**AI Versus Human Intelligence in Marketing**

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The growing influence of data and technology is one of the defining trends of modern society. One major element of this trend, the use of artificial intelligence, has the potential to be one of the most transformative innovations in society today. Artificial intelligence (AI) is an area of computer science that focuses on development of technology which can “collect, process, and act on data in ways that simulates human intelligence” (Canhoto & Clear, 2020). A closely related concept is called machine learning. This concept is commonly thought of as a higher level of AI (Jarek & Mazurek, 2019; Canhoto & Clear, 2020). As opposed to using predefined algorithms, machine learning technology allows computers to take in data and establish links between individual pieces of that data. Thus, computers can “learn” by themselves (Jarek & Mazurek, 2019).

Artificial intelligence and machine learning technologies are already being implemented in business practices in many ways. For example, chatbots that provide customer support are often automated (Jarek & Mazurek, 2019). There is one conception of AI in business that is generally favorable. A world where a computerized system could sense when you run out of toilet paper, and automatically ship you more, sounds convenient. However, there are also potential negative implications of increased use of AI. For example, one study done by Bloomberg revealed that use of AI technology resulted in same day delivery not being offered to a disproportionate number of low income communities, whose residents were predominantly African American. This application resulted in what was essentially redlining, administered through the use of an algorithm (Dow Jones & Company, 2019).

Already, consumers have displayed mixed emotions about the use of these technologies. One study showed that 55% of consumers claim to have used AI before in some form. However, in the same study, 42% of respondents claim that they do not trust the technology (Dujmovic, 2017). Despite how consumers may feel, AI is gaining traction for marketing, as availability of big data increases, and it begins to lower costs of operations. For example, Amazon uses drones for deliveries, and Redballoon uses AI to reach new customers (Huang & Rust, 2020). The purpose of this paper is to understand the extent that AI and ML technologies replicate the more subjective aspects of human processing to replace or augment marketing tasks. And furthermore, to understand what implications this has for the uses of AI in marketing

**Literature review**

 In Huang and Rust’s 2018 paper on intelligence in service, they propose a 4 intelligence model, where they categorize human intelligence and artificial intelligence into four categories, consistent with service tasks. These four intelligences are mechanical, analytical, intuitive, and empathetic. Mechanical intelligence refers to the ability to perform routine tasks that do not take a great deal of skill or thought. These tasks only require minimal levels of task automation for AI and can mostly be programmed via more basic algorithms. The second level of intelligence is analytical intelligence. The key tenet of analytical intelligence is the ability to problem solve. AI in this intelligence will be able to learn and adapt using data. Still under this intelligence, tasks should be systematic and consistent. This kind of processing is characteristic of the direction of networked machines. The first two intelligences are the two types that are commonly seen and accepted in many areas of practice today (Huang & Rust 2018).

The last two types of intelligences, empathetic and intuitive, are more advanced than the first two. The authors argue that these two developments occur later in the evolution of AI. Intuitive intelligence requires the ability to react to unfamiliar situations and think creatively. These are the kinds of skills that marketing managers employ in their jobs. A key distinction here is understanding rather than synthesizing information. Empathetic intelligence refers to the ability to understand and respond to emotions. This includes skills such as cultural sensitivity and leadership. These skills, the authors argue, are characteristic of individuals such as psychologists and politicians (Huang & Rust 2018).

Within their paper, the authors also posit their theory of job replacement. This is an attempt to categorize and predict the way that AI will impact human labor. The authors make a distinction between jobs, tasks, and labor activities. They define jobs as the collection of tasks that an employee does. This can be thought of in the traditional way we see job titles. Tasks are the activities one does within their job. Labor is the act of employees and customers co-producing service. The authors argue that there are many cases where AI will outperform human intelligence. The main drivers for this are AI’s self learning and connectivity characteristics. In conjunction, machine learning capabilities having access to mass amounts of shared information allow it to make fewer mistakes than human actors would. Ultimately, the authors argue that there is a world in which AI will advance to not only expand to every intelligence, but that this could also lead to total job replacement. To combat this, they recommend that AI automation remain at the task level (Huang & Rust 2018).

The most important aspect of this framework is the 4 intelligence model, because it provides a framework for understanding the aspects of intelligence to evaluate how well AI performs against human intelligence in that aspect (Huang & Rust 2018). The research on the progression of AI intelligence is varied. Certain studies provide support for Huang and Rust’s theory by demonstrating and elaborating on the varying intelligence levels of AI. Furthermore, they also demonstrate different levels of integration in different contexts.

One survey of AI applications by Jarek and Mazurek (2019) revealed that AI has already been implemented in a wide variety of marketing activities. This survey analyzes AI uses in terms of marketing mix theory, which focuses less on intelligence levels, but rather on business objectives for AI to address. In particular, the authors argue that use of AI is advantageous for consumers as well as marketing management. The study indicates that AI is being applied in areas such as, voice recognition, text recognition, autonomous vehicles, and more. The kinds of applications from the survey indicate that the majority of the automation remains at what Huang and Rust refer to as the ‘task level’. On the job level, this has not yet resulted in job replacement, rather the authors indicate that it simply reduces time spent on laborious tasks and creates a bigger emphasis on creative and strategic parts of the job. The tone of the article is overall optimistic about the progression of AI usage (Jarek & Mazurek 2019).

Despite Huang and Rust’s assertion that the higher levels of intelligence may not be fully developed in AI yet, there is research to show that automation is moving in that direction. Moerland, Broekens & Broekens published a survey on emotion reinforcement in the machine learning context (Moerland, Broekens & Broekens, 2018). The article posits that there are underlying dimensions of emotion in humans, and there are parallel dimensions that can be implemented for robot learning technologies. The article draws on theories of human emotion. They argue that emotions can be a result of extrinsic motivation or intrinsic motivation, or via a value and reward system. Extrinsic motivation which comes from being in a state of homeostasis, or a relative equilibrium of physiological processes. This can be replicated in technology through inner resource status (for example achieving ideal power usage/battery percentage). Intrinsic motivation comes from appraisal, meaning personal relevance of information. Furthermore, another important finding of the study was that emotions are actually useful for the AI agent. Emotions aid AI in the efficiency of learning, human-robot dynamics, as well as emotion dynamics (Moerland, Broekens & Broekens, 2018). This supports Jarek and Mazurek’s (2019) argument that incorporating emotions follows the natural progression of AI. However, in Jarek and Mazurek’s article, they imply that empathetic intelligence is only useful for highly empathetic jobs, whereas Moerland, Broekens, and Broekens argue that emotion may actually be useful in any application (Huang & Rust, 2018; Moerland, Broekens & Broekens, 2018).

These applications show support for aspects of Huang and Rust’s theories, however none conclusively prove that these theories are accurate. While there is some support for certain features, like the continued development toward emotional capabilities, (Moerland, Broekens and Broekens, 2018), these cases are at a very undeveloped level and the actual higher level intelligence that they describe is not present in business applications (Moerland, Broekens and Broekens, 2018; Jarek & Mazurek 2019).

 There are a number of studies that have demonstrated the shortcomings of AI in business decisions as well. Through a series of three case studies on businesses in the financial service industry, Lee and Shin (2020) studied and compared different machine learning algorithm frameworks in practice. The study demonstrated the fact that there can be certain limitations when implementing machine learning strategies for business decisions. This study uses a framework of four categories of machine learning. Supervised machine learning which uses data sets that are already labeled and are assigned desired outputs. Unsupervised learning is used for finding connections between individual data points and grouping data without previously assigned labels. Semi-supervised learning: a multiple stage process where some labeled data is used with a machine learning technology to label the rest. Reinforcement learning uses rewards to train machine learning algorithms on desired functions (Lee & Shin, 2020).

The key finding of this study was that, although there are many benefits to incorporating AI and machine learning into business activities, selecting the best AI and ML algorithms for the task at hand can be challenging. Different algorithms produce different levels of accuracy, interpretability for customers, and different classifications of data. There are tradeoffs that have to be made when one feature is emphasized (Lee & Shin, 2020). This challenges Huang and Rust’s theory because they argue that under higher intelligences, the lower intelligences run smoothly and in conjunction with one another. This article proves that this may not be the case, and where certain aspects of intelligence may be maximized, this may mean other areas must be reduced accordingly (Lee & Shin, 2020).

While Lee and Shin (2020) argue that certain AI techniques can be used to maximize accuracy and accurate data classification, other scholars might argue that even when maximizing for data accuracy, this does not resolve issues of bias in data outcomes. In a 2021 content analysis on a nonprofit organization’s algorithm training dataset, Köchling et al. revealed that sometimes, algorithms can exacerbate biases in data. In this study, datasets used for hiring activities contained biases in the form of gender and ethic representation. It looked at both a predictive model, akin to standard AI, and two machine learning algorithms. The key finding of the study was that the predictive model and both of the machine learning algorithms they studied replicated the biases from the training data. Not only this, but these biases from training data tended to actually be exacerbated in the predictive results even when there was balanced representation of gender and ethnic groups in the analyzed data. In the context of Huang and Rust’s theory, this has serious implications. First, if usage of AI and ML technologies does become as widespread as they claim, then existing biases, which surely exist in much of the available online data, will be exacerbated. This could be detrimental to organizations and particularly for minority groups. It also makes the case for why more of the higher-level intelligences that they speak about might be important. If these algorithms had more of the cultural sensitivity that is characteristic of empathetic intelligence, there may be opportunities for algorithms to self-correct (Huang & Rust, 2018).

Another 2021 study, by Nichifor, Trifan, and Nechifor, also challenges the supremacy of AI in business decisions. Through a content analysis of chat bot conversations from ten online stores in Romania, this study revealed that in a number of cases, use of AI in the form of chatbots resulted in lower customer satisfaction. Responses were evaluated in terms of response time and the quality of information delivered via the chatbot. When users realized that they were interacting with a bot, it negatively affected their perceptions and purchase decisions. However, when responses were more personalized, customer experiences improved. This paper brings about an interesting concept because it demonstrates a barrier that Huang and Rust may not have considered, consumer resistance to AI, even on the task level. Customer pushback was, in part, because they did not feel that a chatbot could fully understand and appreciate the uniqueness of their situations the way a human could. As previously discussed, Huang and Rust assert that the lower levels of intelligence do not necessarily need the same understanding of emotional dynamics as higher intelligences. However, this article asserts that for some tasks, like answering a simple question via a chatbot (i.e. synthesizing information), there are instances where human intelligence will still beat computer intelligence (Nichifor, Trifan, & Nechifor, 2021). This study points to a need for more humanization, even in lower levels of AI, and indicates that people want AI to act more humanly as well as humanely.

While Nichifor, Trifan, and Nechifor shed light on negative consumer responses to AI interactions for lack of personalization, Plane et al., (2017) elaborate on other potential reactions to bias in. AI Plane et al., (2017) published an article on user perceptions of discrimination as a result of algorithmic advertising. The authors performed a series of 3 surveys on a broad range of respondents sourced from Amazon’s Mechanical Turk site. These surveys displayed a range of different advertisement targeting scenarios and gauged respondent’s perceptions of the way the ads were targeted. The result indicated that respondents responded negatively both in scenarios where reductive and discriminatory ad targeting was a result of human targeting or algorithmic targeting. This indicates that hiding behind algorithms as an explanation for discriminatory advertising is not a valid excuse for consumers. In one area of the study, individuals from underrepresented socioeconomic groups reported feeling angry and betrayed when ads were reductive or discriminatory based solely on demographic features. This relates to In Huang and Rust’s 2018 work because it shows that harmful biases are one of the potential dangers of overestimating the intelligent ability of AI.

Woodruff et al., (2018) published a study on the perceptions of algorithm fairness and data bias. The authors held a series of focus groups with residents of the San Francisco bay area. Participants were asked a series of questions about algorithm unfairness and discrimination. The findings indicated black participants were three times more likely than white participants to consider the problems with discriminatory ad targeting as being more harmful and severe. There were several insights that are important to this paper. First, participants were aware of algorithm unfairness, and felt that these types of microaggressions were consistent with the types of microaggressions they witnessed in the offline world. However, consistent with Plane et al.’s (2017) study, participants indicated that they nonetheless expected companies to address and reduce these microaggressions regardless of how the bias came into the system. Secondly, participants were particularly concerned about the role that technology played in amplifying the issues of racism and discrimination. This goes beyond Plane et al.’s (2017) study and addresses the issue that results when biases as a result of limited intelligence AI are amplified.

Overall, the literature points to a growing trend in both the depth and the breadth of AI. Although its uses in marketing are generally somewhat limited by pushback and still developing technology, it is easy to see a world where it could increase rapidly. If marketers want to use AI in a way that is both beneficial for consumers and society, they would do best to investigate the limitations of AI’s emotional and cultural capabilities so that these things are not overlooked when use of this technology is scaled.

**Brand Application**

**Yelp: Current State**

Yelp is a crowdsourced review platform that helps connect people to a variety of businesses in their local area. Reviews consist of 1-5 star ratings, with the option to add descriptions and photos. Launched in 2004, the company was created by two former paypal employees, Russel Simmons, and Jeremy Stoppleman. The company started as what was essentially a huge email list, built locally, community by community. It grew quickly, and by 2010, it had amassed about $30 million in revenue. In 2009, Yelp engaged in negotiations with Google regarding a potential acquisition, but ultimately this deal did not go through and the company ended up going public in 2012 (Evans, 2019). Since its launch, the company has grown and evolved, establishing itself in countries across Europe and Asia, and expanding its services to offer things like reservations and delivery through partnerships. Currently, the platform covers establishments ranging from restaurants, bars, salons, gas stations, and more. The most commonly reviewed establishment type is restaurants (Team, 2019). Importantly, Yelp uses AI and ML algorithms to understand, sort, and recommend content from all kinds of businesses around the world (Evans, 2019; Yelp Investor Relations, 2020).

Yelp’s greatest strength is its market share. It is one of the biggest players in the industry. It is free to view and post reviews, and this low barrier to entry has allowed the website to amass a large number of users. The company reports having over 38 million mobile users and 91 million web visitors every month as well as over 200 million reviews on the website (Yelp Investor Relations, 2020). In addition, its low cost of operation has allowed the company to grow over the course of the years.

Yelp also has a few major weaknesses. First, the company has faced a number of external threats, including competitors like Facebook and google gaining traction. The company was involved in a lawsuit against Google in 2017, where they accused Google of scraping data from Yelp's website (Evans, 2019). Yelp must work hard to maintain a competitive edge, especially considering Google’s interest in self advertising its own review services over competitors. Furthermore, the company has also come under fire for its connection with discriminatory practices. Multiple studies have shown that yelp reviews have been linked to issues of gentrification and racial biases. One study found that more white predominant neighborhoods, restaurants were rated more positively using words like “cozy” and in predominantly black neighborhoods, reviews used words like ‘gritty’ and ‘dangerous’ (Zukin et. al, 2017). Additionally, Yelp’s predominant weakness is its reputation for unfair business practices, particularly with small businesses. On numerous occasions, Yelp has been accused of unfairly pressuring businesses to buy ads, with aggressive sales reps offering to move bad reviews down in exchange for ad purchases. These tactics have been compared to a mafia-style approach (Evans, 2019; Clark, 2013). Furthermore, when businesses have raised issues about these practices, Yelp has brought litigation to silence them (Clark, 2013). There is even a documentary called “Billion Dollar Bully” meant to expose yelp’s predatory business practices and mistreatment of small businesses. In these and other cases, issues of fake reviews on the site have been raised a number of times (Evans, 2019; Clark, 2013).

**Yelp: Marketing and AI**

Yelp is unique in that it serves 3 major customer segments. These 3 groups include: users, who view content, content contributors, who write reviews, and businesses, who are the subject of the reviews and can also buy advertisements from the site. Currently, Yelp has different value propositions and methods for marketing to its different customer segments. Users are targeted based on demographics, location, and budget profile. For users, the platform gives them a place to browse local businesses, with the ability to look at photos, read reviews, and learn about pricing and services. For contributors, yelp rewards them with special promotions account perks and gives them a place to interact with the community. For businesses, yelp is a platform that can increase visibility and revenue for their businesses. It is also a place for them to promote their businesses if they wish to purchase ads from Yelp. Over 90% of Yelp’s annual revenue comes from selling local ads, 96% in 2020 (Team, 2019).

Because Yelp is a multi-sided platform, they are tasked with trying to maintain the three different customer segments. In the early days, Yelp marketing focused on a grassroots approach to reward current reviewers and entice new members, rewarding the most active reviewers with open bar parties and events (Bowman, 2017). To this day, Yelp still throws parties for the “Yelp Elite Squad”, consisting of the members who post the highest frequency and quality of reviews (Harris, 2015).  As the company grew, they realized that they had to increase marketing efforts with the businesses themselves. One of the most iconic and recognizable methods they employed was the yelp sticker. These stickers have phrases like “people love us on Yelp” and are commonly displayed in establishments' windows (Bowman, 2017). The growth process is self reinforcing, as more customer reviews and higher viewership creates more demand for businesses to engage with the site, and businesses that encourage their customers to review their yelp also drives the process. Given that most of its revenue comes from local ads, marketing to businesses is arguably the most important job of the yelp marketing team.

Currently, Yelp uses AI in a few ways. In 2016, the company launched an AI powered algorithm to perform image analyses on user submitted photos, as well as to predict characteristics like “classy ambiance”.  The company also uses ML technology on its advertisement targeting, a decision that they claim aims to promote the most relevant ads to individuals based on users intentions and context on the platform. The two types of ML models are objective targeting and click through rate prediction (Dubey, 2020).

Despite Yelp’s success thus far, there are several steps that the company can implement to improve its position in the marketplace. The marketing objectives for these efforts are to increase sales and increase market share. Although Yelp is currently one of the biggest players in the online review space, competitors like Google and Facebook also provide popular and rapidly improving alternatives, thus Yelp still needs to focus on maintaining and growing market share. Furthermore, given Yelp’s massive presence, many businesses are aware of yelp, but improved marketing efforts could increase ad sales to these businesses that already exist in Yelp’s customer base. I propose that Yelp implement changes to work towards a more empathetic, human-centric AI.

As previously mentioned, the Yelp model uses AI and ML technologies to understand, sort, and recommend content. People have different expectations for what these algorithmic programs can and should do. We can organize our thoughts about this using four dimensions: These are AI’s ability to *think rationally* (ex: calculate best performing ads per demographic segment), *think humanly* (understand how certain prejudices may affect reviews), *act rationally* (ex: promote better performing businesses through the algorithm), and *act humanely* (factor socioeconomic considerations into marketing strategies). If we consider these concepts in terms of the 4 intelligences, the rational aspects rely more on the mechanical/analytical intelligence capabilities, however the human aspects rely more on the intuitive and empathetic intelligences.

So for example, AI that lacks empathetic intelligence may have a hard time understanding and addressing certain cultural differences between individuals or groups, thus making it harder for it to act humanely (remember the previously mentioned instance where minority communities are effectively redlined from amazon services as a result of data that is not considered from a cultural perspective). The job of businesses that use AI for marketing is to recognize AI’s limitations along these dimensions, and then use this information to supplement AI with the appropriate measures.

Why should Yelp specifically care about creating a more empathetic AI? There are several reasons. First, because of the wide reach that the site has, the outputs and implementations of its algorithms have massive implications. Some of the biggest companies in the world are using algorithmic systems like these. On the largest scale, companies that span across countries and continents touch millions of lives, and the effects of their business practices can shape and change the landscape of society. More and more, consumers expect companies to take social implications into account, and studies show that consumers respond negatively when they feel targeted ads are reductive or don’t consider cultural sensitivity (Woodruff et al., 2018; Plane et al., 2017). At the launch of their IPO, Stoppleman claimed “we want to be the Amazon of local” (Evans, 2019). The Amazon’s and Google’s of the world embrace a human-centric approach to these things (Robertson, 2019). Although their outcomes are not devoid of bias or harm, they recognize the importance of actively pursuing a more empathetic approach to AI and ML.

On a more practical level, given the fact that the vast majority of Yelp’s revenue comes from local advertisements, they should have a substantial interest in maintaining a good relationship with local businesses. Furthermore, Yelp’s reputation for fake reviews, and its connection with discrimination are damaging to the company’s reputation, and therefore brand equity. Building a marketing campaign around Yelp’s new and improved algorithmic structure would likely improve its reputation and increase ad sales.

**3 Pronged Approach**

I propose that yelp use a 3-pronged approach to working toward a more empathetic and human-centric AI. The first prong is the introduction of more multidisciplinary skills among the AI/ML team. One major problem that AI faces is that, in many cases, job descriptions and degrees do not emphasize an importance for soft skills or humanities focused backgrounds. Lee and Shin’s (2020) findings indicate that there are different frameworks for algorithmic learning, some of which emphasize more supervised or human-involved algorithm training and processing. Certain frameworks are better for maximizing different outcomes. If the important outcome at hand is to maximize sociocultural considerations, then building the framework around these considerations necessitates an understanding of the dynamics at hand. This is also important because research indicates that incorporating aspects of emotion leads to improved algorithmic processing not just at the highest level of algorithm performance, but on all levels (Moerland, Broekens & Broekens, 2018).

When looking into Yelp’s active AI/ML focused job postings, it is clear that this problem is present at Yelp. Typical of these roles, there is an emphasis on the technical programmatic skills and experience, but no requisite of an understanding of the social or cultural implications of the software. Here are some examples of some skills that could be added to job postings: “Consider a wide variety of sociological implications from training data, to implementation”, “experience with humanities or liberal arts such as sociology, social work, sustainability, etc, encouraged”. Skillset postings such as “a love for writing beautiful and maintainable code” could instead be changed to “a love for writing socially responsible and maintainable code”. These concepts could alternatively manifest themselves in a new position created that specifically calls for someone with a background in both AI and social impact to work closely with the engineers to continuously improve the Yelps algorithm’s empathetic and sociocultural considerations.

The second prong of this campaign is the introduction of toxicity ratings. Köchling et al, 2021 demonstrated the way that training data can not only ingrain biases in a ML algorithm, but can also multiply these biases through implementation. Inclusion of racist or biased reviews can lead to harmful biases in training data can lead to harmful associations and, thus, implementations. This can be seen in the previously mentioned occurrences of associating certain communities with certain types of language (Zukin et. al, 2017). Although Yelp does ban overtly racist posters, the smaller microaggressions are more subtle, thus harder to address.  Especially now, in the wake of Covid 19, racism and prejudice have become even more prevalent. Using a program like Jigsaw’s toxicity rating system could move prejudiced comments toward the bottom of the list of reviews and leave the neutral ones toward the top. These kinds of rating systems use machine learning to recognize what words tend to be associated with toxic comments. Toxic comments can include phrases such as “these types of people” or alluding to other racist sentiments. Neutral negative comments could describe portion sizes or bland flavoring. In the past, Yelp has responded to issues surrounding its comment sorting strategy by standing by the claim that the algorithm is responsible for recommending or flagging comments. It is important that yelp addresses these issues because as Plane et al., 2017, and Woodruff et al., 2018 note, consumers have negative reactions to bias regardless of whether the source of the bias is human or algorithmic. Therefore, hiding behind the algorithm excuse is not enough to satisfy customers on this issue.

The third prong of this plan is to address data representativeness. Another way that bias can appear in ML is not having training data that is representative of the population. 61 percent of yelp reviewers are college graduates and 20% have graduate degrees, meaning that only 19% of the reviews are left by those with less than college education. Furthermore, almost half of users make over 100k a year (Yelp Investor Relations, 2020). Although yelp does not specifically ask for all this data in its user accounts, proxies such as zip code can be taken into account. This dataset disproportionately represents a certain group of people. To correct for this, reviews from underrepresented populations could be weighted to represent general population demographics.

To address the issue of representativeness, Yelp must get to the root of the problem. Nichifor, Trifan, and Nechifor (2021) demonstrate the fact that individuals have reservations about AI interactions when they do not feel that the algorithms sufficiently understand the uniqueness of their situations. To make more accurate and well thought out recommendations, ML programs need to have data on the preferences of all its users. Obtaining data from a particular segment and applying these rules to all segments can reproduce biases. To fix this, Yelp could also do outreach to encourage reviews in underrepresented communities. This could be in the form of Yelp pop-up events where local restaurants could distribute menus or samples. Although Yelp does do some events for its most loyal reviewers, there is not enough emphasis on reaching underrepresented communities. Gathering this data is not only good for these communities, but also better for Yelp in the long run because they will have more complete and accurate data on click through rates, and other information for ad targeting.

In conclusion, by understanding the limits of artificial intelligence, we can incorporate the aspects of cultural understanding and empathy that are unique to human intelligence. In this way, we reduce the harms and biases that can result from overestimating the neutrality and intelligent abilities of AI.

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