may wonder whether individuals would behave differently when they have different financial incentives when investing on platforms. However, it is unclear whether the introduction of a monetary incentive could lead to a better or more realistic implementation of eye tracking. Indeed, research suggests that the presence of a financial incentive improves performance in memory- and recall-related tasks and in dull tasks for which intrinsic motivation may be low (such as coding words) (Camerer & Hogarth, 1999). In other tasks, incentives can hinder performance, for example, by causing anxiety and making people self-conscious. In most cases, however, the presence or absence of a financial incentive does not affect mean performance.

Second, our focus on human capital suggests that other characteristics of crowdfunders such as gender (Bapna & Ganco, 2020; Cumming et al., 2021b), cognitive style (analytical versus intuitive) (Allison & Hayes, 1996), or social perception skills (Baron & Markman, 2003) may influence signal set formation. Crowdfunders may also build different signal sets depending on the fundraiser's characteristics (e.g., when the fundraiser is passionate about their business idea (Davis et al., 2017). This research question is consistent with the findings of Allison, Davis, Webb, and Short (2017), who document that issue-relevant information, such as entrepreneurs' education, matters most when crowdfunders possess greater ability and motivation to make careful evaluations.

Third, we have explicitly focused on signal attention, the first cognitive aspect of effective signaling (Drover et al., 2018). While we provide a more nuanced perspective regarding how prospective crowdfunders view campaigns, we have not examined the second cognitive aspect of effective signaling, namely signal interpretation. More insights are needed regarding how investors interpret complex signal sets. Moreover, our findings do not suggest that more or less extensive signal sets lead to better or worse investment decisions. For example, some investors may make better decisions based on fewer pieces of information. Ultimately, future work will need to link signal set formation (and signal set interpretation) to actual investment outcomes.

Finally, while the use of remote webcam-based eye tracking is novel and promising for future research, its novelty also entails certain limitations. While there is a growing field literature on newly developed machine learning algorithms underlying improved webcam-based eye tracking technologies, explicit tests comparing their accuracy and validity to more traditionally used lab equipment, for instance, are still rare. Factors such as differences in head movements, illumination conditions, and webcam resolution – which may vary across participants in non-lab settings – may affect the accuracy of the technology. However, the Eyesee calibration procedures used both prior to and during the test do take this into account. While we would welcome more research in this area, Semmelmann and Weigelt (2018) provide reassurance regarding the applicability of this technology, given the design of our study. It is also clear that the use of webcam-based eye tracking tools is not yet advisable in studies that require high gaze resolution (i.e., dissection of singular items in a crowded display), or focus on very sensitive information (high spatio-temporal resolution, e.g., rapid and continuous recognition of faces embedded in pictures with complex scenes) (Cristina & Camilleri, 2018; Semmelmann & Weigelt, 2018).

**Practical Implications**

Our study has important implications for entrepreneurs, equity crowdfunding platforms, equity crowdfunders, and policymakers. Our findings suggest the importance that entrepreneurs and equity crowdfunding platforms carefully design campaign webpages, especially home pages, as many prospective crowdfunders limit their attention to informational signals on the home page. Moreover, our study also provides entrepreneurs with insights into the factors investors with different human capital attend to when evaluating their campaigns.

Our findings should raise awareness that equity crowdfunders may be ignoring many important informational signals when considering equity crowdfunding campaigns. These concerns are especially acute for people with limited general human capital and people with more specific human capital. For example, the fact that some individuals focus less on financial data in campaigns shows that they may be unintentionally investing in risky firms that may lack internal funds or debt capacity, be tied to riskier banks, or lack access to other forms of equity (e.g., Blaseg et al., 2021; Walthoff-Borm et al., 2018).

Our findings also have important implications for policymakers in their attempts to protect crowdfunders against losing their money on a risky – or worse – fraudulent start-up (Hornuf & Schwienbacher, 2017). In response, policymakers have pointed out the necessity for firms to provide additional information in crowdfunding campaigns (see, for example, the 2018 European

Commission proposal for a regulation on European crowdfunding services providers (European Commission, 2018)). Our study highlights the need to reconsider this approach, since prospective investors ignore many informational signals available in crowdfunding campaigns.

**Conclusion**

While signaling theory usually assumes that attention is always given to observable signals, we explicitly examined how different investors create different signal sets. Adopting a cognitive perspective and using state-of-the-art online eye tracking technology, we find that prospective crowdfunders with more general human capital (i.e., higher overall education levels and/or general entrepreneurial experience) construct broader signal sets, take more time to form signal sets, and construct signal sets with a different relative composition than their counterparts with less general human capital. Conversely, prospective crowdfunders with more specific human capital (i.e., equity crowdfunding experience and/or industry-specific experience) construct narrower signal sets, take less time to form signal sets, and construct signal sets with a different relative composition than their counterparts with less specific human capital. Overall, signal attention—even to *observable* signals—should not be taken for granted, and there is significant variability in signal set formation across prospective equity crowdfunders. We hope that this study will foster more research using eye tracking method to further increase our theoretical understanding of the hitherto difficult-to-capture cognitive processes that underly entrepreneurship and entrepreneurial finance.

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**Figure 1: Homepage of the campaign, containing different AOIs such as Campaign dynamics, Product characteristics, Previous investors**

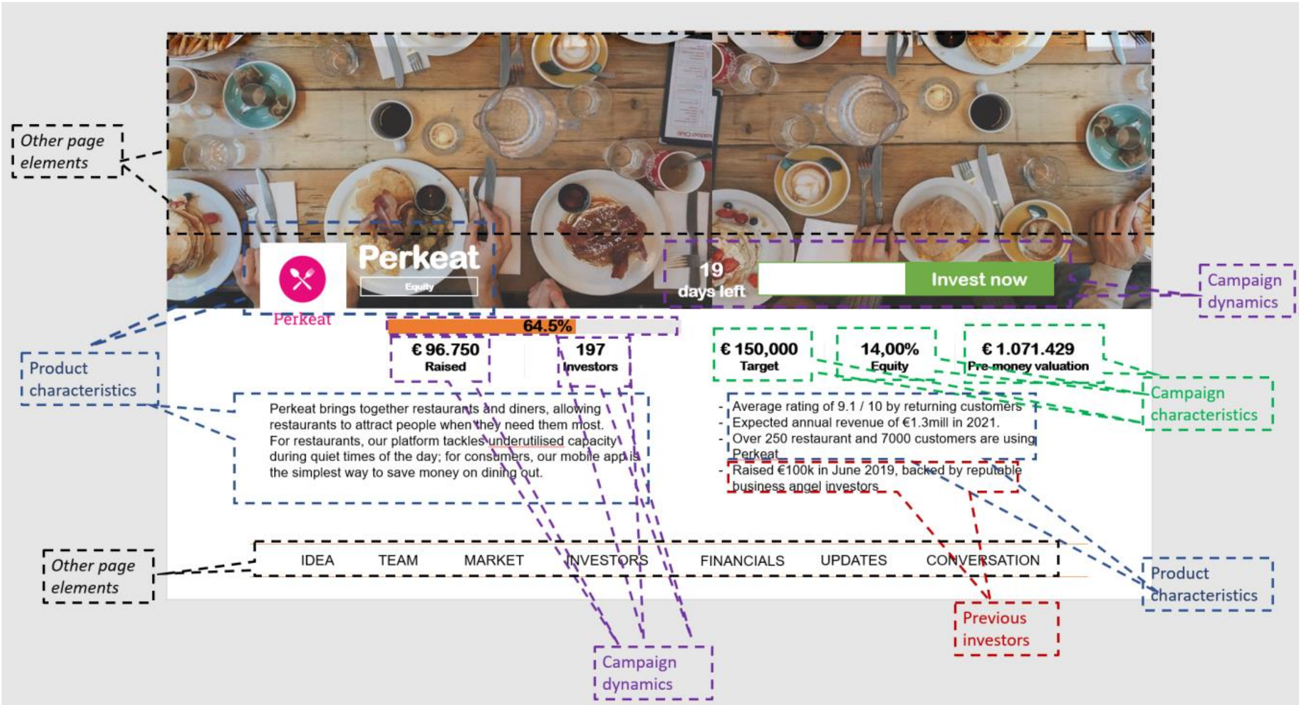


**Figure 2. Illustration of a heat map for one of the campaigns' tabs**

## Table 1: Descriptive Statistics and Correlation

| | Variables | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | Signal set size | 3.97 | 1.99 | – | | | | | | | | | | | | | | | | | | | |
| **2** | Time taken to form signal set (ln) | 3.34 | 0.96 | .79*** | – | | | | | | | | | | | | | | | | | | |
| **3** | Relative time spent Product AOI | 0.60 | 0.18 | –.54*** | –.42*** | – | | | | | | | | | | | | | | | | | |
| **4** | Relative time spent Team AOI | 0.02 | 0.07 | .51*** | .40*** | –.38*** | – | | | | | | | | | | | | | | | | |
| **5** | Relative time spent Market AOI | 0.04 | 0.08 | .57*** | .46*** | –.48*** | .29*** | – | | | | | | | | | | | | | | | |
| **6** | Relative time spent Investors AOI | 0.01 | 0.04 | .45*** | .30*** | –.35*** | .29*** | .25*** | – | | | | | | | | | | | | | | |
| **7** | Relative time spent Financials AOI | 0.03 | 0.09 | .43*** | .30*** | –.43*** | .14*** | .19*** | .27*** | – | | | | | | | | | | | | | |
| **8** | Relative time spent Strategy AOI | 0.02 | 0.04 | .65*** | .60*** | –.29*** | .29*** | .52*** | .27*** | .26*** | – | | | | | | | | | | | | |
| **9** | Relative time spent Camp Dyn AOI | 0.17 | 0.13 | –.42*** | –.32*** | –.21*** | –.29*** | –.39*** | –.29*** | –.31*** | –.45*** | – | | | | | | | | | | | |
| **10** | Relative time spent Camp Ch AOI | 0.09 | 0.09 | –.32*** | –.24*** | –.11** | –.25*** | –.33*** | –.24*** | –.28*** | –.40*** | .29*** | – | | | | | | | | | | |
| **11** | Relative time spent Critique AOI | 0.01 | 0.04 | .35*** | .25*** | –.31*** | .08*** | .39*** | .17*** | .14*** | .16*** | –.22*** | –.21*** | – | | | | | | | | | |
| **12** | Post-secondary education | 0.77 | 0.42 | .04 | .05 | –.01 | .03 | .04 | .00 | –.01 | .03 | –.01 | –.02 | .01 | – | | | | | | | | |
| **13** | Entrepreneurial experience | 0.14 | 0.34 | .02 | .06 | –.08* | .11* | .02 | .00 | –.03 | .03 | .05 | –.01 | .03 | .02 | – | | | | | | | |
| **14** | Equity crowdfunding experience | 0.10 | 0.30 | –.08* | –.12** | .04 | –.05 | –.00 | –.02 | –.07* | –.08* | .05 | .00 | –.02 | .07* | .14* | – | | | | | | |
| **15** | Industry-specific experience | 0.12 | 0.32 | –.04 | –.05 | .01 | –.01 | –.05 | –.03 | –.04 | .01 | .05 | .03 | –.02 | .04 | .15* | .06 | – | | | | | |
| **16** | Age | 34.27 | 11.7 | –.09** | .01 | .01 | –.05 | –.08* | –.13*** | –.02 | –.11*** | .09** | .11** | –.01 | .10* | –.16* | –.09** | –.06 | – | | | | |
| **17** | Gender | 0.31 | 0.46 | –.06 | –.03 | .03 | .02* | –.03 | –.08* | –.07* | –.05 | .04 | .02 | .01 | .04 | –.02 | –.04 | –.01 | .08* | – | | | |
| **18** | Campaign | 1.50 | 0.50 | .01 | –.01 | –.24*** | –.01 | –.01* | –.05 | –.04 | –.06 | .31*** | .12*** | .00 | .01 | –.01 | .00 | –.01 | .00 | –.01 | – | | |
| **19** | First evaluated | 0.50 | 0.50 | .01 | .10* | .00 | .01 | –.09* | –.04 | –.03 | –.06 | .08* | –.02 | –.01 | –.01 | .01 | –.03 | –.04 | .01 | –.01 | .20*** | – | |
| **20** | Willingness to invest | 4.68 | 1.64 | .09* | .09* | –.10** | .06 | –.05 | –.02 | –.03 | .05 | –.00 | .04 | .04 | .03 | .04 | .02 | .05 | –.08* | .03 | .05 | .01 | – |

Notes. N = 915

**Table 2: Results of Regression Analyses *Signal set size* and *Time taken to form a signal set***

| | Model 1 | Model 2 |
|---|---|---|
| **Dependent variable:** | **Signal set size** | **Time taken to form a signal set** |
| Post-secondary education | .09*(.04) | .16*(.08) |
| Entrepreneurial experience | .08†(.05) | .21*(.10) |
| Equity crowdfunding experience | –.17** (.06) | –.44***(.10) |
| Industry-specific experience | –.09†(.05) | –.19†(.10) |
| Age | –.01***(.01) | –.01(.00) |
| Gender | –.06†(.03) | –.07(.07) |
| Campaign | .01(.03) | –.06(.06) |
| First Evaluated | –.01(.03) | .18**(.06) |
| Willingness to invest | .03*(.01) | .05**(.02) |
| Constant | 1.38***(.09) | 3.07***(.17) |
| *Wald chi$^2$* | 39.63*** | / |
| *F-statistic* | / | 5.5*** |

**Table 3 Results of Regression Analyses Relative Compositions AOIs**

| **Dependent variable:** | **Product AOI** | **Team AOI** | **Market AOI** | **Investors AOI** | **Financials AOI** | **Strategy AOI** | **Camp Dyn AOI** | **Camp Ch AOI** | **Critique AOI** |
|---|---|---|---|---|---|---|---|---|---|
| Post-secondary educational | –.01 (.01) | .06*(.03) | .05†(.03) | .02†(.01) | .04(.03) | .02†(.01) | –.01(.01) | –.01(.01) | .03(.03) |
| Entrepreneurial experience | –.05*(.02) | .11**(.04) | .05(.03) | .03†(.02) | –.00(.04) | .03†(.01) | .01(.02) | –.01(.01) | .03(.03) |
| Equity crowdfunding experience | .04† (.02) | –.10*(.04) | –.05(.04) | –.04*(.02) | –.15**(.05) | –.05**(.02) | .02(.01) | .01(.01) | –.06(.04) |
| Industry-specific experience | .01(.02) | –.03(.03) | –.08*(.03) | –.03(.02) | –.09†(.05) | –.02(.02) | .02(.01) | .01(.01) | –.04(.04) |
| Age | .00(.00) | –.01***(.00) | –.01***(.00) | –.01***(.00) | –.01†(.00) | –.01***(.00) | .01**(.00) | .01***(.00) | –.01†(.00) |
| Gender | .01(.01) | –.01(.02) | –.04†(.02) | –.02†(.01) | –.08**(.03) | –.03*(.01) | .02(.01) | .00(.01) | –.01(.03) |
| Campaign | –.09***(.01) | –.02(.02) | –.02(.02) | –.01(.01) | .00(.02) | –.01(.01) | .09***(.01) | .03***(.01) | –.01(.02) |
| First Evaluated | .02†(.01) | –.01(.02) | –.02(.02) | –.00(.01) | –.00(.02) | –.01(.01) | .01(.01) | –.01(.01) | –.02(.02) |
| Willingness to invest | –.01**(.00) | .01(.01) | .01*(.01) | –.01(.03) | –.02*(.01) | .01†(.00) | –.00(.00) | .00(.00) | .01(.01) |
| Constant | .77***(.03) | –.16*(.07) | –.09(.06) | –.01(.03) | –.26***(.07) | –.01(.03) | –.01(.03) | –.00(.02) | –.20*(.07) |
| *F-statistics* | 8.34*** | 2.68** | 3.74*** | 3.45*** | 3.43*** | 4.42*** | 12.87*** | 3.92*** | 1.45 |

Notes. All models represent Tobit regressions (because the dependent variables are bounded between 0 and 1). N = 915 in all models. † ≤ .10, *$p$ ≤ .05, **$p$ ≤ .01, ***$p$ < .001 (two-tailed tests). Robust standard errors are in parentheses.